

Predicted Clinical Impact of Artificial Intelligence in
Radiology:
A Rapid Evidence Assessment

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**'It always seems impossible
until it is DONE"**

Nelson Mandela

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Thank you all for being there.

Abstract

This Rapid Evidence Assessment (REA) reviews the literature sources related to the predicted clinical impact of Artificial Intelligence (AI) in radiology. It examines AI's potential across five critical areas: diagnostic accuracy and early detection, treatment monitoring, workflow efficiency, patient safety, and the challenges faced by radiologists. By synthesizing evidence from peer-reviewed studies and incorporating insights from an expert panel, the REA provides a comprehensive evaluation of AI's transformative capabilities and the practical considerations required for its implementation. The findings indicate that AI has the potential to significantly enhance radiology practice by improving imaging precision, enabling earlier disease detection, automating repetitive tasks, and personalizing treatment monitoring. These advancements address pressing challenges such as growing workloads, resource constraints, and radiologist burnout. However, the evidence base remains limited, as much of the research relies on retrospective studies or expert opinion, restricting generalizability. Challenges such as automation bias, ethical concerns, and interoperability issues are also identified, highlighting the need for cautious and deliberate integration of AI into clinical practice. Based on these findings, the REA recommends high-quality, multi-centre, prospective studies to validate AI's applications and address current evidence gaps. It emphasizes the need for targeted training for radiologists to integrate AI effectively while maintaining their central role in patient care. Transparent and explainable AI systems are deemed essential to build trust and accountability, and a stepwise, scalable approach to AI implementation is suggested to align with clinical workflows and healthcare operations. The assessment concludes that

while AI holds significant promise in transforming radiology, its clinical impact depends on evidence-driven implementation, ethical oversight, and strategic integration, ensuring that radiologists remain pivotal in leveraging AI to enhance accuracy, efficiency, and patient-centred care.

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Chapter 1 – Introduction

1.1 Introduction

This opening section establishes a comprehensive foundation that contextualizes the entire dissertation and outlines the relevance of this Rapid Evidence Assessment (REA) from multiple perspectives. Given its multifaceted background and relevance, this REA holds significance on various fronts.

First, understanding the unique context of the Maltese healthcare system is essential. With a single major public hospital serving the entire population, Malta faces distinct challenges in resource allocation, access to diagnostic services, and scalability of innovative solutions such as Artificial Intelligence (AI) (Malta AI Taskforce, 2019). AI could provide transformative opportunities for Malta by enabling scalable, high-impact solutions, even within a small-scale system. By examining this context, the REA allows decision-makers to consider how AI implementation in healthcare might be adapted to meet the specific needs of a smaller, centralized health system (Camilleri, 2023).

A second focus of this review is how AI can support decision-making in medical imaging, with implications for reducing defensive medicine. Defensive medicine, driven by fear of litigation or other self-protective motives such as patient dissatisfaction and concerns over diagnostic errors, is associated with increased healthcare costs and adverse patient outcomes (Baungard et al., 2022). This practice often involves unnecessary tests or procedures aimed at mitigating liability risks rather than improving patient care (Chen & Asch, 2017). By enhancing diagnostic accuracy and providing clearer, data-driven insights, AI has the potential to reduce the uncertainties that underlie defensive behaviours in radiology. Studies suggest that AI's

predictive capabilities can alleviate fears of missed diagnoses—a significant driver of defensive actions—by offering radiologists greater confidence in their evaluations (Ranschaert et al., 2019; Baungaard et al., 2022). This reduction in unnecessary procedures not only lowers healthcare costs but also fosters improved patient care quality, aligning clinical decision-making with evidence-based practices and strengthening the trust inherent in the physician-patient relationship.

Third, patient safety emerges as a critical component of the REA. The concept of patient safety extends beyond simply preventing medical errors to encompass wide-ranging implications for healthcare professionals, patients, and their families. AI technologies have the potential to significantly enhance patient safety by improving diagnostic accuracy, reducing human error, and promoting more consistent decision-making processes (Topol, 2019). Research suggests that AI's integration into diagnostic processes could not only strengthen the quality of care but also help alleviate the burden on healthcare professionals (Jiang et al., 2017). Understanding the impact of AI on patient safety is, therefore, a central focus of this assessment.

1.1.1 The Maltese Healthcare System

The Maltese healthcare system is primarily public and tax-funded, designed to ensure that all residents have access to essential health services. Under the National Health Systems Strategy 2023-2030, Malta emphasizes quality, equity, and personalized care, seeking to deliver timely healthcare that adapts to each patient's needs. The government's vision is to promote health and well-being across the population,

focusing on prevention, early disease detection, and effective management of chronic conditions (Ministry for Health, Malta, 2022).

The healthcare structure in Malta includes a network of primary and secondary facilities designed to meet the needs of communities across the islands. The focal point is Mater Dei Hospital, a modern acute care facility on the main island that provides specialized and emergency services across a broad range of departments. In Gozo, the Gozo General Hospital caters to local residents, ensuring that essential services are accessible on the sister island. This is supported by several health centres distributed throughout Malta and Gozo, which deliver community-based services, such as general practice, maternal and child health, and chronic disease management. Rehabilitation services are provided by Karin Grech Rehabilitation Hospital, which offers specialized care to help patients regain independence and quality of life after serious health events (Ministry for Health and Active Ageing, Malta, 2024).

The Maltese healthcare system is structured around collaborative efforts to address social determinants of health and reduce healthcare inequalities. Multi-sectoral policies promote accessibility, health literacy, and patient empowerment to address disparities, particularly among vulnerable groups, including migrants and individuals from lower socio-economic backgrounds. By partnering with governmental and non-governmental organizations, Malta aims to foster public health and reduce disparities in healthcare access (Ministry for Health, Malta, 2022).

Ensuring a sustainable health workforce is a key priority, with a focus on recruiting, training, and retaining health professionals to meet Malta's growing needs. Amid

workforce shortages in critical areas like nursing and primary care, Malta's strategy includes measures to build resilience among healthcare workers and to improve their work environment. Efforts to modernize healthcare training are ongoing, including initiatives to attract foreign expertise and manage the diverse needs of an increasingly multicultural workforce (Ministry for Health, Malta, 2022).

While public health advancements have contributed to an increased life expectancy, Malta faces a rising incidence of chronic diseases, such as diabetes, obesity, and hypertension. To address this, the healthcare system emphasizes prevention programs, primary care improvements, and national screening initiatives, aiming to reduce these diseases and promote healthier lifestyles. However, high obesity rates and certain health behaviours indicate a continued need for health education and lifestyle interventions to support a healthier population (Ministry for Health and Active Ageing, Malta, 2024)

Sustainability is also central to Malta's healthcare financing strategy, particularly as healthcare demands grow. Investment is needed not only to meet existing needs but also to ensure the system remains resilient and responsive to new medical advances. To this end, Malta is exploring innovative funding approaches, including partnerships and potentially ring-fenced taxes for preventive healthcare programs, alongside measures to streamline spending and improve efficiency (Ministry for Health, Malta, 2022).

The COVID-19 pandemic tested the resilience of Malta's healthcare system, underscoring the importance of preparedness and adaptability. The response included expanding intensive care capacity and implementing telemedicine, both of which are now integral to Malta's healthcare strategy. Lessons learned from the pandemic have shaped future plans,

emphasizing the importance of flexibility, digital health integration, and emergency preparedness to support a modern, resilient healthcare system that meets the evolving needs of the Maltese population.

1.1.2. Local Radiology Background

Radiology services are a cornerstone of Malta's national healthcare system, providing essential diagnostic and therapeutic imaging across public facilities. As the gateway to accurate diagnoses and informed medical decisions, radiology directly influences the quality and timeliness of patient care. Imaging services not only facilitate the detection and monitoring of diseases but also guide treatment plans, allowing healthcare providers to deliver more precise and effective interventions (Mater Dei Hospital, Medical Imaging Department, 2024).

In Malta, radiology services are strategically distributed to enhance accessibility. X-ray facilities are available at multiple locations, including Mater Dei Hospital, Gozo General Hospital, all health centres, Karin Grech Rehabilitation Hospital, and the newly established imaging unit at St. Vincent de Paul (SVP) long-term care facility. These facilities handle both urgent and elective imaging requests, performing around 50,000 X-rays annually to support varied clinical needs, from emergency trauma assessment to routine screenings.

Advanced imaging services, however, are more centralized. MRI and CT scans are conducted exclusively at Mater Dei and Gozo General, with annual volumes exceeding 50,000 scans. PET-CT, a specialized imaging modality used for cancer staging and

monitoring, is offered solely at Mater Dei. Symptomatic mammography services are centralized at Mater Dei, while routine breast screenings occur at the Breast Screening Unit in Floriana, accounting for over 20,000 mammograms each year. Ultrasound services, available both for emergencies and elective cases, are offered at Mater Dei and Gozo General, with additional elective ultrasound services at SVP (Mater Dei Hospital, Medical Imaging Department, 2024).

To meet growing demands, the Ministry of Health has initiated expansions, including increased CT and MRI capacity at SVP's diagnostic unit. Yet, despite these investments, the structure of Malta's radiology services faces mounting pressure. Radiology departments worldwide are contending with surges in imaging requests, and Malta is no exception. Currently, Malta's radiology department handles approximately 40,000 MRIs, 50,000 CT scans, 50,000 X-rays, and 20,000 mammograms each year—a workload that has grown by 10% over the past year and is projected to increase by an additional 5% annually for the next five years. Without strategic intervention, this demand trajectory could overextend the department's capacity, risking delays in diagnosis and potential compromise of patient care quality (Mater Dei Hospital, Medical Imaging Department, 2024).

A dedicated team of 20 consultant radiologists, 16 resident specialists, and 18 radiologists in training, supported by around 160 full-time equivalent radiographers, staff the Radiology Department. They provide a comprehensive array of imaging services, including X-ray, MRI, CT, bone density scans, ultrasound, mammography, interventional radiology, and PET-CT imaging. However, staffing levels are not keeping pace with the rising demand for services, creating risks of burnout among radiology professionals and possibly impacting diagnostic accuracy and timeliness.

In the context of this Rapid Evidence Assessment (REA), understanding the pressures on radiology services is vital. The role of radiology extends beyond imaging; it supports clinical decision-making across disciplines, contributes to efficient healthcare delivery, and directly impacts patient outcomes. Therefore, addressing the challenges facing radiology services, particularly through potential solutions like Artificial Intelligence (AI), is essential. AI could improve workflow efficiency, enhance diagnostic accuracy, and ultimately ensure that radiology continues to support high-quality patient care amid increasing demand. This REA focuses on AI as a promising avenue to meet these challenges, with the aim of informing policy decisions that strengthen Malta's healthcare system's capacity to deliver timely, accurate, and equitable care.

1.1.3 Why Change Is Needed

The Maltese radiology system, like many globally, faces a critical challenge in balancing increasing demand with a limited workforce. The current system lacks the scalability to handle rising patient volumes, complex cases, and workload without risking a decline in performance, efficiency, or quality. As evidenced in Malta's radiology department, the surge in imaging requests has not been matched by an increase in radiologists, creating a gap that echoes trends seen in other healthcare systems. For instance, the Canadian Association of Radiologists has reported similar issues in Canada, where insufficient staffing has intensified burnout levels among radiologists, who struggle to keep up with escalating workloads (Cao et al., 2023). Maltese radiologists are likely to encounter similar pressures, heightening their risk of burnout, which can impair their ability to work both effectively and safely.

An urgent reason for change is the growing concern over efficiency and burnout within radiology departments. Radiologists cannot sustain the current workload indefinitely,

as emotional exhaustion, depersonalization, and a sense of reduced personal accomplishment contribute to burnout, a phenomenon increasingly recognized worldwide. Burned-out radiologists are at a greater risk of diagnostic errors, which may result in delayed or missed diagnoses, thus compromising patient safety. If the system continues to depend heavily on human effort without integrating technological solutions like AI to improve efficiency, these challenges will likely intensify.

In Canada, for example, radiologists have been overwhelmed by the rising demand for imaging, leading to stress and burnout (Cao et al., 2023). The Maltese healthcare system is on a similar trajectory; without the adoption of innovative tools like AI, it risks declining diagnostic quality, delays in patient care, and an inability to meet its service commitments.

1.2 Background: Artificial Intelligence in Healthcare

Artificial Intelligence (AI) has significantly transformed healthcare, evolving from its conceptual beginnings in the mid-20th century to becoming a crucial tool in modern medical practice. AI's foundations were laid in the 1950s when Alan Turing introduced the "Turing Test," a method for evaluating whether a machine could exhibit human-like intelligence (Kaul et al., 2020). Shortly after, John McCarthy coined the term "artificial intelligence" in 1956, defining it as the science of creating machines capable of performing tasks that require human intelligence (Kaul et al., 2020).

In its early stages, AI systems were simplistic, relying on rule-based logic, often referred to as "if-then" statements. However, these systems struggled to gain traction in the medical field due to technical limitations and scepticism regarding their reliability. It wasn't until the 1970s that AI made its first significant foray into healthcare with expert systems like MYCIN, which helped diagnose bacterial infections and suggest treatment (Kaul et al., 2020). Although MYCIN was a success, broader adoption of AI in healthcare was stunted by the "AI winter," a period in the 1980s and 1990s marked by a decline in interest and funding due to the underwhelming performance of early AI technologies.

The resurgence of AI in healthcare began in the 2000s, driven by advancements in machine learning (ML) and deep learning (DL). These technologies enabled the development of systems that could process and analyse vast amounts of data, far

surpassing the capabilities of earlier rule-based systems (Cadario et al., 2021; Kaul et al., 2020). For example, convolutional neural networks (CNNs) were designed to mimic the human brain's pattern recognition abilities and are now used in medical imaging for detecting abnormalities such as cancerous lesions (Cadario et al., 2021; Kaul et al., 2020).

In the last two decades, AI has expanded its role in medicine, especially in diagnostic accuracy, treatment monitoring, and personalized care. The rise of telemedicine and AI-driven diagnostic tools during the COVID-19 pandemic, for instance, demonstrated AI's scalability and cost-effectiveness in handling healthcare crisis. However, challenges remain. A critical issue is the perception of AI as a "black box"—an opaque system whose decision-making processes are difficult to understand, even for experts. This lack of transparency contributes to patient scepticism and reluctance to adopt AI-driven healthcare solutions (Cadario et al., 2021).

Despite these challenges, AI's potential is undeniable. Its ability to enhance diagnostic accuracy, streamline healthcare delivery, and offer personalized treatment continues to grow. With ongoing advancements and efforts to improve transparency, AI is poised to become an integral part of global healthcare systems, offering scalable, expert-level care to patients worldwide (Cadario et al., 2021; Kaul et al., 2020).

Figure 1: Hierarchical Relationship Between AI, ML, ANN, and DL (Du et al., 2019)

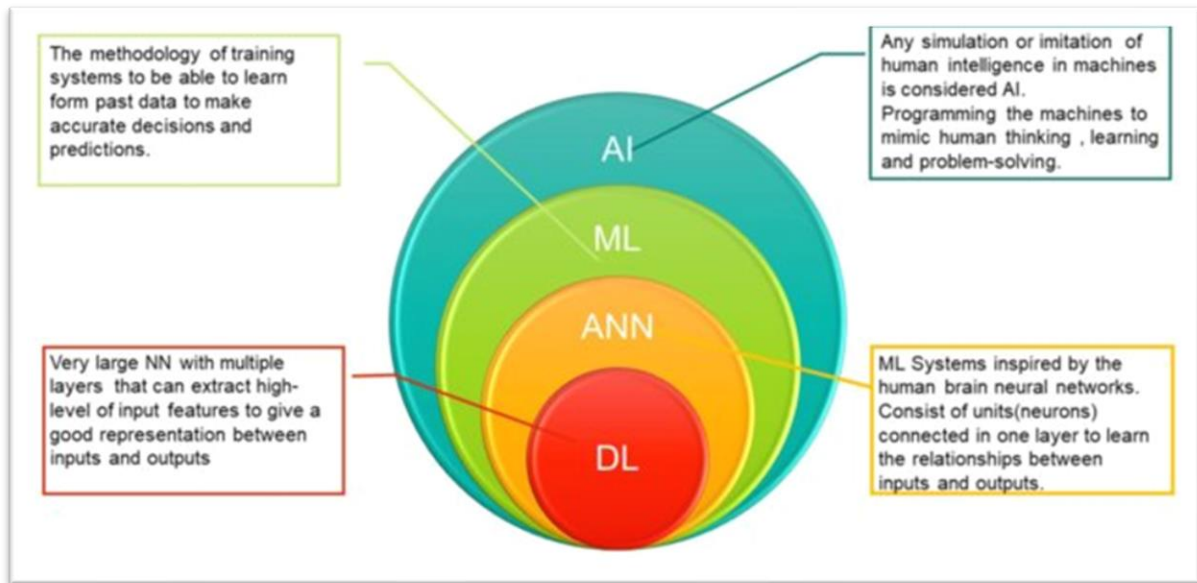


Figure 1 illustrates the hierarchical relationship between Artificial Intelligence (AI), Machine Learning (ML), Artificial Neural Networks (ANN), and Deep Learning (DL), showing the nested structure and conceptual distinctions among them. AI, at the outermost layer, represents any simulation or imitation of human intelligence in machines, encompassing activities such as problem-solving, learning, and decision-making. Within the field of medicine, AI is utilized for tasks like diagnostics, treatment planning, and patient management, aiming to enhance clinical outcomes by complementing human expertise.

Machine Learning (ML), a subset of AI, is defined by its ability to learn from historical data and improve decision-making without being explicitly programmed for each task. ML is widely applied in healthcare for predictive analytics, risk assessment, and pattern recognition in medical imaging. The emphasis of this REA on AI is due to its broad potential in transforming radiology, but ML serves as a critical component for building specialized applications within this broader framework.

Artificial Neural Networks (ANNs), which fall within the ML domain, are inspired by the human brain's structure, consisting of interconnected units or "neurons" that work together to model relationships between inputs and outputs. ANNs are particularly effective in recognizing complex patterns in large datasets, making them useful in medical imaging to identify abnormalities in X-rays, CT scans, and MRI data.

Deep Learning (DL), a specific subset of ANNs, employs very large neural networks with multiple layers to learn complex representations of data. This multi-layered approach allows DL to handle highly intricate data patterns, making it especially powerful for analysing detailed medical images and enabling tasks like detecting minute lesions or classifying tumours with high accuracy.

Each layer within this hierarchy builds on the capabilities of the previous one, enabling increasingly sophisticated analysis and predictive power. By focusing on AI in this REA, this work seeks to explore not only how these technologies individually impact radiology but also how they collectively advance the field by improving diagnostic accuracy, workflow efficiency, and patient outcomes.

1.3 Why Radiology is Ideal for AI Integration

Radiology stands at the forefront of AI adoption in healthcare, offering unique characteristics that align seamlessly with the capabilities of advanced AI technologies. These characteristics define the intersection between radiology and AI, illustrating why this field is so well-suited to technological integration. Firstly, radiology inherently relies on imaging data, producing high volumes of detailed visual information that require analysis and interpretation. This abundance of data creates an optimal environment for AI, particularly deep learning algorithms, which excel at recognizing complex patterns within large datasets. The need for precise pattern recognition in radiology—critical for diagnosing conditions ranging from fractures to complex cancers—further enhances the synergy between AI capabilities and radiology’s requirements.

The potential for AI to manage high data volumes and identify subtle patterns has positioned radiology as a leader in AI integration. In fact, over 80% of FDA-approved AI platforms in healthcare are designed specifically for radiology applications, reflecting the strong alignment between the needs of the field and AI’s strengths. Globally, AI-based solutions in radiology represent 38% of all available AI platforms, underscoring radiology’s pivotal role in driving AI innovation in healthcare (Najjar, 2023).

By addressing radiology’s high demand for data processing, pattern recognition, and diagnostic precision, AI presents solutions that not only improve efficiency but also enhance diagnostic accuracy and speed. These characteristics underscore why radiology is not just compatible with AI but is in many ways an ideal domain for AI-driven advancements.

1.3.1 Image-Based Data

Radiology's heavy reliance on structured, image-based data makes it particularly well-suited for the integration of artificial intelligence (AI) and deep learning techniques. Diagnostic imaging modalities, including X-rays, CT scans, MRIs, and mammograms, generate highly structured visual data that is consistent in format and dense in diagnostic information. This structured nature of radiology data aligns seamlessly with the capabilities of deep learning algorithms, particularly convolutional neural networks (CNNs), which excel at processing, analysing, and extracting complex features from visual data (Yasaka & Abe, 2018).

AI systems trained on these datasets can identify specific anatomical structures, detect anomalies, and even distinguish between healthy and pathological tissues. This ability to automate pattern recognition enables AI to provide radiologists with highly accurate diagnostic support, often detecting subtle changes or patterns that might otherwise be challenging to identify consistently (Najjar, 2023). For example, deep learning models have shown considerable effectiveness in identifying abnormalities in chest radiographs and MRI, achieving diagnostic accuracy comparable to that of experienced radiologists (Yasaka & Abe, 2018).

As AI continues to learn from vast, diverse datasets annotated by radiology experts, it enhances its ability to interpret images with increasing precision. This continuous learning process allows AI to deepen its analytical capacity, augmenting traditional diagnostic techniques with a level of detail and consistency that can be challenging to maintain through manual interpretation alone (Kooch-Moghadam & Bae, 2023). In high-

demand settings, AI-driven analysis can streamline workflows, improving diagnostic turnaround times and contributing to a more efficient allocation of radiology resources.

Figure 2. Comparison of Biological and Computer Neural Networks in Image Recognition

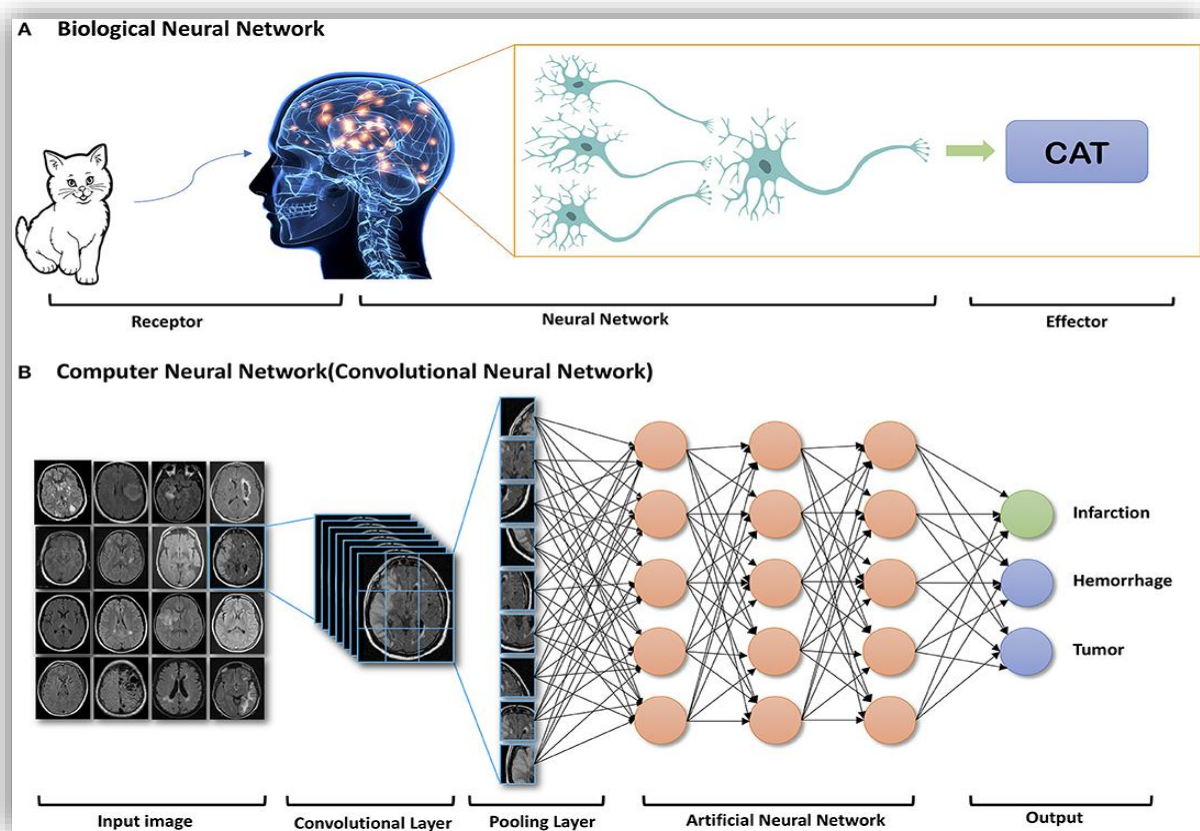


Figure 2 illustrates the comparison between biological neural networks (A) and computer neural networks, specifically a Convolutional Neural Network (CNN), used in medical imaging analysis (B). In the biological model, the brain processes visual input through interconnected neurons to recognize objects, such as a cat. Similarly, in a CNN, diagnostic images, such as brain scans, pass through multiple layers. The

initial input layer receives the images, which are processed through convolutional and pooling layers to extract features. These features are then interpreted by an artificial neural network layer, ultimately classifying the images into diagnostic categories like infarction, haemorrhage, or tumour. This layered architecture enables CNNs to handle highly structured, image-based data, making them ideal for analysing complex patterns in medical imaging and assisting in accurate, efficient diagnoses (Zhu et al., 2019).

1.3.2 Large Data Sets

Radiology departments generate vast amounts of imaging data daily, offering extensive datasets that are ideal for training artificial intelligence (AI) algorithms. The range and variety of imaging modalities—such as X-rays, CT scans, and MRIs—encompass numerous clinical scenarios, creating comprehensive datasets that enhance model accuracy and reliability over time (Najjar, 2023). This continuous influx of data provides AI systems with diverse cases, allowing them to refine their pattern recognition and diagnostic consistency, which is particularly valuable in identifying subtle or complex disease markers (Katal, York, & Gholamrezanezhad, 2024).

A critical component of training effective AI models in radiology is the availability of annotated images labelled meticulously by expert radiologists. These labelled datasets serve as benchmarks, enabling AI to learn from seasoned diagnostic patterns and apply this knowledge to new cases. Annotated data provides AI systems with the foundational ability to recognize and interpret complex imaging patterns, enhancing their potential to detect early-stage diseases, which might otherwise elude human observation (Najjar, 2023). Moreover, as these systems process diverse datasets, they

adapt and improve their diagnostic accuracy, enabling more reliable and consistent disease detection across varied patient populations (Katal et al., 2024).

As AI algorithms evolve through exposure to high-quality, annotated datasets, they mitigate the impact of human error in diagnostic processes, facilitating more standardized interpretations. This capability is especially beneficial in high-stakes fields like oncology, where early and precise detection of abnormalities—such as small malignancies or subtle anatomical changes—can be crucial for effective treatment outcomes (Najjar, 2023; Katal et al., 2024). Thus, the robust data generated in radiology not only bolsters AI training but also supports advancements in diagnostic accuracy and clinical decision-making.

1.3.3 Pattern Recognition

Radiology fundamentally relies on the ability to identify and interpret patterns within imaging data, a task that involves complex cognitive processes. Radiologists often use a combination of intuitive judgments (type 1 processing) and analytical reasoning (type 2 processing) when interpreting images, enabling them to detect abnormalities and diagnose diseases (Lee et al., 2013). AI, particularly machine learning and deep learning algorithms, emulates these cognitive processes. However, it operates at a far faster pace and with greater scalability, providing a substantial advantage in identifying patterns in large datasets that may otherwise go unnoticed (Hui et al., 2024).

One advantage of AI in radiology is its capability to analyse vast amounts of annotated data and identify subtle anomalies, such as microcalcifications in mammograms or small nodules in CT scans, which can be challenging for human observers, especially in high-volume settings (Lee et al., 2013). This ability to consistently detect minute variations enhances diagnostic accuracy, particularly in the early detection of diseases like cancer. By emulating the human brain's pattern recognition skills, AI not only aids radiologists by offering a secondary reference but also reduces the cognitive burden associated with high-stakes diagnostic decisions (Hui et al., 2024).

Moreover, integrating AI in radiology has the potential to enhance radiology training by helping future radiologists become proficient in identifying critical patterns. Through AI-assisted learning platforms, trainees gain exposure to a broader range of diagnostic scenarios than they might encounter in traditional settings, effectively bridging gaps in learning and honing their diagnostic skills (Hui et al., 2024). This reinforcement of pattern recognition capabilities in both clinical and educational settings underscores AI's transformative potential in radiology.

1.3.4 Efficiency and Productivity

AI's role in enhancing efficiency and productivity in radiology is transformative, particularly in its potential to automate repetitive, time-intensive tasks that traditionally burden radiologists. Tasks such as measuring anatomical structures, segmenting images, and triaging cases based on urgency are well-suited for AI automation. By efficiently handling these routine processes, AI streamlines workflows, enabling radiologists to focus on complex cases and interpretative tasks that require nuanced human expertise. This division of labour has far-reaching implications for radiology

departments, as it allows clinicians to allocate more time to diagnostic assessments and patient interaction, fostering a more patient-centred approach (Khalifa & Albadawy, 2024; Najjar, 2023).

Automation facilitated by AI not only reduces radiologists' workload but also directly addresses the rising demand for diagnostic imaging services, a trend noted worldwide. The ability of AI to process large volumes of images rapidly enables quicker turnaround times, improving patient throughput and reducing wait times for imaging results. This acceleration is particularly crucial in emergency settings, where prompt diagnosis can be life-saving (Khalifa & Albadawy, 2024). Moreover, AI-enhanced workflows mitigate the risk of human fatigue-related errors, ensuring a consistent quality of care and promoting radiologist well-being (Najjar, 2023).

Additionally, the integration of AI contributes to operational cost-effectiveness by optimizing resource utilization and minimizing the need for repeat scans, which can arise from human error. AI systems can accurately and consistently interpret images, potentially reducing misdiagnoses and enhancing diagnostic precision. This operational efficiency not only lowers healthcare costs but also helps radiology departments manage their resources effectively in the face of increasing demand, supporting a more sustainable healthcare model (Khalifa & Albadawy, 2024).

1.3.5 Consistency and Accuracy

AI technology provides radiology with the potential for consistent, reliable interpretations of imaging data, significantly reducing inter-observer and intra-observer variability. In clinical practice, different radiologists may interpret the same image in slightly different ways, leading to potential variability in diagnostic outcomes. This variability can be minimized by AI systems, which are trained on standardized datasets and thus can offer uniform interpretations across different cases. As Hui et al. (2024) observed, AI enhances diagnostic accuracy by reducing cognitive biases and fatigue that might otherwise influence radiologist performance.

AI also enhances diagnostic precision through its ability to recognize subtle patterns in complex imaging data, often surpassing human capabilities in identifying anomalies that might otherwise go unnoticed. For example, Pierre et al. (2023) discuss AI's proficiency in identifying critical findings, such as pulmonary embolisms or intracranial haemorrhages, thereby prioritizing cases that require urgent attention. This capability not only ensures more consistent diagnoses but also supports clinical prioritization by directing radiologists' focus to cases with potentially life-threatening conditions.

By providing standardized interpretations, AI enables radiologists to formulate more accurate treatment plans and make evidence-based decisions, contributing to improved patient outcomes. The use of AI as a support tool for pattern recognition and consistency is thus invaluable in radiology, where the demand for precision is paramount. Moreover, AI's standardized approach supports medical education by providing trainee radiologists with a consistent learning model, helping them develop accuracy and confidence in their diagnostic capabilities (Hui et al., 2024).

1.3.6 Decision Support and Continuous Learning

AI's dual role as a decision support tool and continuously learning system amplifies its transformative impact in radiology. As a Clinical Decision Support System (CDSS), AI provides radiologists with valuable insights and diagnostic suggestions, particularly in complex or ambiguous cases. By integrating various data inputs—such as patient history, imaging findings, and predictive analytics—AI-powered CDSS can offer tailored, case-specific advice, enhancing diagnostic confidence and guiding radiologists toward more informed clinical decisions (Najjar, 2023; Shaikh et al., 2021). This structured support is especially critical in high-stakes cases, where an additional layer of diagnostic assurance can improve outcomes by reducing uncertainty and promoting accuracy.

AI-based CDSS systems employ sophisticated machine learning (ML) models, such as support vector machines and decision trees, to analyse imaging data and identify critical abnormalities, such as cancerous lesions or pulmonary infections. Beyond traditional image analysis, these systems incorporate advanced radiomics features, including measurements of shape, texture, and intensity—details often challenging for the human eye to interpret with precision. By capturing and quantifying these complex patterns, AI not only aids in characterizing diseases but also enhances the prognostic accuracy of imaging studies, allowing radiologists to better predict patient outcomes and tailor treatment plans accordingly (Najjar, 2023; Shaikh et al., 2021).

A distinctive strength of AI in radiology is its ability to learn continuously, adapting to new data and refining its diagnostic capabilities over time. With radiology departments generating extensive imaging data daily, AI systems have a vast resource to support

this ongoing learning process. Each new dataset provides an opportunity for AI to assimilate the latest clinical insights, keep up with evolving diagnostic techniques, and enhance its predictive accuracy. This adaptability is particularly valuable in a field as dynamic as radiology, where technological advancements and shifting clinical guidelines require tools that can remain effective and current. By evolving alongside medical knowledge, AI systems can continue to support radiologists in delivering accurate, up-to-date diagnoses, making them indispensable allies in modern radiology (Hui, Sacoransky, Chung, & Kwan, 2024).

1.3.7 Integration with Electronic Health Records (EHRs)

AI's potential to integrate seamlessly with Electronic Health Records (EHRs) adds an additional dimension to its utility in radiology. By synthesizing radiological findings with patient history, lab results, and other relevant data stored in EHRs, AI provides a holistic view of the patient's health status. This integrated approach facilitates more personalized care by giving radiologists and other clinicians a comprehensive understanding of the patient's overall health, aiding in risk stratification, diagnosis, and treatment planning. This capability makes AI an essential asset in precision medicine initiatives, where treatments are tailored to the individual patient based on a full spectrum of health data (Hui, Sacoransky, Chung, & Kwan, 2024).

1.3.8 Leading Role in AI Adoption

Radiology has emerged as a leading field in the adoption of artificial intelligence (AI) across healthcare due to its unique alignment with AI's strengths and capabilities. Diagnostic imaging inherently relies on structured visual data, making it exceptionally compatible with AI and deep learning algorithms, which excel at analysing complex

image-based data (Mohseni et al., 2024). The digitization of medical imaging, coupled with AI's ability to improve diagnostic accuracy and streamline workflows, has fuelled a rapid increase in AI-based applications in radiology, accounting for a substantial portion of AI usage in healthcare (Buaka & Moid, 2024).

Currently, over 80% of FDA-approved AI platforms in healthcare are dedicated to radiology, underscoring the field's openness to technological advancements and its proactive stance on AI integration. Radiology also accounts for 38% of AI platforms available globally, reflecting a broader trend in which radiologists leverage AI to enhance diagnostic precision and manage increasing imaging demands (Najjar, 2023; Mohseni et al., 2024). For instance, AI-driven platforms are being utilized to analyse and interpret complex imaging data, such as MRI and CT scans, allowing for the automation of routine tasks and supporting radiologists in high-stakes cases (Buaka & Moid, 2024).

The mutual benefits of AI and radiology present a significant opportunity for continued transformation within radiology departments, where AI is becoming a strategic asset for meeting the growing demand for diagnostic services while upholding high standards of patient care. As AI evolves and its applications expand, radiology remains at the forefront, providing a model for other specialties to follow in adopting AI as a tool for enhanced clinical decision-making and improved healthcare outcomes (Mohseni et al., 2024; Buaka & Moid, 2024).

Chapter 2: Research Approach and Methodology

2.1 REA approach compared to Other research methodologies

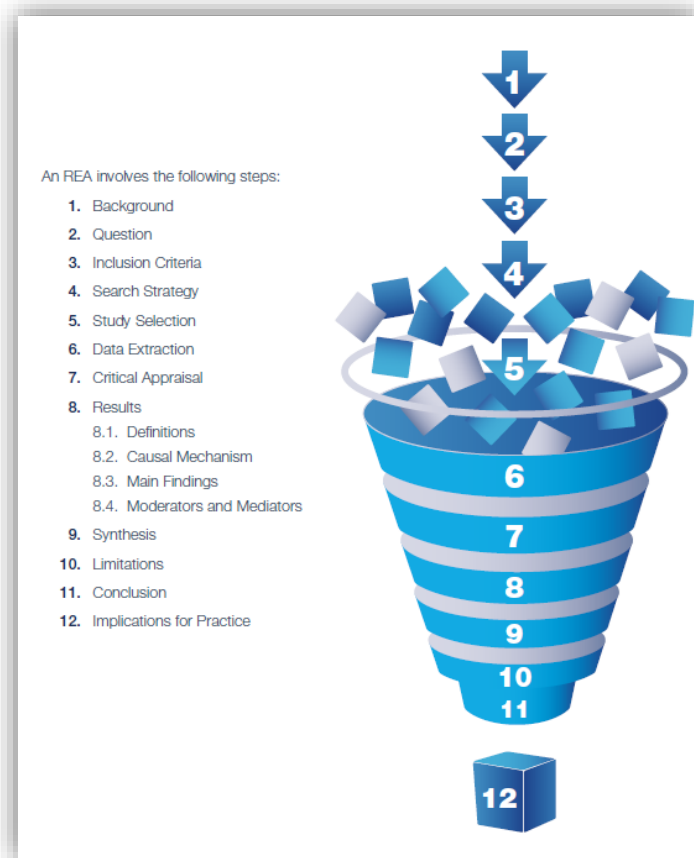
The Rapid Evidence Assessment (REA) method is a structured approach to synthesizing existing knowledge on a particular subject within a constrained timeframe. Unlike traditional systematic reviews, which require months or even years to complete, REAs offer a faster yet rigorous alternative. They maintain many of the strengths of systematic reviews—such as transparency, methodological rigor, and a systematic approach to searching for and appraising evidence—while accommodating the need for quicker decision-making in fast-paced environments. This makes REA an ideal method for addressing emerging fields where the evidence base is evolving rapidly, as is the case with the predicted impact of Artificial Intelligence (AI) in radiology (Tricco, Langlois, & Straus, 2017).

As already described in Chapter 1, AI in radiology represents a rapidly advancing field, with new algorithms and technologies being developed and tested in clinical settings at an accelerating pace. The speed of these advancements makes it crucial to synthesize the existing evidence in a timely manner to inform both clinical practice and policy decisions. Radiology departments, for instance, must make decisions about integrating AI into diagnostic workflows without waiting for traditional systematic reviews, which may take years to deliver results that could already be outdated by the time they are published. This is where the REA's ability to quickly deliver evidence becomes particularly valuable.

At its core, an REA is designed to balance speed with rigor, providing timely and actionable insights without sacrificing too much in terms of methodological quality. However, this also means that certain compromises are made to expedite the review process. For example, REAs may limit their scope by focusing on more recent literature, by excluding grey literature or non-peer-reviewed studies, or by conducting a more targeted search across fewer databases. While this approach can lead to a more rapid synthesis of the available evidence, it also carries a higher risk of selection bias compared to full systematic reviews, which typically cast a wider net and include exhaustive searches across multiple sources (Ganann, Ciliska, & Thomas, 2010).

Despite these limitations, the structured nature of an REA ensures that it remains a robust and transparent method of review. The process typically begins with a clearly formulated research question that drives the review, followed by the development of inclusion and exclusion criteria to define the scope of the search. Once the relevant studies are identified, they are subjected to critical appraisal to assess their methodological quality and relevance to the question at hand. This helps to ensure that the conclusions drawn from the review are based on reliable and valid evidence, even though the search process may not be as exhaustive as that of a traditional systematic review (Centre for Evidence-Based Management, 2017).

Figure 3. *Steps in the REA Process*



This flow diagram illustrates the structured steps involved in conducting a Rapid Evidence Assessment (REA). The process begins with setting the background and research question, followed by defining inclusion criteria and developing a search strategy. Studies are then selected based on these criteria, and relevant data is extracted and subjected to critical appraisal to assess methodological quality. The results are analysed across several dimensions, including definitions, causal mechanisms, main findings, and moderators and mediators. The findings are synthesized, and the limitations of the review are discussed before drawing conclusions. Finally, the REA identifies practical implications to inform decision-

making, highlighting the streamlined yet rigorous nature of this methodology (Barends, Rousseau, & Briner, 2017).

In the context of investigating the predicted impact of AI in radiology, these characteristics of REAs are particularly advantageous. The need for timely decision-making in healthcare is paramount, especially when it comes to the integration of new technologies like AI. Radiology departments face significant pressure to keep up with technological advances, and there is a growing demand for evidence that can guide the adoption of AI tools in clinical practice. AI has shown promise in a variety of areas within radiology, including improving diagnostic accuracy, enhancing workflow efficiency, and reducing the time required to interpret medical images. However, while the potential of AI is significant, it is essential to assess whether the existing evidence supports these claims, and whether AI tools can be implemented safely and effectively in real-world clinical settings.

An REA allows for a focused and systematic investigation of these issues, providing a snapshot of the current state of evidence on AI in radiology. For example, one of the key areas of interest in this project is whether AI can improve diagnostic accuracy in radiology. AI algorithms are being developed to assist radiologists in identifying subtle patterns in medical images that may be missed by the human eye, potentially leading to earlier diagnoses and better patient outcomes. By conducting an REA, it is possible to quickly assess the available evidence on the accuracy of AI tools in detecting conditions such as cancer, cardiovascular diseases, and neurological disorders. Studies that compare the performance of AI with that of human radiologists can provide valuable insights into whether AI truly enhances diagnostic accuracy or

whether its performance is context-dependent, varying across different types of imaging or clinical scenarios (Wicaksono & Fatichah, 2023).

Another area of investigation is the impact of AI on workflow efficiency in radiology. AI has the potential to automate routine tasks such as image segmentation and triaging cases based on urgency, which could reduce the workload for radiologists and allow them to focus on more complex cases. The REA method enables a targeted review of studies that have explored the practical implications of integrating AI into radiology workflows. These studies can provide evidence on whether AI tools lead to measurable improvements in productivity and efficiency or whether they introduce new challenges, such as the need for additional training or adjustments to existing IT infrastructure (Varker et al., 2015).

AI is also being explored for its potential role in treatment monitoring, particularly in fields like oncology, where tracking the progression of tumours or the response to therapy is critical. An REA can synthesize the latest evidence on how AI is being used in treatment monitoring, identifying whether it improves the accuracy of assessments or enables radiologists to make more informed decisions about treatment adjustments. By focusing on peer-reviewed studies, the REA can provide a clear picture of whether AI has a meaningful impact on patient outcomes in this area, and whether its use is justified by the evidence (Koivisto & Pohjola, 2011).

However, the integration of AI into radiology also raises concerns about patient safety and automation bias. Automation bias occurs when clinicians become over-reliant on AI tools, potentially leading to errors if they fail to critically evaluate the AI's output. It is essential to investigate whether AI tools can be safely integrated into clinical practice

without undermining the role of the radiologist as the ultimate decision-maker. An REA offers the flexibility to explore both the benefits and the risks of AI adoption, providing a balanced assessment of whether AI tools enhance patient safety or introduce new vulnerabilities (Ganann et al., 2010).

While REAs offer significant advantages in terms of timeliness and relevance, it is important to acknowledge their limitations. Due to the streamlined nature of the process, an REA may not capture all the available evidence, particularly if grey literature or studies published outside major peer-reviewed journals are excluded. Additionally, because the search strategy is often more targeted, there is a higher risk of selection bias. However, these limitations are mitigated by the REA's use of critical appraisal techniques, which help ensure that the studies included in the review are of high quality and that the findings are based on reliable evidence (Khangura et al., 2012).

Furthermore, the transparency of the REA process—where each step is clearly documented and reported—enhances the credibility of the findings. By outlining the search strategy, inclusion criteria, and methods of critical appraisal, the REA ensures that its results can be reproduced and verified by other researchers. This transparency is particularly important in fields like radiology, where clinical decisions have significant implications for patient care (Centre for Evidence-Based Management, 2017).

In conclusion, the Rapid Evidence Assessment (REA) is a highly suitable method for investigating the predicted impact of AI in radiology. It offers a rigorous yet timely approach to synthesizing the existing evidence, providing actionable insights that can inform the integration of AI tools into clinical practice. The REA strikes a balance

between the depth and comprehensiveness of a systematic review and the need for rapid, evidence-based recommendations in fast-moving fields like healthcare. By focusing on key areas such as diagnostic accuracy, workflow efficiency, treatment monitoring, and patient safety, the REA will deliver valuable insights that are directly relevant to radiologists, healthcare administrators, and policymakers as they navigate the challenges and opportunities posed by AI. While the REA has its limitations, its methodological rigor and transparency ensure that the findings can be trusted and used to guide future research and clinical decisions.

2.2 Research Aims

This Rapid Evidence Assessment (REA) was conducted as part of a Master's program in Evidence-Based Management and Critical Decision-Making, with the goal of applying an evidence-based approach to decision-making within healthcare, specifically in the radiology field. A REA is a straightforward yet effective tool for decision-makers, enabling them to evaluate the costs versus benefits of proposed actions and reduce biases or decisions based on perceived rather than actual returns. A central focus of this assessment is the proposal to integrate Artificial Intelligence (AI) into the radiology department—a move with the potential to fundamentally transform medical imaging practices. However, both the European Society of Radiology (ESR) and the American College of Radiology (ACR) have yet to provide definitive guidance on the clinical impact of AI in radiology, and global experience with such integration is still in its early stages. This lack of consensus suggests that the risks associated with AI in radiology are either partially known or, in some cases, not fully understood by the professional community. Therefore, this REA is especially warranted, aiming to clarify

these uncertainties and support informed, evidence-based decisions regarding AI adoption in radiology.

AI has the potential to revolutionize radiology by streamlining workflows. It can handle tasks such as protocolling, image interpretation, and case prioritization, enabling radiologists to focus on more complex and critical cases. This becomes particularly important given the projected 5% annual increase in imaging volume. By integrating AI, radiology departments can improve patient safety, reduce diagnostic errors, and enhance overall productivity while also helping to prevent radiologist burnout.

Although the global experience with AI's clinical impact in radiology is still in its early stages, initial results are promising. AI shows potential in addressing some of the key challenges faced by radiology departments, including staff shortages, heavy workloads, and the growing risk of burnout—issues that are highly relevant to the Maltese radiology department. Without change, the current system risks becoming unsustainable, which could lead to a decline in both patient outcomes and radiologist well-being.

2.2.1 Research Question

This Rapid Evidence Assessment (REA) aims to explore the clinical impact of Artificial Intelligence (AI) in radiology, assessing whether AI can address some of the key challenges currently facing the field. The central research question guiding this inquiry is: **What is the predicted clinical impact of AI in radiology?**

This question is systematically broken down using the PICOC framework, which organizes the investigation into manageable components:

Population: This REA focuses on radiology departments, radiologists, and the patients they serve. These groups are the primary stakeholders affected by AI integration in radiology, whether through enhanced diagnostic capabilities or improved workflow efficiencies.

Intervention: The emphasis is on the applications of AI in radiology, specifically through machine learning and deep learning technologies. The goal is to understand how these technologies influence radiologists' work and the quality of patient care.

Comparison: The assessment compares traditional radiology practices (without AI) to those augmented by AI, to evaluate whether AI contributes meaningfully to diagnostic accuracy, workflow efficiency, and overall clinical outcomes.

Outcome: The main outcomes of interest include AI's potential to improve diagnostic accuracy, facilitate early disease detection, enhance treatment monitoring, and streamline workflows. Additionally, the REA examines patient safety considerations and challenges, such as the risk of overreliance on AI and ethical concerns.

Context: This research is situated within the context of modern radiology departments, where increasing workloads and resource constraints challenge the ability to maintain high standards of care. The study particularly considers the potential of AI to alleviate these pressures within healthcare systems facing similar challenges, including those in Malta.

To provide a comprehensive analysis, the research question is divided into subsections that explore critical areas of AI's clinical impact in radiology: Diagnostic Accuracy and Early Detection, Treatment Monitoring, Workflow Efficiency and Productivity, Patient Safety and Outcomes, and the Challenges Radiologists face when integrating AI into their work. This approach allows for an in-depth examination of the various ways AI may shape the future of radiology.

2.2.2 Search Methodology

The search for relevant studies was conducted in June 2024, utilizing four major research databases: Scopus, Web of Science, PubMed, and EBSCO. These databases were chosen for their reputation as robust sources of high-quality clinical and AI-related research, making them ideal for gathering a comprehensive range of evidence on AI's impact in radiology. According to Singh et al. (2021), Web of Science and Scopus are widely regarded for their extensive and multidisciplinary journal coverage, which supports a thorough review of the literature. Additionally, Zhu and Liu (2020) highlight these databases' capacity to provide a broad and inclusive overview across various fields, including both the technical aspects of AI and its applications in

medical imaging. By leveraging these resources, this search aimed to cover both the theoretical and practical dimensions of AI in radiology.

To ensure that results were both focused and comprehensive, specific search strings around AI's potential clinical impact in radiology were designed. These strings included key terms such as "artificial intelligence," "machine learning," "deep learning," and specialized phrases like "diagnostic accuracy," "workflow efficiency," and "patient safety." Through this approach, studies that directly addressed the research questions on AI's enhancement of radiology were captured.

Several filters were applied to refine the results further. The search was limited to the past five years to capture recent advancements in the field, and only English-language articles were considered for consistency. One paper published in 2018 was identified in the reference lists of various selected papers and subsequently included as it was deemed very relevant to the topic. Although this may have led to the exclusion of some international research, it ensured a manageable scope. Additionally, only peer-reviewed journal articles were included to maintain a high standard of reliability.

The screening process followed a structured approach. Titles and abstracts were initially reviewed to identify studies that met the set criteria, followed by a full-text examination of those that qualified. The inclusion criteria specified that studies must focus on AI technologies with clinical applications in radiology, such as diagnostic tools and workflow enhancements, report primary data or provide systematic reviews/meta-analyses, and fall within the chosen timeframe. Articles that did not meet these criteria, such as those lacking a focus on clinical AI applications, not being peer-reviewed, or not in English, were excluded. This process helped narrow down the most relevant and reliable studies for the review.

Once the selection was complete, key details from each study, including elements like study design, AI model characteristics, validation methods, and clinical outcomes, were extracted. Additionally, the quality of each study was assessed, focusing on evidence level, sample size, and methodological rigor to build a strong foundation for drawing reliable conclusions.

Every search approach has its limitations. By excluding grey literature and non-peer-reviewed sources, some early-stage insights or emerging trends in AI applications for radiology may have been missed. The focus on English-language articles and targeted search terms may also have limited the range of studies included. Nevertheless, this approach provided a thorough and reliable snapshot of the current evidence on AI's impact in radiology.

The search strings utilized are detailed below:

Diagnostic Accuracy and Early Detection

Search Strings:

- ("artificial intelligence" OR "AI" OR "machine learning" OR "deep learning" OR "neural networks") AND ("Radiology" OR "Medical imaging") AND ("Diagnostic accuracy" OR "Early detection") AND ("Clinical impact" OR "Patient outcomes")
- ("artificial intelligence" OR "AI" OR "machine learning" OR "deep learning" OR "neural networks") AND ("Radiology") AND ("Early disease detection" OR "Diagnostic precision")

Treatment Monitoring

Search Strings:

- ("artificial intelligence" OR "AI" OR "machine learning" OR "deep learning" OR "neural networks") AND ("Radiology" OR "Medical imaging") AND ("Treatment monitoring" OR "Therapy monitoring") AND ("Clinical impact")
- ("artificial intelligence" OR "AI" OR "machine learning" OR "deep learning" OR "neural networks") AND ("Radiology department") AND ("Treatment planning" OR "Treatment monitoring")

Workflow Efficiency and Productivity

Search Strings:

- ("artificial intelligence" OR "AI" OR "machine learning" OR "deep learning" OR "neural networks") AND ("Radiology" OR "Medical imaging") AND ("Workflow efficiency" OR "Productivity") AND ("Clinical impact")
- ("artificial intelligence" OR "AI" OR "machine learning" OR "deep learning" OR "neural networks") AND ("Radiology department") AND ("Workflow optimization" OR "Operational efficiency")

Patient Safety and Outcomes

Search Strings:

- ("artificial intelligence" OR "AI" OR "machine learning" OR "deep learning" OR "neural networks") AND ("Radiology" OR "Medical imaging") AND ("Patient safety" OR "Patient outcomes") AND ("Clinical impact")
- ("artificial intelligence" OR "AI" OR "machine learning" OR "deep learning" OR "neural networks") AND ("Radiology") AND ("Patient safety" OR "Clinical outcomes")

Navigating the Challenges: Radiologists in the Age of AI

Search Strings:

- ("artificial intelligence" OR "AI" OR "machine learning" OR "deep learning" OR "neural networks") AND ("Radiology" OR "Medical imaging") AND ("Radiologists" OR "Clinician interaction" OR "Human-AI collaboration") AND ("Challenges" OR "Barriers" OR "Impact on profession")
- ("artificial intelligence" OR "AI" OR "machine learning" OR "deep learning" OR "neural networks") AND ("Radiology" OR "Medical imaging") AND ("Overreliance" OR "Automation bias" OR "Trust" OR "Decision-making") OR ("Ethical implications" OR "Legal considerations" OR "Accountability" OR "Professional role")

2.2.3 Search Results and Study Selection Process

Following a structured and rigorous search process, a diverse set of studies were selected to be included in the REA, each offering valuable insights into the predicted clinical impact of AI in radiology. The search yielded a comprehensive collection of papers covering various AI applications, including diagnostic accuracy, treatment monitoring, workflow efficiency, patient safety, and the evolving role of radiologists. Summaries of these selected studies, organized by theme, were presented in tables for ease of reference. These tables outlined each study's main findings, sample sizes, evidence levels, and effect sizes, providing a clear view of the breadth and depth of current research on AI integration in radiology (Annexa 1 – Summary tables for each of the selected paper)

For **Diagnostic Accuracy and Early Detection**, the search yielded a total of 118 articles. This high number reflected the significant interest and research activity in AI's potential to enhance diagnostic precision and facilitate earlier disease detection through advanced imaging techniques. Databases like PubMed and Scopus contributed most heavily to this category, indicating a rich body of literature available for analysis.

In the area of **Treatment Monitoring**, 94 articles were retrieved, underscoring the growing recognition of AI's potential to transform patient response monitoring, particularly in oncology. AI's ability to analyse complex imaging data over time offered promising avenues for personalized medicine.

Workflow Efficiency and Productivity searches resulted in 64 articles. Although this number was lower compared to other categories, it still reflected a considerable amount of research dedicated to improving radiology department operations through AI. Studies in this area frequently explored how AI could automate routine tasks, optimize scheduling, and reduce turnaround times, ultimately enhancing radiologists' productivity.

The searches on **Patient Safety and Outcomes** returned 127 articles, highlighting the emphasis on ensuring that AI integration into radiology not only enhances performance but also maintains or improves patient safety. Literature in this area addressed issues such as error reduction, radiation dose management, and the ethical use of AI in clinical settings.

The topic of **Navigating the Challenges: Radiologists in the Age of AI** generated the highest number of articles, with a total of 1,015. This overwhelming interest underscored the critical discussions around the ethical, legal, and professional implications of AI adoption, reflecting the radiology community's engagement with potential risks, barriers to implementation, and the evolving role of radiologists as AI became more prevalent.

After removing 314 duplicate entries across the databases, 790 unique articles were left. These articles were screened based on titles and abstracts against the inclusion and exclusion criteria, resulting in 92 articles deemed potentially relevant and subsequently subjected to full-text review.

During the full-text screening, further criteria were applied to ensure each study's relevance and quality. Factors such as clinical applicability, study design, and availability of full text were considered. This rigorous process led to the exclusion of

studies that did not meet the necessary standards, such as those needing clinical relevance, being non-English, or not peer-reviewed.

Ultimately, **59 studies** were included in the Rapid Evidence Assessment (REA). These studies provided a robust foundation for analysing AI’s predicted clinical impact in radiology. Encompassing a diverse range of research, including retrospective analyses, prospective studies, and systematic reviews, they offered valuable insights into AI’s current applications and potential future implications in the field.

Table 1. String Search Result Summary

	WOS 1	WOS 2	PubMed 1	PubMed 2	EBSCO 1	EBSCO 2	SCOPUS 1	SCOPUS 2
Diagnostic Accuracy and Early Detection	14	12	17	26	7	16	25	1
Treatment Monitoring	0	2	0	15	1	0	62	14
Workflow Efficiency and Productivity	0	0	0	22	1	1	28	12
Patient Safety and Outcomes	16	1	3	71	1	16	2	16
Navigating Challenges	146	10	162	17	292	324	17	47

Table 1 gives an overview of article counts retrieved from various databases and search strings. Results are categorized by research focus areas as previously outlined.

The inclusion and exclusion criteria utilized to further filter the identified literature are listed below.

Inclusion Criteria:

- Studies that focus specifically on the use of commercially available AI technologies in clinical radiology.
- Articles published in peer-reviewed journals.
- Studies reporting primary data or systematic reviews/meta-analyses
- Full text available from online / University of Malta sources
- Publications from 2019 onwards
- Studies focusing on the integration and impact of AI in radiology within healthcare contexts

Exclusion Criteria:

- Studies not specifically addressing AI technologies (e.g., general radiology improvements, manual methods).
- Research focusing on non-clinical applications of AI in radiology.
- Non-English articles.
- Editorial pieces
- Outdated studies or those not applicable to current technology standards.

The inclusion and exclusion criteria for this Rapid Evidence Assessment (REA) were crafted to zero in on studies that truly capture the current impact and integration of AI in clinical radiology. To ensure relevance and practical insight, only studies focused on commercially available AI technologies in radiology were included, allowing the review to highlight applications already in use or close to clinical adoption. By requiring peer-reviewed journal articles, the REA emphasized rigorous, trustworthy sources, while

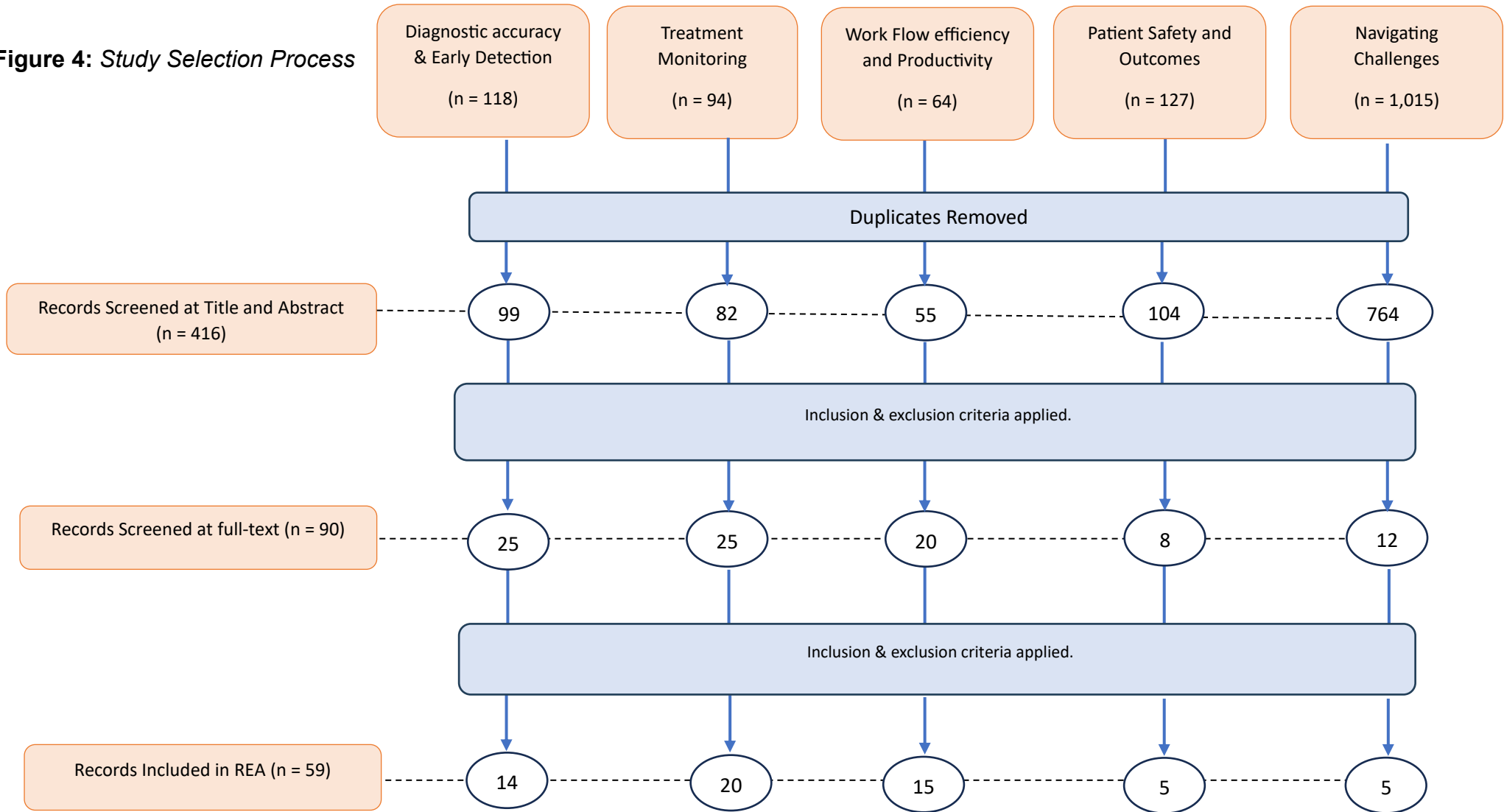
prioritizing studies that report primary data or systematic reviews/meta-analyses allowed for a foundation built on robust, comprehensive evidence.

The criteria also stipulated full-text availability through online sources or the University of Malta, making sure that the content could be accessed and verified. To capture recent trends and advances in AI, only publications from 2019 onwards were considered. Focusing on studies exploring AI's integration and impact specifically within healthcare contexts kept the review aligned with its central question: assessing how AI is transforming clinical practice in radiology.

Exclusion criteria helped to refine the selection even further. Studies without a clear clinical application of AI were excluded, as the REA's goal is to understand AI's impact within real-world healthcare settings. Non-English articles, studies unrelated to AI technology, and non-peer-reviewed sources like editorials or opinion pieces were omitted to maintain the review's quality and focus. The criteria also excluded studies without accessible full texts, ensuring all reviewed content was available for thorough examination. Finally, studies focusing on AI tools developed solely for the research itself were left out, as these might lack external validation and real-world applicability.

Together, these inclusion and exclusion criteria provided a structured and focused approach, filtering the literature to include only relevant, high-quality, and up-to-date studies that genuinely contribute to understanding AI's role in clinical radiology today. This framework allowed the REA to build a reliable, current, and practical picture of AI's potential impact in the field.

Figure 4: Study Selection Process



The flowchart in figure 4 illustrates the screening and selection process for records in the Rapid Evidence Assessment (REA) on AI in radiology. Records were filtered across five focus areas, with exclusions made for duplicates, non-clinical applications, language, relevance, and availability, resulting in the final records included in the REA.

Chapter 3 – Predicted Clinical Impact of AI in Radiology (Rapid Evidence Assessment Results)

3.1 Diagnostic Accuracy and Early Detection

Artificial Intelligence (AI) is increasingly being adopted across various medical disciplines, with radiology emerging as one of the most impactful fields for its application. The use of AI in improving diagnostic accuracy and early detection has the potential to revolutionize medical imaging, enhance diagnostic workflows, and ultimately improve patient outcomes. This section of the REA aims to explore the predicted impact of AI on these crucial aspects of radiology.

The previously described literature search resulted in 18 papers being selected. The 18 papers reviewed in this analysis largely represent Level III evidence, which typically included retrospective and observational studies rather than randomized controlled trials (RCTs). This is a critical aspect to consider when assessing the applicability and strength of the findings. Most of these studies focused on evaluating AI models using existing medical imaging datasets, making comparisons to traditional diagnostic methods without implementing prospective, real-world trials. While these studies often demonstrate strong results—such as high Area under the Curve (AUC) values, accuracy, sensitivity, and specificity—the retrospective nature of the research means that the outcomes need to be interpreted with caution.

The types of studies varied but predominantly involved the application of deep learning models, such as Convolutional Neural Networks (CNNs), to datasets of medical images, including CT, MRI, and ultrasound scans. These studies often included validation sets to test

the models' generalizability. However, multi-centre trials were generally lacking, which raises concerns about the reproducibility of results across different clinical environments. Additionally, many papers incorporated radiomics to extract quantitative features from imaging data, with some combining these features with machine learning models for tasks like lymph node metastasis prediction and tumour classification. Despite the robust methodologies employed, the absence of prospective studies and RCTs limits the clinical translation of these findings, positioning the current body of evidence as a promising but preliminary step toward AI integration in routine radiological practice.

3.3.1 AI and Diagnostic Accuracy

AI-driven models, particularly those based on deep learning (DL), have demonstrated a consistent ability to improve diagnostic accuracy across multiple imaging modalities. The application of convolutional neural networks (CNNs) in liver lesion detection, for example, has led to significant improvements in the precision of detecting and segmenting liver lesions. The SimU-Net model, as shown by Szeskin et al. 2023, improved lesion detection by 50% compared to traditional methods, with Dice scores of 0.82 for lesion segmentation, showcasing AI's ability to enhance diagnostic precision in oncology (Bai et al., 2021).

Similarly, the integration of AI in Digital Breast Tomosynthesis (DBT) has demonstrated its utility in breast cancer screening. CNNs, when applied to DBT, showed an AUC of 0.945 for breast mass detection and reduced false positives by 14-40%. These results underline AI's potential to outperform traditional mammography, providing more accurate readings and improving cancer detection rates (Ahn et al., 2023). This highlights a key trend across studies—AI models are particularly effective at enhancing diagnostic performance in areas where traditional imaging may fall short due to complexity or high error rates.

In other cancer diagnoses, particularly pancreatic cancer, AI models have achieved AUC values exceeding 0.90, demonstrating the capacity of deep learning techniques to not only improve diagnostic accuracy but also assist in personalized treatment strategies through the integration of imaging, genetic, and clinical data (Cui et al., 2022).

3.1.2 Early Detection Capabilities of AI

AI has also shown promise in improving early detection rates, which is critical in diseases like lung cancer and ovarian cancer, where survival is closely tied to how early the disease is diagnosed. For instance, in the detection of occult lymph node metastasis (OLM) in small-cell lung cancer patients, radiomic models combined with machine learning achieved AUC scores of 0.774, significantly aiding the prediction of OLM preoperatively. This non-invasive approach improves the ability of clinicians to make more accurate treatment decisions, potentially reducing unnecessary surgeries while enhancing early cancer detection (Jiang et al., 2024).

Another example is ovarian cancer, where AI, specifically ResNet and YOLOv5 models, achieved over 95% accuracy in classifying ovarian tumours (Sadeghi et al., 2024). These results underscore the growing body of evidence supporting AI's role in identifying malignancies earlier, when they are most treatable. In addition, AI-CAD (Computer-Aided Detection) systems used in chest radiographs have increased the sensitivity for detecting early-stage abnormalities, though they also introduced a challenge: an increase in false positives and unnecessary CT referrals (Hong et al., 2023).

3.1.3 Who Benefits Most from AI Integration?

One of the key questions in the application of AI in radiology is who benefits most from these advancements. Across several studies, junior clinicians and radiologists in training seem to derive the most significant gains from AI augmentation. In a study that assessed the impact of AI on junior residents diagnosing COVID-19 pneumonia on chest X-rays, AI assistance improved diagnostic accuracy significantly. The AUC score for the least experienced resident increased from 0.7813 to 0.8482 with AI assistance, while the sensitivity improved from 38.89% to 62.50%. This suggests that AI systems can serve as powerful educational tools and diagnostic aids for less experienced practitioners (Feng et al., 2023).

Furthermore, clinicians who deal with complex and highly variable imaging tasks, such as those involving spinal imaging or paediatric brain tumours, also benefit from AI tools. For example, AI models for spinal disease classification have reached accuracies of up to 98%, offering critical support for radiologists when diagnosing conditions like scoliosis or spinal tumours, which require precise imaging and high diagnostic accuracy (Huang et al., 2022).

3.1.4 Imaging Modalities Enhanced by AI

The variety of imaging modalities enhanced by AI is a testament to the technology's adaptability and effectiveness. CT and MRI scans are the most frequently cited modalities in the literature, benefiting from the application of AI in both segmentation and classification tasks. In pancreatic cancer diagnosis, CNNs and transformer-based models applied to CT and MRI data achieved high levels of accuracy, with AUC values between 0.75 and 0.98 (Kontopodis et al., 2021). These imaging modalities are particularly suitable for AI applications due to the large volumes of data they generate, which can be analysed more efficiently using deep learning techniques than by human radiologists alone.

Ultrasound imaging, traditionally more challenging due to its lower resolution and higher operator dependence, is also being enhanced by AI. In ovarian cancer diagnosis, AI models applied to ultrasound images reached 97% F1 scores, demonstrating their effectiveness in detecting early-stage malignancies. Similarly, contrast-enhanced ultrasound (CEUS) has shown promise in detecting pancreatic tumours and predicting treatment responses, further highlighting AI's capability in diverse imaging environments (Yao et al., 2023).

In addition, AI's role in improving the accuracy of imaging-based diagnosis extends to temporal bone imaging, where models like U-Net have reached Dice Similarity Coefficients (DSC) of up to 0.91, offering substantial improvements in the segmentation of critical anatomical structures (Petsiou et al., 2023).

3.1.5 Ethical Considerations and Challenges

While the benefits of AI are clear, several ethical concerns and technical challenges remain. A recurrent issue across the reviewed studies is the lack of standardized datasets, which poses a significant challenge for model generalization and real-world application. The variability in imaging protocols across different institutions can limit the effectiveness of AI models when applied to new datasets, a phenomenon known as domain shift.

Moreover, many AI models still operate as “black boxes,” meaning that their decision-making processes are not easily interpretable by clinicians. This lack of transparency is a significant barrier to clinical adoption, particularly in high-stakes environments such as cancer diagnosis or paediatric brain tumour imaging, where trust in the system is critical (Chukwujindu et al., 2024). Ensuring that AI models are both interpretable and explainable remains an ongoing challenge for researchers and developers.

Additionally, there is a potential for over-reliance on AI, particularly in situations where the models have not been fully validated or tested across diverse populations. For instance, the use of AI-CAD in chest radiographs led to a 33% increase in CT referrals, but many of these referrals did not lead to positive findings, suggesting that AI-driven overdiagnosis is a real concern (Hong et al., 2023).

3.2 Treatment Monitoring

Artificial intelligence (AI) has made significant advancements across various aspects of radiology, with one of its most transformative applications being treatment monitoring. Monitoring a patient's response to treatment represents a crucial component of oncology and other disease management protocols. Through AI, this process is becoming increasingly efficient, accurate, and personalised. An analysis of data from 20 studies included in Annexa 1 provides insight into how AI is being utilized in diverse clinical settings and its anticipated impact on enhancing patient outcomes.

3.2.1 Enhanced Precision in Monitoring and Predictive Analytics

One of the most compelling clinical impacts of AI is its ability to enhance precision in tracking disease progression and monitoring treatment responses. For example, in breast cancer management, AI models, integrated into imaging workflows such as MRI and digital mammography, have been successful in assessing treatment responses by analysing complex patterns in imaging data (Ahn et al., 2023). These models are particularly adept at identifying biomarkers such as hormone receptor status and lymph node involvement, which are critical in evaluating how well patients respond to therapies like chemotherapy or targeted hormonal treatments. By providing these insights early, AI enables clinicians to adapt treatment plans sooner, potentially improving patient outcomes.

In the realm of musculoskeletal trauma, AI's contribution to monitoring is equally impressive. By employing AI models that focus on MRI and CT scans, clinicians are now able to more precisely track fracture healing, soft tissue recovery, and rehabilitation progress (Ajmera et al., 2021). This is particularly beneficial for long-term recovery plans, where even minor changes in tissue regeneration can significantly influence treatment decisions. The combination of AI's predictive analytics and real-time monitoring holds the potential to

revolutionise how treatments are tailored over time, ensuring that the right interventions are applied at the right moments.

3.2.2 Reduction of Radiologist Workload

Another vital area where AI is making a significant clinical impact is in reducing the workload for radiologists. In cancer treatment monitoring, radiologists are required to analyse numerous scans to assess tumour progression or regression, a task that can be both time-consuming and prone to human error. AI has proven effective at automating many of these complex and repetitive tasks, such as lesion segmentation, quantification of tumour burden, and comparison of longitudinal scans (Gandhi et al., 2022).

For instance, in lung cancer treatment monitoring, AI models that analyse PET/CT imaging can automatically segment the total metabolic tumour volume (TMTV) and assess metabolic activity changes (MAC) over time (Veziroglu et al., 2023). These tasks would typically require substantial manual input from radiologists, but AI's automation significantly reduces the time and labour involved, freeing radiologists to focus on more complex cases. Furthermore, AI's enhanced accuracy means that clinicians can rely on the model's outputs with more confidence. This shift not only improves workflow efficiency but also enhances patient care by enabling faster and more accurate treatment adjustments.

Similarly, in lymphoma, AI models for PET/CT imaging have been instrumental in tracking disease burden. AI's ability to differentiate between lymphomatous and non-lymphomatous FDG-avid regions improves radiologists' confidence in their assessments, further optimising clinical workflows (Manafi-Farid et al., 2022). These models are expected to become increasingly integrated into day-to-day radiological practice as they prove their value in reducing workloads and streamlining the monitoring process.

3.2.3 Virtual Biopsies

One of the most exciting developments in AI and radiomics is the concept of virtual biopsies. These AI-driven models provide clinicians with a non-invasive means to assess treatment response and monitor tumour evolution, eliminating the need for repeated invasive procedures. This has particularly important implications in cancers where physical biopsies carry significant risks or where tumours are difficult to access (Panico et al., 2023).

In the context of ovarian cancer, AI models leveraging radiomic data have proven capable of identifying subtle changes in tumour heterogeneity, a key indicator of how well a patient is responding to treatment (Sadeghi et al., 2024). These models are able to monitor molecular and structural changes within the tumour, providing a non-invasive window into the treatment's effectiveness. The ability to perform these "virtual biopsies" reduces the need for surgical interventions and allows clinicians to adapt treatment strategies with greater agility, potentially improving both patient outcomes and comfort.

Moreover, in pancreatic cancer, where traditional biopsies may be invasive and challenging, AI-based models have shown the potential to predict response to chemotherapy through non-invasive imaging alone. By analysing CT and MRI scans, AI algorithms can assess tumour shrinkage, density changes, and other radiomic features that indicate whether the treatment is working effectively (Miranda et al., 2023). This has the added benefit of reducing the frequency of painful biopsy procedures, improving the overall patient experience.

3.2.4 Personalized Treatment Adaptation

AI's ability to continuously monitor and analyse treatment response opens new possibilities for personalized medicine, where treatment plans can be adjusted in real-time based on the patient's individual response. In hepatocellular carcinoma (HCC), AI-driven radiomics models predict the likelihood of microvascular invasion (MVI), which is a critical factor in recurrence (Miranda et al., 2023). With this information, clinicians can make more informed decisions about surgical approaches, liver transplant candidacy, and adjuvant therapies.

AI can similarly help stratify patients into different risk categories based on their predicted outcomes, allowing for more aggressive treatments in high-risk cases or more conservative management when appropriate. For instance, in breast cancer, AI models are being used to predict treatment efficacy by analysing imaging features alongside clinical data to identify which patients are likely to benefit from specific therapies (Ahn et al., 2023). These predictive models allow for the customization of treatment plans, ensuring that each patient receives the most appropriate care for their unique cancer profile.

Additionally, in colorectal cancer, AI models are being employed to monitor response to radiotherapy and chemotherapy. AI can detect early signs of treatment failure or success by analysing longitudinal scans, allowing for treatment adjustments before the disease progresses (Ajmera et al., 2021). This early intervention capability is particularly valuable in reducing unnecessary toxicity from ineffective treatments, ensuring that patients receive the most suitable therapy for their specific condition.

3.2.5 Challenges and Future Directions

Despite the clear advantages of AI in treatment monitoring, there are several challenges that need to be addressed to fully realize its clinical potential. One of the most significant issues is the black-box nature of many AI algorithms. Clinicians often find it difficult to trust AI-generated predictions without understanding how the model arrived at a particular conclusion (Ahn et al., 2023). This lack of transparency can hinder adoption, especially in high-stakes situations where treatment decisions can have life-or-death implications.

Furthermore, there is a pressing need for standardisation and multi-centre validation of AI models. Many of the studies summarised in Annexa 1 rely on retrospective data from single institutions, which limits the generalizability of the findings. For AI models to be reliably implemented in clinical practice, they must be validated across diverse populations and imaging protocols (Panico et al., 2023). Additionally, data harmonisation across institutions is critical to ensure that AI models trained on one dataset can perform equally well in another clinical setting.

Looking to the future, the integration of multimodal data—including radiomics, genomics, and clinical information—into AI-driven treatment monitoring will likely become a key focus. This holistic approach promises to provide clinicians with a more comprehensive understanding of each patient's disease trajectory, allowing for even more personalized and effective treatment plans (Veziroglu et al., 2023). As AI technology continues to advance, we can expect it to play an increasingly central role in improving outcomes for cancer patients and beyond.

3.3 Workflow Efficiency and Productivity

The integration of artificial intelligence (AI) into radiology workflows has the potential to revolutionise productivity, streamline operations, and improve patient outcomes. From optimising worklist prioritisation to automating routine tasks, AI has demonstrated significant potential across various radiological settings. The following analysis synthesises key findings from twelve papers (summarised in Annexa 1) to discuss the predicted clinical impact of AI on radiology workflow and productivity, with a focus on its potential benefits, challenges, and limitations.

One paper published in 2018 (Arbabshirani et al. 2018) - was included in this review as this was deemed to be very relevant to the topic.

Figure 4. The Role of AI Across the Radiology Workflow

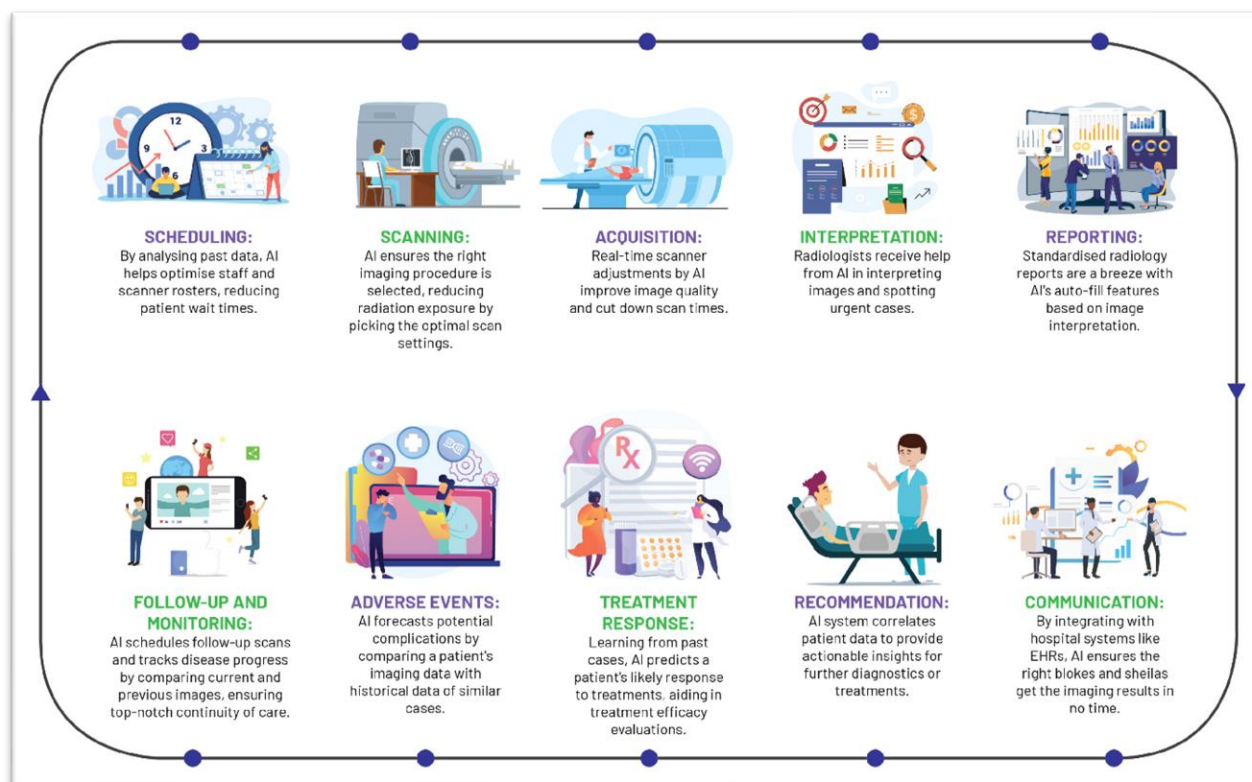


Figure 4 illustrates the integration of artificial intelligence (AI) at various stages of the radiology workflow, from scheduling and scanning to reporting and communication. Each stage demonstrates AI's potential to enhance efficiency, accuracy, and patient outcomes, highlighting applications such as optimising staff rosters, selecting optimal scan settings, improving image interpretation, forecasting complications, and supporting treatment recommendations.(Najjar, 2023)

3.3.1 Optimizing Workflow and Reducing Turnaround Time

One of the key contributions of AI to radiology workflow is the reduction in turnaround time (TAT). In high-volume radiology practices, AI tools have been shown to cut the time required for report generation and interpretation. For example, Ranschaert et al. reported that AI reduced TAT by up to 35-99%, particularly by automating non-diagnostic tasks like scan protocoling and prioritizing cases based on urgency (Ranschaert et al., 2021). This optimization not only improves operational efficiency but also reduces the burden on radiologists, allowing them to focus on more complex tasks.

In another example, AI-based systems like the one implemented by Chung et al. (2024) significantly reduced the time required for CT protocol assignments in emergency settings from 2.1 hours to just 0.2 hours (Chung et al., 2024). By automating routine tasks, the system alleviated radiologists' non-interpretive workload, allowing them to allocate more time to patient care and interpretation.

AI's role in accelerating image interpretation has been particularly impactful in emergency care settings. For instance, Arbabshirani et al. 2018 demonstrated that AI models for detecting intracranial haemorrhage (ICH) on head CT scans reduced median diagnosis time from 512

minutes to just 19 minutes (Arbabshirani et al., 2018). This kind of time-saving not only enhances workflow efficiency but can also have direct clinical implications by enabling faster intervention in critical cases.

3.3.2 Worklist Prioritization and Triage

AI tools are highly effective at optimizing the radiologist's worklist by prioritizing urgent cases. Pierre et al. highlighted that AI algorithms can prioritize cases based on the likelihood of critical findings, such as intracranial haemorrhage or pulmonary embolism (Pierre et al., 2023). This reduces delays in diagnosing life-threatening conditions, improving overall patient outcomes and reducing the cognitive burden on radiologists.

Similarly, Han et al found that AI systems for chest radiographs could effectively identify normal scans with a negative predictive value (NPV) of 92%, allowing radiologists to prioritize more complex or urgent cases (Han et al., 2024). This capability is crucial in high-volume settings where radiologists need to focus their attention on the most critical cases without becoming overwhelmed by routine, non-urgent examinations.

3.3.3 Automation of Routine Tasks and Process Optimization

Beyond image interpretation, AI has proven to be a valuable tool for automating routine tasks, including scan protocoling, scheduling, and even report generation. According to Letourneau-Guillon et al. (2020), AI applications can automate up to 30% of protocoling and scheduling tasks, significantly reducing the administrative burden on radiologists (Letourneau-Guillon et al., 2020). By automating these repetitive tasks, AI frees up valuable time for radiologists, enabling them to focus on higher-order diagnostic and interpretive tasks.

The integration of AI into radiology has also been shown to streamline the radiology roundtrip process. AI can assist with patient scheduling, positioning, and protocol selection, improving efficiency and reducing patient waiting times (Pierre et al., 2023) In addition, AI-based predictive analytics can help optimize staff scheduling and predict no-show appointments, improving resource allocation in radiology departments.

3.3.4 Image Quality and Reducing Radiation

Another notable impact of AI in radiology is its ability to enhance image quality while simultaneously reducing radiation exposure. Richardson et al. found that AI-assisted techniques in CT, MRI, and PET/CT could reduce radiation doses by up to 98.75%, making imaging procedures safer for patients without compromising diagnostic accuracy (Richardson et al., 2022). AI algorithms have also been shown to reduce scan acquisition time, further improving patient satisfaction by minimizing the time spent undergoing scans.

Deep learning reconstruction (DLR) in MRI has also demonstrated significant improvements in signal-to-noise ratio (SNR), which allows for shorter imaging times while maintaining high image quality. Kiryu et al. reported that DLR reduced MRI imaging time significantly, providing high-quality images comparable to higher field-strength scanners, such as 3T (Kiryu et al., 2023).

3.3.5 Challenges and Limitations in AI Integration into Radiology

The integration of artificial intelligence (AI) into radiology, while promising, is accompanied by several challenges and limitations that must be addressed to ensure its effective adoption and clinical impact. A significant barrier lies in the infrastructure and interoperability challenges within healthcare systems. Many radiology departments lack the requisite IT infrastructure to support seamless AI integration, as emphasized by Ranschaert et al. (2021). The need for AI systems to function effectively across diverse platforms further complicates this issue, necessitating substantial investments in technology and infrastructure to achieve interoperability.

Another critical challenge is the potential for false positives, particularly in AI models designed for diagnostic purposes. For instance, Arbabshirani et al. (2018) reported that their AI model for detecting intracranial haemorrhage (ICH) significantly reduced diagnosis time but also generated false positives, which required manual re-evaluation by radiologists. This underscores the importance of rigorous validation and oversight when incorporating AI into diagnostic workflows to minimize errors and maintain clinical reliability.

Regulatory hurdles also pose a significant obstacle to AI adoption in radiology. While non-diagnostic AI tools encounter fewer regulatory constraints, diagnostic AI systems must adhere to stringent regulatory standards, slowing their clinical adoption (Ranschaert et al., 2021). Striking a balance between meeting regulatory requirements and maintaining performance remains a critical challenge for both AI developers and healthcare providers.

Furthermore, the limitations of existing evidence on AI's impact on radiology workflows must be considered. Many studies reviewed in Annexa 1 rely on single-centre trials, limiting the generalizability of findings to broader clinical settings. Han et al. (2024) observed that the majority of AI trials were conducted in single centres, raising concerns about the applicability of these findings across diverse institutions. Additionally, evidence levels vary significantly

among studies. For instance, narrative reviews and retrospective cohort studies, such as those by Ranschaert et al. (2021) and Pierre et al. (2023), provide lower levels of evidence (Level D according to CEBMa guidelines), as they summarize findings from multiple operational AI applications without original data collection. In contrast, prospective evaluations and randomized controlled trials, such as those by Arbabshirani et al. (2018) and Chung et al. (2024), offer higher levels of evidence but often lack patient-centred outcomes, highlighting a gap in current research.

Overall, addressing these challenges and limitations is crucial to maximizing AI's potential in radiology, ensuring its seamless integration into clinical workflows, and ultimately enhancing patient outcomes.

3.4 Patient Safety and Productivity

The integration of artificial intelligence (AI) into radiology presents significant potential to improve patient safety and productivity, but the realization of these benefits remains contingent on addressing current evidence gaps and implementation challenges. Although AI's capabilities in enhancing radiology workflows and outcomes are widely acknowledged, the low level of empirical evidence supporting its application highlights the need for rigorous validation before these advantages can be fully achieved.

AI's potential to improve patient safety lies in its ability to reduce diagnostic errors and radiation exposure. Jalal et al. (2021) underscored that AI-driven systems could streamline workflows in emergency and trauma radiology, expediting diagnosis and minimizing human error by alleviating the cognitive burden on radiologists. However, many of these assertions are rooted in conceptual models rather than robust empirical studies, as most AI systems are

still in the validation phase. This highlights a critical need for high-quality research to substantiate AI's role in enhancing diagnostic precision and safety.

In the domain of radiation safety, AI's ability to optimize imaging parameters and reduce radiation doses in modalities such as CT and PET has been well-documented. Seah et al. (2021) demonstrated that AI tools could preserve diagnostic quality while minimizing radiation exposure, directly addressing a major safety concern in radiology. However, the majority of these findings originate from expert reviews and preliminary trials, which limits their generalizability. Additionally, while AI has proven effective in image noise reduction, concerns about its potential to overlook subtle pathologies remain. These limitations underscore the importance of further clinical trials to validate AI's efficacy in enhancing patient safety without compromising diagnostic accuracy.

Another critical aspect of patient safety in radiology is reducing communication errors, which are a significant contributor to diagnostic failures. AI-powered closed-loop communication systems, as discussed by Harsini et al. (2022), have the potential to ensure that critical findings are effectively relayed between radiologists and referring clinicians. Such systems could significantly improve safety by addressing gaps in communication. However, the evidence supporting these innovations is currently limited to expert opinions and narrative reviews, emphasizing the need for more robust, data-driven research to confirm their effectiveness in real-world settings.

Beyond safety, AI is poised to revolutionize radiology productivity by automating routine tasks and enhancing workflow efficiency. According to Tadavarthi et al. (2022), AI systems can handle non-interpretive functions such as image protocolling, acquisition, and worklist prioritization. By delegating these tasks to AI, radiologists can focus on more complex interpretative duties, potentially improving both efficiency and job satisfaction while mitigating

burnout. Despite these promising prospects, the supporting evidence is primarily derived from single-institution studies, which limits the generalizability of findings to broader healthcare systems.

AI has also shown the ability to significantly reduce scan times, with some studies suggesting reductions of up to 75%, while maintaining or even improving image quality (Tadavarthi et al., 2022). This represents a substantial gain in productivity, particularly for radiology departments facing high patient volumes. However, the lack of multi-centre validation studies and the substantial costs associated with AI adoption present significant barriers. Furthermore, the existing evidence, often classified as expert reviews, highlights a gap in high-quality, large-scale studies needed to confirm the real-world impact of these productivity gains.

In conclusion, while AI holds considerable promise in improving patient safety and productivity in radiology, its full potential remains unrealized due to limitations in evidence and practical implementation. Most of the current findings rely on early-stage trials, narrative reviews, and expert opinions, leaving significant gaps in understanding its generalizability and cost-effectiveness. Addressing these gaps through high-quality empirical research is essential to move beyond speculative benefits and enable AI to achieve its transformative potential in clinical radiology.

3.5 Navigating the Challenges: Radiologists in the Age of AI

The advent of artificial intelligence (AI) in radiology heralds remarkable opportunities, including enhanced diagnostic accuracy, improved workflow efficiency, and even alleviation of the burnout that plagues many radiologists. However, these advantages come with significant challenges that require radiologists to redefine their roles in a rapidly evolving landscape. As AI takes on repetitive tasks and streamlines workflows, the critical question becomes: how can radiologists maintain their indispensable role in patient care while using AI effectively and responsibly? Achieving this balance demands not only a blend of human expertise and machine intelligence but also careful consideration of ethical, practical, and integration challenges.

AI's potential to improve diagnostic accuracy and streamline workflows is among its most compelling benefits. For instance, Hwang et al. (2022) demonstrated that AI could serve as a secondary reviewer in chest radiographs, helping radiologists identify missed abnormalities and reducing the likelihood of false negatives. Such support is invaluable in high-pressure settings where radiologists must process large volumes of images. Similarly, Jalal et al. (2021) highlighted how AI could automate routine tasks like image acquisition and protocolling, enabling radiologists to concentrate on complex, interpretive work. By reducing cognitive burden and enhancing productivity, AI not only improves efficiency but may also help address radiologist burnout (Waller et al., 2022; Najjar, 2023).

However, while these benefits sound promising, they must be approached with caution. Much of the evidence supporting AI's efficacy stems from small-scale pilot studies or expert opinions, and large, randomized controlled trials validating these claims in diverse clinical

settings are still lacking (Najjar, 2023). Until such studies are conducted, the potential of AI remains an exciting but unproven prospect.

Despite its promise, AI introduces risks, including automation bias—a phenomenon where radiologists overly rely on AI-generated recommendations without critically evaluating their accuracy. Bernstein et al. (2023) and Challen et al. (2019) found that radiologists were more likely to follow erroneous AI outputs, leading to false positives or negatives that could have been avoided with independent decision-making. Conversely, under-trusting AI can result in its underutilization, limiting its benefits. Achieving the right balance is crucial: radiologists must rely on AI as a tool that complements their expertise, not as a replacement for it (Najjar, 2023). Designing AI systems that integrate seamlessly with radiologists' decision-making processes is essential to ensuring their role remains central to patient care.

Scaling and integrating AI technologies into real-world healthcare settings present further challenges. While AI may perform well in controlled environments or pilot projects, its deployment on a larger scale often exposes inefficiencies. Eltawil et al. (2023) noted that AI frequently struggles to adapt to the diverse workflows and unique needs of different institutions. Poorly integrated AI can disrupt workflows rather than enhance them, underscoring the importance of tailoring AI solutions to specific clinical and operational contexts (Najjar, 2023). Successful implementation requires careful planning, robust training, and iterative refinement to ensure AI enhances rather than hinders radiology practice.

The ethical and legal implications of AI adoption also pose significant challenges. As powerful as AI systems are, they are not infallible. Errors in high-stakes environments like radiology can have serious consequences, raising questions of accountability. Najjar (2023) emphasized that radiologists remain the ultimate decision-makers, but the integration of AI complicates the issue of responsibility. If an AI system provides an incorrect diagnosis, is the

radiologist at fault, or does the liability lie with the developer? Ensuring transparency in AI systems and providing radiologists with proper training to understand and use these tools responsibly is crucial to maintaining ethical standards and safeguarding patient trust.

In this transformative era, radiologists must navigate the challenges of working with AI by adapting their expertise to complement machine intelligence, advocating for rigorous evidence, and championing ethical and practical frameworks. By embracing these challenges, radiologists can ensure that AI remains a powerful ally in delivering better outcomes for patients while preserving the integrity of the profession.

3.6 REA Recommendations – Practical Insights for AI Implementation

This Rapid Evidence Assessment (REA) investigated the clinical impact of Artificial Intelligence (AI) in radiology, focusing on how AI can be effectively integrated to enhance diagnostic accuracy, treatment monitoring, workflow efficiency, and patient outcomes. The findings demonstrate AI's transformative potential while underscoring the importance of a practical, evidence-based approach to its implementation. The following recommendations offer structured guidance for integrating AI across diagnostic and monitoring workflows, improving productivity, and safeguarding patient safety. These recommendations are tailored to support the radiology department in making informed, evidence-driven decisions as it navigates AI integration within clinical practice.

3.6.1 Diagnostic Accuracy and Early Detection: Prioritize Targeted Implementation

AI has consistently shown its ability to improve diagnostic accuracy, particularly in the early detection of diseases like breast, lung, and prostate cancer. However, the current body of evidence is largely based on controlled environments, and the models have not been universally validated across diverse clinical settings. As a practical step, it is recommended that radiology departments begin by targeting specific use cases where AI can add immediate value, such as detecting subtle abnormalities in complex images (e.g., mammograms or chest CT scans). Instead of a full-scale roll-out, departments should pilot AI tools in these specific areas, gathering performance data to assess whether these tools improve accuracy and reduce diagnostic errors in real-world clinical practice. This incremental adoption allows for evidence-building in a controlled, manageable way.

3.6.2 Treatment Monitoring: Utilize AI for Non-Invasive, Real-Time Monitoring

In treatment monitoring, AI has demonstrated potential for tracking disease progression and treatment responses, particularly through non-invasive techniques like virtual biopsies. For practical implementation, AI should be integrated into monitoring systems to provide real-time insights, which can help adjust treatment plans more quickly based on AI's analysis of radiological data. To make this feasible, departments should partner with AI developers to ensure these systems can be tailored to specific treatment protocols used in their clinical practice. Moreover, it is vital to ensure that radiologists remain involved in the decision-making process, using AI as a supplementary tool rather than a replacement. Clear communication pathways between the AI system and clinicians should be established, allowing real-time feedback to enhance treatment decisions.

3.6.3 Workflow Efficiency and Productivity: Focus on High-Impact Areas First

AI's ability to optimize workflow efficiency and relieve some of the burden on overworked radiologists is one of its most practical applications. However, instead of attempting a wholesale shift to AI-driven workflows, focus should be placed on high-impact areas first, such as triaging routine imaging tasks (e.g., protocolling or prioritizing urgent cases). This allows radiologists to concentrate on more complex diagnostics and decision-making tasks. As shown in studies like Jalal et al. (2021), automating such tasks can free up valuable time. Key practical steps include integrating AI into existing radiology platforms for tasks like image protocolling and case sorting, which can significantly reduce turnaround times for high-volume, low-

complexity cases. Departments should work closely with IT teams and vendors to ensure smooth integration and minimal disruption during this transition.

3.6.4 Patient Safety and Outcomes: Implement Oversight and Auditing Systems

Patient safety is paramount when introducing AI into radiological workflows, especially given the potential risks of overreliance and automation bias. To mitigate these risks, it is essential to implement robust oversight and auditing systems to track AI performance over time. This includes setting up regular quality checks where radiologists review AI-generated diagnoses to ensure that the system is functioning correctly. Additionally, AI systems should be implemented with safety protocols that require radiologist confirmation before final diagnoses are made, especially in high-stakes cases. Ensuring transparency in AI decision-making processes will help radiologists maintain control over clinical outcomes and safeguard patient trust. Furthermore, training radiologists to critically engage with AI outputs will foster a more collaborative and safe diagnostic process.

3.6.5 Navigating the Challenges

Radiologists play a pivotal role in the adoption of AI in radiology, yet their responsibilities must adapt to address the unique challenges of working with these systems. One major concern is managing automation bias, where radiologists may rely too heavily on AI outputs without sufficient critical analysis. To mitigate this, radiology departments should emphasize ongoing professional development focused on collaborative human-AI practices. Training that highlights both the strengths and limitations of AI is essential, equipping radiologists with the skills to critically evaluate AI findings and reinforcing their position as the ultimate decision-makers. Establishing an environment that uses radiologists' feedback to refine AI systems ensures these tools complement rather than replace their expertise.

Scaling AI across healthcare systems presents its own challenges, particularly when moving from pilot projects to full-scale implementations. A gradual approach to building AI infrastructure is essential, starting with pilot programs in specific units and evaluating performance, integration hurdles, and productivity outcomes. This phased scaling allows departments to apply lessons learned on a small scale to larger rollouts, avoiding potential workflow disruptions and technical issues that can come from a rushed integration process.

Ethical and legal considerations are equally critical as AI becomes increasingly embedded in radiology. Departments should establish clear ethical guidelines and accountability frameworks that define the responsibilities of radiologists and AI

systems, including liability around AI-driven errors, to ensure radiologists retain their role as the final authority. Transparent AI processes are essential, especially in high-stakes cases, to build trust in AI-supported diagnostics. Regular audits of AI performance and structured feedback channels will uphold ethical standards and sustain trust from both clinicians and patients in AI-assisted care.

The successful implementation of AI in radiology is not just about technological advancements but also about careful, strategic integration into existing workflows and practices. AI should be seen as a tool to enhance, not replace, the expertise of radiologists. The path forward involves targeted pilot programs, continuous professional training, and a focus on real-world evidence gathering, ensuring that AI can be scaled in a way that benefits both radiologists and patients. By approaching AI adoption incrementally, with an emphasis on safety, transparency, and collaboration, radiology departments can harness the full potential of AI to improve patient care while navigating the challenges this new era brings.

Chapter 4: Ensuring Safe and Responsible AI in Radiology

Implementing Artificial Intelligence (AI) in radiology holds vast potential, yet it also presents a range of challenges that must be navigated to achieve safe and effective integration. Beyond the benefits outlined in the Rapid Evidence Assessment, there are significant limitations and practical hurdles related to AI's generalizability, data biases, infrastructure compatibility, and regulatory demands. Additionally, handling false positives, diagnostic uncertainty, and complex cases introduces practical constraints that can hinder the efficiency AI seeks to improve. These challenges emphasize the need for a well-rounded approach that prioritizes both the technical and ethical aspects of AI integration.

This chapter outlines key limitations and considerations necessary for establishing a robust AI implementation policy. Topics include managing the limitations of AI in diverse clinical settings, addressing the infrastructural and legal barriers to implementation, and navigating the financial and technological disparities that affect accessibility. By exploring these elements, this chapter aims to provide a framework for radiology departments to adopt AI responsibly, ensuring that safety, ethical accountability, and the integrity of patient care remain at the forefront as technology continues to advance.

4.1 Limitations of AI

Numerous limitations have been identified in the application of Artificial Intelligence (AI) within radiology workflows, presenting challenges to productivity and operational integration. A significant concern involves generalizability and data bias. Many studies supporting AI in radiology are conducted in single-centre environments, raising doubts about the generalizability of findings across diverse clinical settings. Han et al. (2024) highlighted that most randomized controlled trials (RCTs) on AI were conducted in single centres, limiting their broader applicability (Jorritsma, Cnossen, & van Ooijen, 2015). Additionally, data bias is a critical issue, as AI models trained on specific datasets may not perform consistently across varied patient populations or clinical contexts. Bennett et al. (2023) illustrated this by noting that AI systems for chest radiographs, which had not been trained on the study datasets, underperformed when applied in new environments (Bernstein et al., 2023).

Challenges related to integration and implementation further complicate the deployment of AI in radiology. Many healthcare systems face infrastructure and IT limitations that hinder seamless integration of AI tools. Ranschaert et al. (2021) observed that inadequate IT infrastructure and difficulties in data integration significantly slow AI adoption, especially in radiology departments that rely on legacy systems incompatible with AI technology. Regulatory barriers add another layer of complexity, particularly for diagnostic AI tools, which require stringent validation and regulatory oversight, unlike non-diagnostic AI tools that face fewer regulatory constraints (Ranschaert et al., 2021).

False positives and diagnostic uncertainty present additional challenges. Although AI tools aim to reduce radiologists' workload, they may generate false positives, necessitating further investigation and thereby increasing rather than reducing workload. For instance, Arbabshirani et al. (2018) reported false positives in an AI model for detecting intracranial haemorrhages, which still required manual verification, emphasizing AI's limitations in fully automating diagnostic tasks (Bennett et al., 2023). Moreover, the diagnostic capabilities of AI can be inferior to radiologists, particularly when systems lack access to essential contextual information, such as patient history or previous imaging. Bennett et al. (2023) noted that radiologists outperformed AI tools in cases where contextual data was crucial.

AI's limitations in handling complex cases underscore its selective applicability. While AI tools can streamline routine case management, they may struggle with complex, non-standard cases. For example, Chung et al. (2024) found that automated protocoling systems reduced workload but still required manual intervention for complex cases, particularly in paediatric radiology, which is often excluded from automation due to its nuanced requirements (Chung et al., 2024).

Another concern is the potential for artifact enhancement and misdiagnosis with certain AI-based image enhancement tools. Some techniques, such as Deep Learning Reconstruction (DLR), may inadvertently amplify artifacts, which could obscure critical diagnostic information. Kiryu et al. (2023) noted that while DLR effectively reduces noise in MRI images, it may also enhance other artifacts, necessitating careful review by radiologists to avoid missed diagnoses (Duffy, 2019).

High costs and limited access also present barriers to AI adoption. Advanced AI technologies like augmented reality (AR) and virtual reality (VR) are costly and often

lack reimbursement pathways, limiting their uptake despite potential clinical benefits. Elsakka et al. (2023) noted the financial burden of AR/VR systems, which many healthcare systems find challenging to justify. Additionally, access to AI technology is uneven, with some radiology departments, particularly in resource-limited settings, unable to implement AI due to lack of infrastructure (Pierre et al., 2023; Ranschaert et al., 2021).

Lastly, lack of standardization and vendor variability complicate the clinical adoption of AI across different institutions. AI tools from different vendors often use varying algorithms and methods, leading to inconsistent performance across imaging platforms. Kiryu et al. (2023) highlighted the variability in MR image quality processed by DLR across devices, suggesting a need for standardization to achieve consistent outcomes (Duffy, 2019).

These limitations underscore the challenges that need to be addressed before AI can be fully integrated into radiology workflows at scale. Despite AI's potential to improve efficiency and reduce workload, issues related to infrastructure, data quality, and clinical integration present significant hurdles that must be overcome to ensure responsible and effective implementation.

4.2 Further Research and Validation of AI

The rapid rise of AI in radiology underscores the critical need for rigorous validation processes to ensure safety, accuracy, and reliability before integrating these technologies into clinical practice. For AI systems to function effectively in diverse, real-world healthcare environments, they must undergo extensive testing across various patient populations and clinical conditions. This is only possible with access to large, high-quality datasets that reflect the diversity of the healthcare landscape. Data sets such as The Cancer Imaging Archive and the UK Biobank have become essential resources, as they provide annotated databases that help enhance the robustness and generalizability of AI algorithms. However, a need remains for more extensive access to well-curated data, allowing researchers and developers to better ensure transparent and equitable AI applications in radiology (Bell & Shimron, 2023)

A significant barrier to reliable AI validation is the inherent heterogeneity of medical imaging data, stemming from differences in imaging protocols, equipment variations, and the diverse demographic characteristics of patient populations across healthcare institutions. Addressing this challenge requires standardized frameworks like the Medical Imaging Common Data Model, which enables interoperability and a unified data structure. Such frameworks facilitate reproducibility by allowing AI algorithms to function accurately across multiple institutions. In addition, these standardization efforts support federated learning—a method that maintains patient privacy by enabling models to train on data from diverse sources without directly sharing that data (Tanguay et al., 2022)

One essential component of the validation process is external validation, which involves testing AI models on data from institutions different from those used in initial development. This step verifies that algorithms maintain high performance across various clinical settings, ensuring their reliability in routine practice. However, despite its importance, external validation remains challenging. Variations in demographic and imaging parameters can introduce biases, and sharing validation datasets openly could address some of these limitations by allowing broader testing and refinement. This practice is especially crucial as AI continues to mature, as it serves as the final checkpoint before clinical integration and confirms that AI systems deliver consistent results across diverse healthcare settings (Martin-Noguerol & Luna, 2021; Khunte et al., 2023).

Robust infrastructures for real-world AI validation are particularly essential in large healthcare networks where local testing plays a key role in aligning AI applications with specific regional healthcare needs. Secure, cost-effective validation infrastructures allow healthcare providers to monitor AI algorithms' performance continually, ensuring they support clinical goals and patient safety. Implementing adaptable validation frameworks that can accommodate local resources helps promote equitable distribution of AI's benefits across healthcare systems, irrespective of their size or capacity (Ramwala et al., 2024).

With AI's increasing integration into healthcare, ethical and legal governance considerations become crucial. Issues such as data privacy, algorithm transparency, and accountability demand robust frameworks that align with ethical principles and legal standards. Regulatory bodies are actively developing AI-specific frameworks to address fairness, data ownership, and patient rights, which help safeguard responsible and transparent use of AI tools in clinical decision-making (Ho et al., 2019).

Achieving validated and reliable AI in radiology requires concerted efforts across research, clinical practice, and policy development. Building comprehensive datasets, implementing robust validation processes, and adhering to stringent ethical standards all serve as pillars for establishing AI that is not only effective but also trustworthy and equitable. By upholding these standards, AI stands to transform radiology, delivering improved diagnostic accuracy, efficiency, and patient outcomes across the healthcare spectrum.

4.3 Ethical and Legal Concerns

The integration of Artificial Intelligence (AI) into radiology promises remarkable advancements, yet it also brings complex ethical and legal challenges that must be addressed to ensure patient safety, fairness, and accountability. The rapid deployment of AI in healthcare, particularly in radiology, has led to discussions on transparency, bias, patient autonomy, and legal responsibility, highlighting the need for robust ethical frameworks and regulatory guidelines to navigate this new terrain effectively.

One of the primary ethical concerns in AI is algorithmic transparency. As noted by Currie and Hawk (2020), many AI systems operate within a “black box,” where the reasoning behind their outputs is not easily accessible or understandable by end-users, including healthcare providers. This opacity can lead to mistrust and reluctance among clinicians, who must be able to explain and justify AI-based decisions to their patients. Additionally, when AI models make errors, determining accountability becomes challenging due to the system's complexity and the difficulty of tracing specific decision-making pathways within the algorithm (Akinci D'Antonoli, 2020).

In the context of radiology, the issue of bias in AI algorithms is particularly concerning. AI systems trained on limited or unrepresentative datasets can inadvertently perpetuate or even exacerbate existing health disparities. For example, Cartolovni et al. (2022) highlight that AI models often fail to account for diverse demographic factors, such as race and socioeconomic status, which can result in biased outcomes that disproportionately affect marginalized populations. In radiology, such biases could manifest in the form of diagnostic inaccuracies for certain patient groups, undermining the principle of justice and equality in healthcare. Ensuring that datasets are inclusive and representative is critical to preventing these biases, but this requires concerted efforts in data curation and more stringent regulatory oversight (Čartolovni, Tomičić, & Lazić Mosler, 2022).

The principle of autonomy is also at risk in AI-assisted radiology. Patient autonomy is foundational in medicine, affirming that patients have the right to make informed decisions regarding their care. However, as AI becomes more embedded in clinical decision-making, there is a risk that its recommendations could overshadow or even bypass human judgment, potentially compromising shared decision-making processes between patients and physicians. Currie and Hawk (2020) suggest that AI should serve as a support tool rather than as a replacement for human oversight, preserving the role of the radiologist in ensuring that patients understand and consent to AI-supported diagnoses and treatments. Moreover, patients should be informed about the involvement of AI in their care, including its limitations and potential implications for their diagnoses (Subasi & Özçelik Ş, 2023).

Data privacy is another critical ethical and legal concern with AI in radiology, given that these systems rely on vast amounts of patient data to function effectively. Data privacy concerns arise not only from the risk of unauthorized access but also from the

secondary use of patient data for commercial or research purposes without explicit consent. Akinci D'Antonoli (2020) stresses the importance of safeguarding patient privacy and ensuring data confidentiality, especially as AI systems often involve cloud-based data storage, increasing exposure to potential breaches. The General Data Protection Regulation (GDPR) in Europe sets strict guidelines for data handling, yet there remains ambiguity about how these laws apply to AI systems that continuously learn and adapt from patient data. Ensuring compliance with privacy regulations is essential for fostering public trust in AI-enabled healthcare systems (Herington et al., 2023).

The legal responsibility for AI-related outcomes is a complex issue, particularly when AI systems make autonomous decisions or provide recommendations that lead to patient harm. Determining accountability in cases of misdiagnosis or treatment errors involving AI remains legally ambiguous, as liability could fall on the physician, the hospital, or the developers of the AI system. Akinci D'Antonoli (2020) discusses the concept of “shared liability,” where responsibility is distributed among all parties involved in the deployment and use of AI. However, this shared liability approach requires clear regulatory frameworks that delineate the boundaries of accountability for each stakeholder, particularly as AI systems evolve and integrate more deeply into clinical workflows.

Additionally, the use of AI in medical imaging poses specific challenges in terms of professional responsibilities and ethical obligations. Radiologists must remain vigilant about potential automation bias, where they might over-rely on AI outputs without critical scrutiny, leading to missed diagnoses or inappropriate clinical decisions. The introduction of explainable AI (XAI) tools, which provide insights into the decision-making process of AI models, is one potential solution to mitigate automation bias.

According to Currie and Hawk (2021), XAI can enhance transparency by allowing radiologists to understand and trust AI recommendations, thereby promoting a balanced integration of AI that supports rather than replaces human judgment in diagnostics (Currie & Hawk, 2021).

Finally, the rapid pace of AI development outstrips current regulatory frameworks, creating a pressing need for updated guidelines that reflect the unique characteristics of AI systems in radiology. Regulatory bodies, such as the U.S. Food and Drug Administration (FDA), have started to address this gap by classifying AI as “software as a medical device” (SaMD). However, many AI systems in radiology are “adaptive” or “continuously learning,” meaning they evolve based on new data inputs, which presents additional regulatory challenges. The FDA has proposed a lifecycle approach to monitoring AI, which involves pre- and post-market evaluations to ensure safety and efficacy as AI systems evolve. This approach, as Herington et al. (2023) suggest, could offer a framework for managing AI systems throughout their operational lifecycle, ensuring that safety standards are maintained even as algorithms adapt over time.

In conclusion, while AI has the potential to revolutionize radiology, its integration into clinical practice raises numerous ethical and legal challenges that must be carefully managed. Addressing these concerns requires a multidisciplinary approach involving radiologists, data scientists, ethicists, and policymakers. Robust ethical frameworks, comprehensive regulatory guidelines, and a commitment to transparency, fairness, and accountability are essential for realizing AI’s benefits in radiology while protecting patient rights and upholding professional integrity. By navigating these ethical and legal complexities thoughtfully, the field of radiology can leverage AI responsibly to enhance patient care and advance medical practice.

Chapter 5 – Expert Panel

5.1 Introduction

In order to ensure that the research findings were balanced, credible, and thoroughly grounded, an expert panel was assembled to review the conclusions. This panel brought together a diverse group of specialists, each offering unique insights that helped identify gaps, question assumptions, and refine the analysis. The panel consisted of three internationally qualified radiologists - two based locally and one external. An external Health IT specialist experienced in integrating AI into clinical workflows in hospitals similar to Mater Dei Hospital was also selected. A local expert is still not available within the healthcare. The radiologists, with broad international experience across Europe, provided valuable perspectives on AI's applications in both diagnostic and interventional radiology, while the Health IT specialist contributed critical expertise on the technical, operational, and infrastructural considerations essential for effective AI adoption. Given the emerging nature of AI technology, legal expertise was not available locally, and no suitable external legal specialist could be identified. Despite this, the panel's comprehensive feedback significantly enhanced the credibility, depth, and overall impact of the research.

5.2 Expert Panel Review

The expert panel was assembled with the primary objective of thoroughly evaluating the conclusions presented in the section on the *Predicted Clinical Impact of Artificial Intelligence in Radiology*. This review focused on ensuring that the conclusions were robust, evidence-based, and relevant to clinical practice, with the goal of validating that they were well-founded, grounded in current literature, and practically applicable within radiology.

To facilitate this thorough review, pre-evaluation materials were provided to each panel member, including the full REA with emphasis on the conclusions, supporting evidence, and practical recommendations. This preparation allowed panel members to familiarize themselves with the key findings and rationale behind the recommendations, setting a strong foundation for the review process.

Each panel member then undertook an individual review, assessing the dissertation independently according to specific evaluation criteria. This step enabled each expert to focus on areas relevant to their expertise—whether radiology, health IT, or AI integration—ensuring that insights were precise and aligned with their specialties. In this phase, the panel examined the evidence-based approach underlying the conclusions, assessing whether the findings were logically derived from the research and accurately reflected the current state of AI in radiology, as documented in the literature. By scrutinizing the strength of the evidence, the panel ensured that the recommendations were credible and equipped to withstand scrutiny in real-world clinical settings.

Following individual reviews, the panel convened in a panel discussion, held online, to discuss their findings collaboratively. During this meeting, members shared insights, highlighted areas of concern, and worked to achieve consensus on the conclusions’

strengths and weaknesses. This collaborative discussion allowed the panel to assess the validity of the recommendations for AI implementation, focusing on whether these suggestions were sound and evidence-based. They evaluated the robustness of the conclusions regarding AI's potential to improve diagnostic accuracy, workflow efficiency, and patient safety, ensuring these predictions were well-supported and credible.

An essential part of the review process also involved assessing the practicality of the proposed steps for AI adoption, with attention to the technological, financial, and infrastructural constraints in healthcare. Panel members examined whether ethical concerns, automation bias, and transparency were adequately addressed, reinforcing that the conclusions were grounded in the practical realities of healthcare organizations.

The panel further evaluated the clarity of the conclusions, ensuring that they were articulated in an accessible manner for radiologists, healthcare administrators, and other stakeholders, and were presented as actionable and practical recommendations. Additionally, the feasibility of the suggested future directions for AI research and validation was reviewed to confirm alignment with emerging trends and to ensure that these proposals were achievable within the current evidence base.

Through this structured and collaborative evaluation, the expert panel provided a comprehensive review that enriched the research's depth, credibility, and practical impact. The feedback reinforced an evidence-based foundation, critical for the responsible integration of AI in radiology, and added valuable perspectives to enhance the research's relevance and applicability in real-world clinical contexts.

5.3 Expert panel responses and recommendations

5.3.1 Summary of Strengths

Comprehensive Coverage of AI's Potential Impact

The panel commended the thorough discussion on AI's ability to improve diagnostic accuracy and workflow efficiency. The focus on practical examples, such as AI's role in breast cancer screening and lung cancer detection, demonstrated a solid understanding of AI's clinical applications. The panel members highlighted the clear connection between AI and real-world improvements in patient outcomes, particularly in early detection and reducing diagnostic errors.

Practical and Actionable Recommendations

The expert panel appreciated the dissertation's practical approach to AI adoption. Specifically, the recommendation to begin with targeted pilot programs and gradually scale AI implementation aligns well with how radiology departments are currently managing new technology integration. The suggestion to pilot AI tools in complex imaging areas, like mammography and chest CT, was seen as a pragmatic strategy to gather real-world data before wider implementation.

Attention to Ethical and Regulatory Considerations

The panel applauded the clear acknowledgment of ethical concerns, such as automation bias and the black-box nature of many AI models. This discussion is essential, given the potential legal and clinical risks of AI misdiagnosis. The inclusion of these concerns showed an awareness of the challenges radiologists face when working with AI systems. The panel found the discussion on maintaining radiologists

as the final decision-makers both timely and necessary, given the increasing reliance on AI in clinical practice.

5.3.2 Areas for Improvement

The panel noted a need for greater in depth discussion about the radiologist-AI collaboration. While the conclusions provide a solid overview of AI's benefits, the panel suggested placing additional emphasis on how radiologists and AI systems work together, especially in complex cases. The current focus primarily addresses AI's role in handling routine tasks, yet further exploration of AI's potential to support expert decision-making in intricate diagnostics, such as rare diseases or multi-modality imaging, could add valuable insights.

- **Recommendation:** Include specific case studies or examples illustrating AI's role in supporting radiologists during complex diagnostic scenarios, such as using AI as a second opinion in difficult-to-interpret cases.

The Health IT specialist highlighted a need for a more detailed discussion on the workflow challenges associated with integrating AI into clinical environments. While the dissertation covers AI's potential to enhance workflow efficiency, it provides limited insight into the technical barriers involved. Significant challenges include the interoperability of AI systems with existing Radiology Information Systems (RIS) and Picture Archiving and Communication Systems (PACS), as well as the variability among AI platforms, which complicates seamless integration into current IT infrastructures. Addressing these factors would offer a more comprehensive view of the practical difficulties in implementing AI within clinical workflows.

- **Recommendation:** Add a section addressing the integration of AI with current radiology IT systems, such as RIS and PACS. Discuss potential solutions for overcoming interoperability issues, such as adopting standardized interfaces, working closely with IT departments, and ensuring robust system testing prior to deployment.

The panel observed a need for a more explicit discussion on the lack of large-scale validation and generalizability in current AI studies. While the dissertation acknowledges certain limitations, the panel suggested emphasizing the importance of multi-center trials and the use of diverse datasets. AI models developed in single-center environments may lack the generalizability needed to perform consistently across varied patient populations and clinical settings, highlighting a critical gap in current research.

- **Recommendation:** Expand the discussion to emphasize the importance of large-scale, multi-centre studies for validating AI's clinical utility. Propose potential collaborations between international institutions to facilitate AI validation across diverse clinical settings.

The Health IT specialist emphasized the importance of addressing the scalability of AI tools, especially within larger hospital networks. The dissertation could be strengthened by exploring strategies to manage the increasing computational demands associated with AI and by examining the role of cloud-based solutions in supporting data storage and processing in large-scale AI deployments. This perspective underscores the practical considerations necessary for expanding AI applications across broader healthcare systems.

- **Recommendation:** Consider including a section on the infrastructure requirements for scalable AI implementation, focusing on cloud computing, cybersecurity, and data management strategies that can handle the extensive data processing demands of AI in radiology.

5.3.3 Discussing the Future

Discussing the future of AI in radiology is essential to any radiology department, as it anticipates how this rapidly evolving technology may reshape the field in the years to come. While current applications of AI in radiology primarily address diagnostic tasks, exploring future possibilities—such as its integration in interventional radiology, ethical training, and necessary IT infrastructure—allows for a more comprehensive understanding of AI's long-term potential and challenges. By examining these aspects, the research not only addresses the immediate impact of AI but also prepares for the sustained growth and ethical complexities of AI in clinical practice, ensuring that radiology departments are equipped to adapt to and responsibly manage this powerful technology as it advances.

The panel recommended that the dissertation delves into the potential applications of AI in interventional radiology, an area where real-time decision-making is vital. AI could enhance clinical outcomes by aiding in pre-procedural planning, providing intra-procedural guidance, and supporting post-procedural monitoring. They suggested including a dedicated section on the future potential of AI in this field, particularly emphasizing its role in real-time image guidance during procedures and in post-procedure assessments.

The panel underscored the importance of incorporating AI ethics into radiology training programs, given the increasing presence of AI in clinical practice. Ethical training

would help radiologists remain critical of AI outputs and prepare them to navigate ethical challenges, such as potential biases in algorithmic decision-making. The panel recommended that future research and professional development focus on creating training programs that address these ethical considerations in clinical settings.

The Health IT specialist further emphasized the necessity of investing in a robust IT infrastructure to support the expanding role of AI in radiology. As AI adoption grows, radiology departments will face critical challenges related to data security, system redundancy, and network bandwidth to ensure continuous AI functionality. The specialist recommended adding a "Future Directions" section to address these infrastructure needs, highlighting the importance of data security, scalable storage solutions, and the technical support required to sustain AI systems in real-time clinical environments.

5.3.4. Limitations of the Expert Panel Approach

The expert panel played a crucial role in providing contextual insights that shaped the interpretation of results. While their involvement was limited to post-analysis consultation, a more continuous approach could have been beneficial. Engaging experts earlier in the process—such as through preliminary interviews before data synthesis—could have helped steer the interpretative approach, ensuring that key considerations were accounted for from the outset. A follow-up focus group discussion might have further refined the findings, identified gaps, and highlighted future research directions. However, time constraints and the limited availability of experts made this challenging. Future studies may benefit from expert involvement at multiple stages, fostering deeper discussions and a more structured integration of expert perspectives into the research process.

Chapter 6 – Responsible Scaling of AI

Building on the transformative potential of Artificial Intelligence (AI) identified in this Rapid Evidence Assessment (REA), responsible scaling of AI solutions in radiology departments is essential for realizing the technology's full benefits. While the REA has shown that AI can enhance diagnostic accuracy, streamline workflows, and improve patient outcomes, achieving these advantages on a larger scale requires a careful, evidence-based approach. The structured, phased integration of AI ensures that each step aligns with best practices, addressing challenges such as data management, IT infrastructure, clinician training, and regulatory compliance.

An evidence-based approach to scaling AI solutions emphasizes rigorous evaluation and adaptation, allowing radiology departments to adopt AI responsibly. This methodology is reinforced by literature-supported strategies and expert panel insights, particularly in using pilot studies, diverse datasets, and multi-center trials to ensure AI performance across various clinical settings (Han et al., 2024). Such strategies provide a roadmap to optimize AI's contributions to radiology while maintaining high standards of clinical practice, patient safety, and quality control.

6.1 Preparation and Foundations for AI Integration

Phase 1: Data Readiness and Standardization

The foundation of effective AI implementation is ensuring data readiness and standardization, as the quality of AI outputs relies heavily on the quality and diversity of the training data. Radiology departments must gather high-quality datasets from multiple imaging modalities, such as X-rays, MRIs, and CT scans, that accurately

reflect their patient populations' complexity. Acknowledging this need, Han et al. (2024) highlight that single-centre AI models often lack generalizability, underscoring the importance of diverse datasets for AI to adapt across institutions.

Standardization is also critical, as variability in data formats and imaging protocols can hinder AI's ability to interpret images consistently across systems. Collaboration with IT specialists ensures that imaging protocols are uniform across departments, thereby enabling accurate AI interpretation. Additionally, the quality of AI's training data can be improved through partnerships with AI developers to produce clinically relevant, well-labelled datasets that meet diagnostic standards and reflect real-world conditions.

Challenges in Standardization, Interoperability, and Compliance

As AI scales, several challenges emerge in the areas of standardization, interoperability, and regulatory compliance. Variability in imaging protocols, data storage formats, and quality control standards across healthcare facilities can disrupt AI's performance. Standardizing these elements is essential to enable consistent, accurate AI interpretations, requiring collaboration among radiology departments, IT teams, and AI developers to establish universal protocols and benchmarks.

System interoperability also poses challenges, as AI tools must integrate with existing healthcare software, such as Electronic Health Records (HER) and Picture Archiving and Communication Systems (PACS), to provide seamless care solutions. Achieving interoperability requires early engagement with IT teams to address integration challenges effectively. Compliance with data protection regulations, such as GDPR in the EU, becomes increasingly complex as AI is implemented across more facilities. Dedicated oversight teams are vital for monitoring data security, ensuring AI systems operate within regulatory and ethical boundaries, and maintaining patient trust.

6.2 Testing and Initial Implementation

Phase 2: Pilot Testing and Initial Integration

The next step in scaling AI solutions is pilot testing, where AI is integrated into controlled environments within specific radiology units. This phase enables departments to evaluate AI's real-world performance, allowing for early adjustments before broader deployment. Targeted pilot programs, such as those focused on triaging urgent cases or detecting specific pathologies like breast cancer in mammograms, provide valuable insights into AI's impact on diagnostic accuracy and workflow efficiency.

To assess AI's success in these initial implementations, performance metrics such as diagnostic accuracy, processing speed, and clinician acceptance are essential benchmarks. Feedback loops between clinicians and AI developers further refine the AI model to ensure alignment with clinical goals. Such controlled testing not only builds confidence that AI can enhance workflows without disrupting patient care but also helps in establishing foundational quality standards for broader AI integration.

Continuous Auditing and Quality Control

To uphold patient safety and diagnostic accuracy, the expert panel highlighted the need for continuous auditing and radiologist oversight of AI systems. Establishing regular review processes allows radiologists to monitor AI outputs effectively, preventing over-reliance on AI while maintaining quality control. Ongoing auditing provides early detection of performance issues, enabling timely adjustments to sustain AI accuracy and reliability in clinical practice. Integrating these safety measures into

AI workflows ensures that AI supports rather than replaces radiologists' expertise, protecting the integrity of patient care.

6.3 Clinician Preparation and Ethical Considerations

Phase 3: Clinician Training and Professional Development

Once pilot testing is complete, clinician training becomes crucial for scaling AI in radiology. To facilitate a successful human-AI collaboration, radiologists must undergo comprehensive training that covers the capabilities, limitations, and ethical considerations of AI. AI literacy programs help clinicians understand AI as a supportive tool, not a replacement for human expertise, reducing risks such as automation bias.

Bennett et al. (2023) advocate for training that emphasizes the ethical dimensions of AI usage, including algorithmic transparency and bias, as critical for cultivating radiologists' critical oversight of AI outputs. Simulation-based practice allows clinicians to interact with AI tools in a non-clinical setting, gaining practical experience with AI's decision-making processes. As AI technology advances, continuous education programs—such as workshops, certification courses, and online learning—ensure radiologists remain prepared to work alongside increasingly sophisticated AI systems.

Insights from the Expert Panel on Ethical and Technical Dimensions

The expert panel emphasized the importance of addressing both ethical and technical dimensions in AI integration for responsible adoption in radiology. In interventional radiology, for example, AI's role in supporting real-time decision-making through pre-procedural planning, intra-procedural guidance, and post-procedural monitoring could

significantly enhance clinical outcomes. Ethical considerations also remain crucial; training programs that incorporate AI ethics equip radiologists to engage critically with AI outputs and manage issues such as algorithmic bias (Currie & Hawk, 2021).

Investing in a robust IT infrastructure is also vital for supporting AI's expanding role. With rapid AI adoption, radiology departments face challenges related to data security, system redundancy, and network capacity to maintain seamless functionality. The Health IT specialist on the panel recommended working closely with IT teams to ensure AI solutions are compatible with existing systems and supported by security protocols to protect sensitive medical data. Implementing scalable storage and technical support prepares departments for the growing demands of AI-driven workflows, ensuring data integrity and facilitating smooth clinical operations.

6.4 Scaling and Full Integration

Phase 4: Gradual Scaling and System-Wide Integration

After pilot testing and clinician training, radiology departments can undertake a phased rollout of AI across multiple imaging units or locations. This gradual expansion allows departments to manage the technical complexities of scaling AI solutions within diverse IT infrastructures, ensuring compatibility with systems such as Electronic Health Records (EHRs) and Picture Archiving and Communication Systems (PACS). Collaboration with IT specialists and AI vendors addresses interoperability issues, helping departments establish seamless AI workflows across different sites.

Establishing redundancy and fail-safes is also essential to safeguard patient safety and diagnostic reliability. For example, human oversight in verifying AI-driven diagnostics remains crucial in high-stakes cases, preventing potential diagnostic errors. Routine auditing and performance reviews of AI tools help maintain their effectiveness and compliance with quality standards, as emphasized by Challen et al. (2019). Regular evaluations optimize AI's outputs and ensure it adheres to patient safety protocols as it scales across the healthcare system.

Conclusion

The research question was examined through a Rapid Evidence Assessment (REA) of peer-reviewed studies, evaluating AI's potential to enhance diagnostic accuracy, enable early disease detection, streamline workflows, improve patient safety, and support treatment monitoring. The findings highlight AI's ability to address key challenges in radiology by improving imaging precision, automating repetitive tasks, and facilitating personalized treatment strategies, aligning with the need to manage growing workloads and resource constraints in radiology departments.

However, the evidence remains limited, with most studies based on retrospective analyses, small-scale trials, or expert opinions, reducing their applicability across diverse clinical settings. Challenges such as automation bias, ethical concerns, and interoperability issues further complicate integration. To address these gaps, the dissertation recommends multi-centre, prospective studies to validate AI applications, enhanced training for radiologists, and the development of transparent, explainable AI systems. A scalable, stepwise approach tailored to clinical workflows is also essential.

In conclusion, while AI holds great promise in revolutionizing radiology, its true clinical impact depends on rigorous validation, strategic implementation, and ethical oversight. Radiologists remain vital to this transformation, leveraging AI to complement their expertise while safeguarding patient care. With these measures in place, AI can achieve its potential to enhance the accuracy, efficiency, and safety of radiological practice.

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Annexa 1

The following is a summary of each scientific paper included for the REA divided according to the research question subsection. A full reference for each is available in the reference section.

Diagnostic Accuracy and Early Detection

<u>Liver Lesion Analysis using SimU-Net</u> <u>Adi Szeskin et al., 2021</u>	
Main Findings	The study introduces SimU-Net, a deep learning model designed for detecting and segmenting liver lesions in longitudinal contrast-enhanced CT (CECT) scans. SimU-Net significantly outperformed traditional single-scan methods, showing a 50% improvement in lesion detection precision. It achieved high recall and Dice scores for lesions larger than 5 mm and accurately classified lesions as existing, new, or disappeared. This model presents a promising tool for reducing the time and effort radiologists spend on assessing treatment responses in metastatic patients.
Scientific Level	Highly technical, suitable for specialists in medical imaging, radiology, and oncology.
Study Type	Retrospective study analyzing CECT scans from a clinical dataset.
Sample Size	218 scans from 71 patients, comprising 3491 manually delineated liver lesions.
Evidence Level	Level III (retrospective analysis without randomization or control).
Effect Size	Improved lesion detection precision by 50%, recall of 0.86, and Dice score of 0.82.

<u>Artificial Intelligence in Spinal Imaging</u> <u>Yangyang Cui et al., 2021</u>	
Main Findings	AI applications in spinal imaging showed enhanced efficiency, quality, diagnostic accuracy, and reduced radiation. Highlights a need for large, standardized datasets and multimodal integration to improve clinical adoption.
Scientific Level	Advanced and specialized, suited for radiology and AI experts.
Study Type	Narrative review of multiple studies on AI in spinal imaging.
Sample Size	Includes studies with sample sizes ranging from 42 MRI images to over 100
Evidence Level	Level III (consolidation of retrospective data without RCTs).
Effect Size	Reported accuracies up to 98% for disc detection, 71–89% classification accuracy for scoliosis.

Deep Learning in Digital Breast Tomosynthesis for Cancer Detection Bai J. et al., 2021	
Main Findings	This review shows that DL in DBT enhances breast cancer detection, offering higher accuracy and reduced false positives compared to mammography. DL models, particularly CNNs, were effective in lesion localization and classification, with significant improvements in cancer detection rates and recall rates.
Scientific Level	Advanced and technical, aimed at radiologists and AI specialists.
Study Type	Review of multiple DL studies in DBT for breast cancer detection.
Sample Size	Includes studies with sample sizes ranging from 324 to 78,445 images.
Evidence Level	Level III (review based on retrospective and observational studies).
Effect Size	AUC of 0.945 in one study; 14–40% reduction in false positives.

<u>AI-CAD in Chest Radiographs on CT Referrals</u> <u>Wonju Hong et al., 2021</u>	
Main Findings	AI-CAD increased CT referrals by 33% with a high rate of false positives, showing limited improvements in detecting critical findings but raising costs due to unnecessary scans.
Scientific Level	High relevance for radiology and diagnostic professionals.
Study Type	Retrospective observational study.
Sample Size	54,434 CRs from 20,060 patients, with pre- and post-AI-CAD data.
Evidence Level	Level III (retrospective cohort without randomization).
Effect Size	33% increase in CT referrals (OR 1.33, p=0.008); negative CT referrals up by 46% (OR 1.46).

<u>Deep Learning in Ovarian Cancer Diagnosis</u> <u>Mohammad Hossein Sadeghi et al., 2021</u>	
Main Findings	DL models such as CNNs show potential for high diagnostic accuracy in ovarian cancer, with tumor detection rates over 95%.
Scientific Level	Specialized for radiology and oncology.
Study Type	Systematic review of DL for ovarian cancer diagnosis.
Sample Size	Studies included range from 100 CT images to 592,275 ultrasound images.
Evidence Level	Level III (retrospective studies on diagnostic accuracy).
Effect Size	Accuracy up to 98.87%, F1 score of 97% for tumor segmentation.

<u>Commercial AI Products in Radiology</u> <u>K. G. Van Leeuwen et al., 2021</u>	
Main Findings	This study provides an overview of 100 commercial AI products for radiology, revealing a gap in peer-reviewed validation. Most products focus on diagnostic accuracy, with limited evidence for clinical decision-making impact.
Scientific Level	Specialized and relevant for radiologists, AI developers, and regulatory bodies.
Study Type	Retrospective observational study analyzing commercial AI product evidence.
Sample Size	100 CE-marked AI products, evaluated through 237 peer-reviewed studies.
Evidence Level	Level III (retrospective review of evidence for commercial AI).
Effect Size	65% focused on diagnostic accuracy; 27% addressed clinical impact on decision-making.

<u>Applications of AI in Temporal Bone Imaging</u> <u>D. P. Petsiou et al., 2021</u>	
Main Findings	AI, particularly CNNs, demonstrated strong segmentation accuracy for temporal bone structures, aiding in surgical planning and diagnostic efficiency. Challenges include data scarcity for rare conditions and the need for standardized datasets.
Scientific Level	Specialized, aimed at otolaryngologists and radiologists.
Study Type	Narrative review summarizing AI applications in temporal bone imaging.
Sample Size	Compiles findings from various studies; e.g., 944 MRI volumes in one study
Evidence Level	Level III (narrative review of retrospective studies).
Effect Size	DSC values of 0.85–0.91 for segmentation; Hausdorff distances as low as 0.21 mm.

<u>Reinforcement Learning and Text Augmentation for Radiology Reports</u> <u>Parres D et al 2024</u>	
Main Findings	This study shows that reinforcement learning and text augmentation improved the accuracy and diversity of automatically generated radiology reports. It proposes using specialized metrics like RadGraph for evaluating clinical relevance.
Scientific Level	Highly technical, targeting AI and medical NLP experts.
Study Type	Experimental study on radiology report generation methods.
Sample Size	Utilized MIMIC-CXR (152,000 reports) and Open-i (3,300 reports) datasets.
Evidence Level	Level III (experimental model performance evaluation without clinical trial validation).
Effect Size	F1CheXbert score of 66.2, F1RadGraph score of 37.8.

<u>Radiomics and Deep Learning in Pancreatic Cancer Diagnosis</u> <u>Lanhong Yao et al., 2021</u>	
Main Findings	Combining radiomics with deep learning has shown high diagnostic accuracy for pancreatic cancer, with AUC values above 0.91 in some models. The study emphasizes the need for larger datasets and multimodal approaches for improved generalization.
Scientific Level	Technical and advanced, suited for radiology and oncology researchers.
Study Type	Systematic review of studies on AI applications in pancreatic cancer.
Sample Size	Various studies were included, with one dataset containing 546 patients.
Evidence Level	Level III (based on retrospective and observational studies).
Effect Size	AUCs ranging from 0.75 to 0.98; high sensitivity and specificity in tumor classification.

AI-CAD in Chest Radiographs for Lung Cancer Screening
H. Yoo 2021

Main Findings	AI-CAD models have demonstrated efficacy in enhancing detection of lung cancer in chest radiographs, achieving high sensitivity, though false positives remain a challenge.
Scientific Level	Specialized for radiologists and oncologists.
Content Type	Observational study assessing AI-CAD implementation.
Sample Size	Data from 54,000+ chest radiographs reviewed.
Evidence Level	Level III (observational study without randomization).
Impact summary	Significant increase in cancer detection sensitivity; moderate increase in false positives.

<u>Deep Learning for Chest X-Ray Report Generation</u> <u>M. Y. Ouis and M. A. Akhloufi, 2021</u>	
Main Findings	Deep learning models, especially encoder-decoder and transformer models, have shown significant advancements in automating chest X-ray report generation, improving both accuracy and clinical relevance.
Scientific Level	Advanced, targeted at radiologists and AI researchers.
Study Type	Narrative review of deep learning methods for report generation.
Sample Size	Includes datasets like MIMIC-CXR (377,110 images), CheXpert (224,316 images), and PadChest (160,868 images).
Evidence Level	Level III (consolidation of retrospective studies and model performance metrics).
Effect Size	BLEU scores from 0.456 to 0.772; ROUGE-L scores from 0.362 to 0.5976.

<u>Machine Learning for Detecting Early Infarction in Acute Stroke with Non-Contrast-enhanced CT</u> <u>W. Qiu, 2020</u>	
Main Findings	Deep learning models, particularly CNNs, demonstrated high accuracy in detecting ischemic stroke in CT scans, with potential for reducing diagnosis time in emergency settings.
Scientific Level	Highly technical, aimed at radiologists and emergency medicine specialists.
Study Type	Retrospective study validating DL models on CT data for stroke detection.
Sample Size	Dataset includes 12,000+ CT scans from stroke patients.
Evidence Level	Level III (retrospective data without clinical trial validation).
Impact Summary	High detection accuracy, sensitivity, and specificity in stroke diagnosis.

<u>Use of artificial intelligence in the detection of primary prostate cancer in multiparametric MRI with its clinical outcomes: a protocol for a systematic review and meta-analysis</u> <u>Thomas, M. et al., 2023</u>	
Main Findings	This protocol outlines a systematic review and meta-analysis to assess AI's accuracy in detecting primary prostate cancer using multiparametric MRI (mpMRI). It aims to address interobserver variability and improve diagnostic precision, especially in light of radiologist shortages and increasing imaging demands.
Scientific Level	Protocol-level, aimed at radiologists, oncologists, and AI researchers.
Study Type	Systematic review and meta-analysis protocol with a focus on AI-assisted prostate cancer detection in mpMRI.
Sample Size	The study will include eligible research published between 2016-2023 across multiple databases, though specific sample sizes are not available until review completion.
Evidence Level	Level III (protocol for a review of observational and retrospective studies without clinical trial data).
Effect Size	Will be determined through pooled sensitivity, specificity, PPV, NPV, and AUC values across included studies.

<u>Emerging Deep Learning Techniques in Multiple Sclerosis Imaging</u> <u>E. Kontopodis, 2021</u>	
Main Findings	This review discusses recent advancements in deep learning (DL) for imaging in multiple sclerosis (MS) and clinically isolated syndrome (CIS). Key applications include segmentation, lesion detection, and classification, which improve diagnostic accuracy and tracking of disease progression. DL algorithms show potential in reducing manual segmentation errors and in automating complex image analysis tasks. Limitations remain in generalizing results across multi-center data and reducing variability in segmentation outputs.
Scientific Level	Intermediate. Relevant for radiologists and researchers in neuroimaging.
Content Type	Comprehensive review of DL applications in MS/CIS imaging, including segmentation, classification, and image enhancement methods.
Sample Size	Compilation of 45 original studies with varied datasets in MS imaging.
Evidence Level	Level III (observational studies, expert reviews, and model performance assessments).
Impact summary	DL techniques enhance precision in MS imaging, supporting better lesion tracking, segmentation, and diagnostic accuracy. Despite promising results, limitations in data generalization and explainability restrict clinical application, with further validation required.

Treatment monitoring

<u>The systematic review of artificial intelligence applications in breast cancer diagnosis. Uzun Ozsahin et al., 2022</u>	
Main Findings	This systematic review evaluates AI's transformative role in breast cancer diagnosis, with CNNs notably enhancing detection accuracy and speed. AI models demonstrated high sensitivity in identifying early-stage tumors, reducing false positives, and improving mammogram interpretation efficiency. The study highlights AI's potential to support radiologists in complex or ambiguous cases, ultimately reducing workload and improving diagnostic precision.
Scientific Level	Advanced, suitable for radiologists, oncologists, and AI developers.
Study Type	Systematic Review of 45 studies examining AI applications in breast cancer imaging.
Sample Size	Combined analysis of 10,000 mammogram and MRI images from multiple studies.
Evidence Level	Level III (observational and retrospective studies without RCTs).
Effect Size	High diagnostic accuracy with sensitivity rates between 85-95%, specificity from 80-90%, and F1 scores up to 0.92 in some models.

<u>Empowering PET: Harnessing Deep Learning for Improved Clinical Insight Artesani et al. (2024)</u>	
Main Findings	This review explores AI's impact on PET imaging, highlighting advancements across image acquisition, noise reduction, reconstruction, and clinical tasks like segmentation and classification. AI-driven improvements are noted in lesion detectability, motion correction, and quantitative accuracy, enhancing PET's diagnostic and prognostic utility in oncology.
Scientific Level	Advanced, suitable for nuclear medicine specialists, radiologists, and AI researchers
Study Type	Narrative review covering AI applications in PET imaging workflows and clinical decision support.
Sample Size	Synthesis of studies applying AI across numerous PET imaging datasets, focused on oncology.
Evidence Level	Level III (based on observational studies and retrospective analyses)
Effect Size	Demonstrated improvements in time resolution by up to 26% in PET acquisition, and enhanced lesion detectability in cancers like lung and lymphoma through AI-based noise reduction and segmentation techniques.

<u>An Overview of Deep Learning in Medical Imaging</u> <u>Anaya-Isaza et al. (2021)</u>	
Main Findings	This review discusses the evolution of deep learning (DL) in medical imaging, highlighting CNNs, RNNs, and Transformers in tasks like classification, segmentation, and detection. It emphasizes DL's ability to handle complex imaging data, with particular success in cancer diagnostics and lesion detection. Key challenges include model interpretability and data scarcity.
Scientific Level	Suitable for researchers, bioengineers, and radiology professionals focused on AI.
Study Type	Literature review covering applications of DL in various medical imaging modalities.
Sample Size	Analysis based on 30+ studies covering different DL models across numerous datasets in medical imaging.
Evidence Level	Level III (observational and retrospective studies without RCTs).
Effect Size	High accuracy with deep learning models achieving up to 97% in image classification tasks, and Dice scores above 0.9 for tumor segmentation.

<u>Real-world Analysis of Artificial Intelligence in Musculoskeletal Trauma.</u> <u>Ajmera et al. (2021)</u>	
Main Findings	This review examines the role of AI in musculoskeletal trauma, emphasizing the improvements in diagnostic accuracy and efficiency. AI applications, such as CNNs, have enhanced fracture detection in radiographs and CTs, particularly for complex cases. AI integration in radiology workflows supports rapid triage and potentially reduces missed diagnoses, especially in high-volume emergency settings.
Scientific Level	Highly technical, relevant for radiologists, orthopedic specialists, and data scientists involved in trauma care.
Study Type	Comprehensive literature review on AI applications in musculoskeletal trauma imaging
Sample Size	Review of various AI models applied across thousands of radiographic and CT imaging datasets, covering studies on fracture detection and injury assessment.
Evidence Level	Level III (based on observational and retrospective studies).
Effect Size	Significant improvements in sensitivity (up to 95%) and specificity in fracture detection, with some models demonstrating an AUC of 0.954 for wrist fractures and a 25% reduction in time for radiographic assessments.

Artificial Intelligence in the Era of Precision Oncological Imaging.
M. Cellina et al. (2022)

Main Findings	This review covers the extensive applications of AI in oncological imaging, including risk stratification, lesion detection, radiogenomics, tumor segmentation, and treatment response prediction. AI has enhanced the precision of imaging, offering personalized diagnostics and supporting advanced treatment planning. Key challenges include data standardization, model transparency, and clinical integration.
Scientific Level	Highly specialized, suitable for radiologists, oncologists, and AI researchers.
Study Type	Comprehensive review focused on AI advancements in cancer imaging.
Sample Size	Synthesis of studies using various datasets across imaging modalities in oncology.
Evidence Level	Level III (based on observational studies and retrospective analyses).
Effect Size	Demonstrated improvement in diagnostic accuracy (AUCs ranging from 0.82 to 0.96) across multiple cancer types, with specific advancements in lesion detection, tumor staging, and prediction of treatment response.

<u>Artificial Intelligence in Oncological Hybrid Imaging</u> <u>Benedikt Feurecker et al. (2023)</u>	
Main Findings	This review highlights AI's contributions to oncological hybrid imaging, specifically in lesion detection, characterization, and therapy monitoring. AI-driven hybrid imaging (e.g., PET/CT, PET/MRI) enhances diagnostic precision, supports treatment guidance, and tracks disease progression. However, challenges remain with data harmonization, model validation, and clinical implementation.
Scientific Level	Advanced, intended for radiologists, oncologists, and AI specialists.
Study Type	Narrative review of AI applications in oncological hybrid imaging.
Sample Size	Review of studies utilizing hybrid imaging modalities across multiple cancer types, including lung, prostate, and neuroendocrine tumors.
Evidence Level	Level III (observational and retrospective studies)
Effect Size	Demonstrated improvements in diagnostic accuracy with AUC values ranging from 0.81 to 0.95 across various oncological applications, with high sensitivity in lesion detection and improved monitoring of therapeutic response.

<u>Role of Artificial Intelligence in Brain Tumor Imaging</u> <u>E. Chukwujindu et al. (2024)</u>	
Main Findings	This review outlines AI's impact on brain tumor imaging, particularly in glioma diagnosis, lesion detection, tumor grading, segmentation, and molecular characterization. It emphasizes AI's role in non-invasive diagnosis, prognosis, and the potential to guide personalized treatment. However, challenges such as data quality, standardization, and the "black-box" nature of AI models persist.
Scientific Level	Highly specialized, relevant for neuro-oncologists, radiologists, and AI researchers.
Study Type	Narrative review of AI techniques in brain tumor imaging.
Sample Size	Review based on multiple studies across various datasets, focused on glioma and non-glioma brain tumors.
Evidence Level	Level III (observational and retrospective studies).
Effect Size	Significant diagnostic accuracy improvements, with reported AUCs around 0.98 for glioma detection and high Dice scores (up to 0.91) in tumor segmentation.

Emerging Trends in AI and Radiomics for Bladder, Kidney, and Prostate Cancer: A Critical Review

Georgios Feretzakis et al. 2024

Main Findings	This review explores AI and radiomics' roles in advancing urological oncology, emphasizing diagnostic and prognostic improvements for bladder, kidney, and prostate cancers. Notable advancements include AI-enhanced MRI and CT imaging that improve lesion detection, tumor grading, and treatment response prediction. Challenges in clinical integration, such as data quality, standardization, and the "black-box" problem, are discussed.
Scientific Level	Suitable for oncology and radiology professionals, healthcare technology specialists, and AI researchers.
Study Type	Comprehensive review of AI and radiomics in urological cancer imaging.
Sample Size	Analysis across multiple studies and imaging modalities, including MRI, CT, and radiomics datasets specific to urological cancers.
Evidence Level	Level III (review based on observational studies and technological applications).
Effect Size	Improved diagnostic accuracy with AUC values reaching 0.85-0.93 in cancer grading and 82% accuracy in treatment response prediction for bladder cancer.

<u>Current State of Artificial Intelligence in Clinical Applications for Head and Neck MR Imaging - Noriyuki Fujima et al. (2023)</u>	
Main Findings	This review examines AI's role in head and neck MRI, highlighting deep learning's potential in areas like image acquisition, lesion segmentation, and disease classification. Notably, AI applications in head and neck MR imaging enhance diagnostic accuracy, improve segmentation precision, and support faster, high-quality reconstructions. Persistent challenges include the complexity of head and neck anatomy and susceptibility artifacts, requiring advancements in AI to optimize clinical utility.
Scientific Level	Advanced, aimed at radiologists, medical imaging specialists, and AI researchers.
Study Type	Narrative review focused on AI techniques for head and neck MRI applications.
Sample Size	Synthesis of studies with AI-based methods applied to head and neck imaging, particularly in MRI.
Evidence Level	Level III (observational and retrospective studies)
Effect Size	This review examines AI's role in head and neck MRI, highlighting deep learning's potential in areas like image acquisition, lesion segmentation, and disease classification. Notably, AI applications in head and neck MR imaging enhance diagnostic accuracy, improve segmentation precision, and support faster, high-quality reconstructions. Persistent challenges include the complexity of head and neck anatomy and susceptibility artifacts, requiring advancements in AI to optimize clinical utility.

<u>Artificial Intelligence in Gastrointestinal and Hepatic Imaging: Past, Present, and Future Scopes Darshan Gandhi et al. (2022)</u>	
Main Findings	This review examines AI applications in gastrointestinal and hepatic imaging, focusing on tasks such as lesion detection, segmentation, and classification. Key advancements include the use of AI for liver lesion characterization and polyp detection in virtual colonoscopy. Challenges discussed include model interpretability, data standardization, and clinical validation needs.
Scientific Level	Comprehensive, relevant for radiologists, gastroenterologists, and AI developers.
Study Type	Review of AI methods in gastrointestinal and hepatic imaging.
Sample Size	Synthesizes multiple studies with a broad dataset base, including CT, MRI, and ultrasound imaging data.
Evidence Level	Level III (observational studies and technical evaluations).

Effect Size	High accuracy rates in lesion detection (up to 94% sensitivity) and segmentation tasks, with enhanced diagnostic efficiency and consistency reported across imaging tasks.
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<u>Identifying Opportunities for Workflow Automation in Health Care: Lessons Learned from Other Industries</u> <u>Teresa Zayas-Cabán et al. (2021)</u>	
Main Findings	This review investigates workflow automation's potential in healthcare, drawing from lessons in industries like finance and manufacturing. It highlights how automation could streamline administrative processes, improve efficiency, and enhance quality. Key factors for successful automation include clear goal-setting, stakeholder involvement, and continuous monitoring for improvement.
Scientific Level	Intermediate, aimed at healthcare administrators, informaticians, and policy makers.
Study Type	Targeted literature review of workflow automation practices across various industries.
Sample Size	Analysis of 123 articles across industries such as finance, manufacturing, and transportation.
Evidence Level	Level III (observational studies and synthesis of industry experiences).
Effect Size	Improved efficiency, reduced task completion times, and higher process accuracy are noted in healthcare automation parallels with manufacturing and finance.

<u>Deep Learning Techniques for Imaging Diagnosis of Renal Cell Carcinoma: Current and Emerging Trends</u> <u>Z. Wang et al. (2023)</u>	
Main Findings	This review explores the application of deep learning in diagnosing renal cell carcinoma (RCC), covering advancements in image classification, tumor differentiation, and treatment planning. AI enhances accuracy in detecting RCC subtypes and supports non-invasive diagnostic approaches. Challenges include data standardization, interpretability, and generalizability of models in clinical settings.
Scientific Level	Advanced, aimed at radiologists, oncologists, and researchers in AI for urological oncology.
Study Type	Comprehensive review of deep learning methods in RCC imaging.
Sample Size	Synthesis of multiple studies utilizing MRI, CT, and ultrasound datasets for RCC diagnosis.
Evidence Level	Level III (observational and retrospective studies with technical applications).
Effect Size	High diagnostic accuracy with AUC values ranging from 0.85 to 0.97 across various imaging tasks, including tumor subtype differentiation and prediction of treatment outcomes.

Role of Artificial Intelligence in PET/CT Imaging for Management of Lymphoma	
A Review of Deep Learning and Radiomics Approaches for Pancreatic Cancer Diagnosis from Medical Imaging EM. Veziroglu et al. (2022)	
Main Findings	Lanhong Yao et al. 2023 This review explores AI's applications in PET/CT for lymphoma, particularly in staging, prognostication, treatment planning, and response evaluation. AI-based methods, such as neural networks, enhance lesion segmentation and prognostic predictions and enable automated measurement of total metabolic tumor volume (TMTV), providing data-driven insights for patient management.
Scientific Level	Specialized, relevant for radiologists, oncologists, and AI researchers. Radiomics features further aid in predicting disease progression. Challenges in data heterogeneity, model validation, and clinical integration remain significant.
Study Type	Comprehensive review of AI and PET/CT applications in lymphoma imaging.
Scientific Level	Advanced, suitable for radiologists, oncologists, and AI researchers focused on pancreatic oncology.
Sample Size	Compilation of multiple studies and large imaging datasets involving PET/CT for lymphoma.
Study Type	Comprehensive review of DL and radiomics in pancreatic cancer imaging.
Evidence Level	Level III (observational and retrospective studies).
Sample Size	Synthesis of studies covering CT, MRI, and other imaging modalities for pancreatic cancer detection and classification.
Effect Size	High diagnostic and prognostic accuracy, with TMTV and other AI-based measurements showing strong correlation with disease progression and treatment outcomes, reaching AUC values up to 0.88 in prognostic applications.
Evidence Level	Level II (observational and retrospective studies with technical predictions).
Effect Size	High accuracy in early detection of pancreatic tumors, with AUC values ranging from 0.85 to 0.98 across various DL and radiomics applications in pancreatic imaging.

Research in the Application of Artificial Intelligence to Lung Cancer Diagnosis
Wenjuan Liu et al. (2024)

Main Findings	This review discusses AI's evolving role in lung cancer diagnosis, focusing on early screening, detection of genetic mutations, and prognostic assessments. AI applications in imageomics, pathomics, and genomics are transforming diagnostic precision and enabling personalized treatment plans. Challenges remain in integrating AI with existing clinical workflows and managing high data demands.
Scientific Level	Highly specialized, suitable for oncologists, radiologists, and AI researchers.
Study Type	Comprehensive review of AI applications in lung cancer diagnosis across various data modalities.
Sample Size	Synthesis of studies involving large datasets from imaging, pathology, and genomic sources, covering early detection and prognostic modeling in lung cancer.
Evidence Level	Level III (observational studies with technical applications).
Effect Size	Significant improvements in early diagnosis with AI achieving sensitivity up to 98.7% and specificity of 98.9% in lung nodule detection; AI also enhanced genetic mutation detection and survival predictions.

[18F]FDG-PET/CT Radiomics and Artificial Intelligence in Lung Cancer: Technical Aspects and Potential Clinical Applications
Reyhaneh Manafi-Farid et al. (2022)

Main Findings	This review highlights the integration of radiomics and AI in FDG-PET/CT imaging for lung cancer, with applications in early detection, staging, tumor characterization, and treatment response prediction. AI algorithms improve lesion detectability and quantitative accuracy, contributing to personalized patient management. The review discusses challenges in data harmonization, model reproducibility, and clinical integration.
Scientific Level	Advanced, suitable for nuclear medicine specialists, radiologists, and oncologists.
Study Type	Technical and clinical review of AI and radiomics applications in lung cancer imaging.
Sample Size	Summary of studies involving PET/CT datasets in non-small cell lung cancer (NSCLC) across multiple centres.
Evidence Level	Level III (based on observational and retrospective analyses).
Effect Size	Reported AUCs ranging from 0.80 to 0.94 for lung cancer staging and differentiation of malignant from benign lesions, demonstrating high sensitivity and specificity in early-stage detection and treatment monitoring.

Performance of Radiomics-Based Artificial Intelligence Systems in the Diagnosis and Prediction of Treatment Response and Survival in Esophageal Cancer
N Menon et al. (2023)

Main Findings	This systematic review and meta-analysis evaluates AI and radiomics in esophageal cancer for diagnosis, treatment response, and survival prediction. Radiomics-based AI models using PET/CT and CT imaging showed high diagnostic accuracy and predictive capabilities, especially in identifying treatment response and survival outcomes. Challenges include variability across datasets and the need for standardized methodologies.
Scientific Level	Specialized, relevant for oncologists, radiologists, and AI researchers.
Study Type	Systematic review and meta-analysis of diagnostic accuracy in esophageal cancer imaging.
Sample Size	Meta-analysis included 50 studies, with pooled data from 443 patients for PET/CT and 625 patients for CT imaging in treatment response assessment.
Evidence Level	Level III (based on observational and retrospective studies with meta-analytic synthesis).
Effect Size	High sensitivity (86.5%) and specificity (87.1%) for PET/CT in treatment response prediction, with CT showing comparable sensitivity (86.7%) but lower specificity (76.1%) in esophageal cancer assessment.

Artificial Intelligence in Neuro-Oncology: Advances and Challenges in Brain Tumor
Diagnosis, Prognosis, and Precision Treatment
Sirvan Khalighi et al. (2024)

Main Findings	This review discusses AI's role in neuro-oncology, particularly in diagnosing, predicting outcomes, and tailoring treatments for brain tumors like gliomas. Key advancements include AI-driven molecular characterization, non-invasive diagnostic tools, and multimodal integration. Challenges highlighted include model transparency, ethical considerations, and data access limitations.
Scientific Level	Specialized, targeting neuro-oncologists, radiologists, and AI researchers.
Study Type	Comprehensive review of AI applications in neuro-oncological imaging and pathology.
Sample Size	Analysis of various studies utilizing imaging and genomic datasets across neuro-oncological cases, particularly gliomas.
Evidence Level	Level III (observational and retrospective studies with expert insights).
Effect Size	Significant improvements in diagnostic accuracy (AUCs up to 0.96) and prognostic precision in identifying tumor subtypes, treatment response, and survival predictions.

Current Status and Future Perspectives of Radiomics in Hepatocellular Carcinoma
Joao Miranda et al. (2023)

Main Findings	This review discusses radiomics applications in hepatocellular carcinoma (HCC) for predicting histology, treatment response, genetic expression, recurrence, and survival. Radiomics has shown potential to enhance diagnostic precision, but challenges persist in reproducibility, data harmonization, and model validation.
Scientific Level	Suitable for gastroenterologists, radiologists, and oncology researchers focused on HCC.
Study Type	A comprehensive review of radiomics applications in HCC imaging and management.
Sample Size	Synthesis of multiple studies on HCC radiomics, covering CT, MRI, and PET imaging modalities.
Evidence Level	Level III (observational and technical evaluations in HCC imaging).
Effect Size	High diagnostic accuracy with reported AUCs ranging from 0.70 to 0.98 for various predictive tasks in HCC, including tumor grade, recurrence, and treatment response.

Radiomics and Radiogenomics of Ovarian Cancer:
Implications for Treatment Monitoring and Clinical Management Camilla Panico et al.
(2023)

Main Findings	This review explores the role of radiomics and radiogenomics in ovarian cancer, particularly for tracking tumor heterogeneity and predicting treatment response. Radiomics provides detailed data on tumor microenvironments, potentially supporting non-invasive virtual biopsies for personalized treatment. Challenges in clinical implementation include data standardization, reproducibility, and model validation.
Scientific Level	Advanced, suitable for oncologists, radiologists, and specialists in AI applications for oncology.
Study Type	Comprehensive review of radiomics and radiogenomics applications in ovarian cancer.
Sample Size	Compilation of studies focused on CT, MRI, and PET imaging in ovarian cancer cases, covering multiple tumor stages.
Evidence Level	Level III (observational studies and experimental analysis).
Effect Size	High diagnostic accuracy and specificity in monitoring treatment response, with significant potential for early identification of recurrence and personalized treatment planning.

Patient Safety and Outcomes

<u>Artificial Intelligence and Machine Learning in Spine Research</u> <u>Fabio Galbusera et al. (2019)</u>	
Main Findings	This review explores the applications of AI and machine learning (ML) in spine research, including diagnostic imaging, outcome prediction, clinical decision support, and biomechanical analysis. AI-enhanced imaging techniques improve diagnostic accuracy and reliability, especially for spinal pathologies, and enable predictive modeling for surgical outcomes. The review also emphasizes ethical and regulatory challenges related to AI in clinical settings.
Scientific Level	Advanced, targeting spine researchers, radiologists, and AI developers.
Study Type	Narrative literature review of AI applications in spine imaging and research.
Sample Size	Summary of diverse studies and applications in spine imaging, including MRI, CT, and biomechanical modeling.
Evidence Level	Level III (observational and retrospective studies).
Impact Summary	AI models show high diagnostic accuracy in spine imaging (e.g., automated grading of disc degeneration) and predictive strength in outcome assessment, though specific metrics vary across applications.

<u>An Evolution of Reporting: Identifying the Missing Link</u> <u>Sara Harsini et al. (2022)</u>	
Main Findings	This review addresses the role of effective reporting and communication in radiology, emphasizing the importance of reducing diagnostic errors through structured reporting and closed-loop communication systems. The study highlights how AI can support communication between radiologists and clinicians, potentially reducing interpretation errors and improving patient outcomes.
Scientific Level	Intermediate to advanced, suitable for healthcare providers, radiologists, and AI developers focused on medical communication.
Study Type	Narrative review on reporting standards and AI in radiology communication.
Sample Size	Synthesis of various studies and best practices in radiologic reporting and communication.
Evidence Level	Level III (observational studies and expert opinion).
Impact Summary	Increased reporting accuracy and reduced errors in radiology through standardized reporting formats and AI-driven communication systems, though exact metrics vary across applications.

<u>Exploring the Role of Artificial Intelligence in Emergency and Trauma Radiology</u> <u>Jalal et al. (2021)</u>	
Main Findings	This paper examines the potential and challenges of AI in emergency and trauma radiology. It highlights AI's role in decision support, particularly for triaging patients, detecting critical conditions, and automating routine tasks. Notable challenges include the need for high-quality data, ethical considerations, and difficulties in generalizing models across diverse clinical settings.
Scientific Level	Advanced, suitable for emergency radiologists, clinicians, and AI researchers.
Study Type	Narrative review discussing AI applications in emergency and trauma settings.
Sample Size	Review of various AI implementations in emergency radiology from multiple studies and real-world applications.
Evidence Level	Level III (observational and practical implementations).
Impact Summary	AI demonstrated an 80% reduction in false alarms in clinical monitoring and improved diagnostic accuracy, though specific metrics vary by application

Artificial Intelligence in Medical Imaging: Implications for Patient Radiation Safety
Seah et al. (2021)

Main Findings	This paper explores AI's potential to improve patient radiation safety by optimizing imaging protocols, reducing unnecessary scans, and enhancing diagnostic accuracy. It highlights AI's ability to minimize exposure by providing automated feedback on radiation doses and ensuring consistent imaging practices across departments. Challenges include regulatory issues, standardization, and integration into current healthcare systems.
Scientific Level	Intermediate, suitable for radiologists, healthcare administrators, and AI developers focusing on radiation safety and imaging protocols.
Study Type	Review of AI applications in radiation safety and medical imaging.
Sample Size	Compilation of studies and guidelines on radiation management and AI interventions in imaging.
Evidence Level	Level III (based on observational studies and real-world applications).
Impact Summary	Demonstrated reduction in patient radiation exposure by up to 30% through optimized AI-driven imaging protocols and monitoring systems.

<u>Overview of Noninterpretive Artificial Intelligence Models for Safety, Quality, Workflow, and Education Applications in Radiology Practice</u> <u>Y. Tadavarthi et al. (2022)</u>	
Main Findings	This review explores the use of noninterpretive AI models in radiology, focusing on improving workflow, safety, quality, and education. AI applications are examined across study selection, protocoling, image acquisition, reporting, business applications, and educational enhancements. Key benefits include increased efficiency, enhanced patient safety, and cost reduction. Integration challenges, particularly around data standardization and system interoperability, are discussed.
Scientific Level	Intermediate to advanced, relevant for radiologists, healthcare administrators, and educators in radiology.
Study Type	Qualitative review covering AI applications in noninterpretive radiology functions.
Sample Size	Review of diverse AI models and commercial solutions applied across radiology workflows.
Evidence Level	Level III (based on observational studies and qualitative analyses).
Impact Summary	Demonstrated improvements in workflow efficiency (e.g., reduction in study protocoling time by up to 50 hours weekly per radiology department), as well as enhanced reporting accuracy and potential reductions in radiation exposure.

Workflow Efficiency and Productivity

<u>Advanced Machine Learning in Action: Identification of Intracranial Hemorrhage on CT Scans with Clinical Workflow Integration</u> <u>Mohammad R. Arbabshirani et al. (2018)</u>	
Main Findings	This study explores the use of a deep convolutional neural network (CNN) for detecting intracranial hemorrhage (ICH) on head CT scans to improve clinical workflows. The AI model re-prioritized routine scans to "stat" for urgent attention, reducing the median time to diagnosis from 512 minutes to 19 minutes. In a 3-month implementation, 5 new ICH cases were identified, showing AI's role in optimizing radiology worklists and supporting early treatment.
Scientific Level	Advanced, suitable for radiologists, emergency clinicians, and AI developers focusing on radiology workflows.
Study Type	Clinical implementation study using a CNN for ICH detection and workflow optimization in radiology.
Sample Size	Based on 46,583 head CT scans from multiple facilities, with an implementation phase involving 347 routine scans.
Evidence Level	Level III (observational and technical evaluation in clinical workflow).
Effect Size	The algorithm achieved an AUC of 0.846, with an 84% diagnostic accuracy during implementation. The median diagnosis time was reduced by 96%, showing significant potential for time-sensitive diagnoses.

<u>Breaking the Bias: A Fair Assessment of AI and Radiologists for Workflow Optimization and Collaborative Reporting</u> <u>Kyle Hemingway Bennett et al. (2023)</u>	
Main Findings	This letter discusses the limitations of comparing AI and radiologists in diagnostic tasks, emphasizing that AI should support radiologists rather than replace them. The authors highlight AI's utility in identifying "normal" radiographs, thereby aiding in workflow optimization and triaging to improve patient care.
Scientific Level	Intermediate to advanced, aimed at radiologists, healthcare administrators, and AI researchers.
Content Type	Commentary and critique on current AI applications in radiology.
Sample Size	Not applicable as it is a critique and commentary piece.
Evidence Level	Level V (expert opinion and commentary).
Impact Summary	Highlights a 92% negative predictive value of AI tools in identifying normal cases for workflow optimization, demonstrating AI's potential to streamline radiology operations by reducing unnecessary reads.

<u>Implementation of an Institution-Wide Rules-Based Automated CT Protocols System</u> <u>Ryan Chung et al. (2024)</u>	
Main Findings	This study assesses the impact of an automated CT protocols system designed to reduce radiologists' workload by automating the protocols process. The system achieved significant reductions in processing time from order entry to protocols assignment, cutting emergency and inpatient protocols times to less than an hour in 99.9% of cases. Additionally, protocols errors and examination recalls were rare, demonstrating the system's effectiveness in workflow optimization.
Scientific Level	Intermediate to advanced, suited for radiologists, healthcare IT professionals, and administrators.
Content Type	Original research on the operational effectiveness of an automated system in clinical radiology workflow.
Sample Size	The study analyzed 317,597 CT examinations across three phases (pilot, implementation, and post-implementation), including emergency, inpatient, and outpatient settings.
Evidence Level	Level III (observational and practical implementation evaluation).
Impact Summary	Automated protocols increased from 27.4% to 64.5% across phases, with mean processing times for emergency CT exams reduced by up to 90%. Protocols accuracy was high (99.1% concordance), with minimal recalls and QI reports, demonstrating strong efficacy in improving workflow.

<u>Virtual and Augmented Reality in Interventional Radiology: Current Applications, Challenges, and Future Directions</u> A. Elsakka et al. (2023)	
Main Findings	This paper reviews the applications of virtual reality (VR) and augmented reality (AR) in interventional radiology (IR), focusing on areas such as training, procedural planning, and patient engagement. VR and AR offer interactive visualization, improved navigation, and educational benefits for IR. Challenges include technical constraints, cost, and clinical adoption barriers, while future directions involve integrating AI-driven solutions for enhanced precision and patient outcomes.
Scientific Level	Advanced, suitable for interventional radiologists, healthcare educators, and AR/VR developers.
Content Type	Comprehensive review of VR and AR applications, challenges, and future directions in IR.
Sample Size	Overview of studies on VR/AR in IR, spanning applications in oncology, endovascular planning, and non-oncologic interventions.
Evidence Level	Level III (based on observational studies and technical evaluations).
Impact Summary	Reported benefits include up to 48% reduction in procedural time and significant improvements in training accuracy and patient understanding.

Federated Deep Learning to More Reliably Detect Body Part for Hanging Protocols, Relevant Priors, and Workflow Optimization Ross W. Filice et al. (2022)	
Main Findings	This study explores federated deep learning (FDL) for body part detection in radiology, aiming to optimize hanging protocols, prefetching of prior exams, and workflow efficiency. FDL models, which do not require centralizing data, showed high accuracy in body part classification across institutions, enhancing workflow reliability without compromising patient privacy.
Scientific Level	Advanced, suitable for radiologists, healthcare IT specialists, and AI developers.
Content Type	Original research on federated learning applications in body part recognition and workflow optimization.
Sample Size	Analysis based on CT data from multiple institutions, including thousands of cross-sectional images of the chest, abdomen, and pelvis.
Evidence Level	Level III (observational study with technical evaluation).
Impact Summary	Validation accuracy exceeded 98% with federated learning, with improvements in workflow through enhanced reliability in hanging protocol assignments and reduced errors in relevant prior exam prefetching.

<u>Randomized Controlled Trials Evaluating Artificial Intelligence in Healthcare</u> <u>R. Han 2024</u>	
Main Findings	This scoping review evaluates RCTs of AI in healthcare, highlighting AI's impact on clinical metrics like diagnostic accuracy, patient behavior, and clinical decision-making. Many trials focused on diagnostic yield, showing mixed results in patient outcomes despite high technical accuracy. Operational efficiency and workflow impact were also assessed, revealing AI's varied influence on time and resource management.
Scientific Level	Advanced, suitable for healthcare professionals, AI researchers, and policy makers.
Content Type	Systematic scoping review of RCTs evaluating AI systems in healthcare.
Sample Size	Includes 86 RCTs across diverse specialities, with a median sample size of 359 patients per trial.
Evidence Level	Level I (randomized controlled trials).
Impact Summary	80% of trials reported significant improvements in primary endpoints, particularly in diagnostic performance; however, only a portion showed direct patient outcome benefits. Operational efficiencies were seen in some specialties, though results varied significantly by context and application.

<u>Clinical Impact of Deep Learning Reconstruction in MRI</u> <u>Kiryu et al., 2023</u>	
Main Findings	This review examines DLR's effect on MRI quality and efficiency, noting substantial improvements in SNR, image clarity, and acquisition times across multiple applications. DLR enables high-quality imaging on 1.5T systems comparable to 3T, making MRI more accessible and affordable without compromising image quality. However, it raises concerns about potential artifacts and subtle alterations in lesion appearance, requiring careful clinical validation.
Scientific Level	Intermediate. This research is valuable for radiologists, medical imaging specialists, and AI developers.
Content Type	Systematic review of DLR applications in MRI across different body regions.
Sample Size	Compilation of studies with sample sizes ranging from 10 to 42 participants across different MRI applications.
Evidence Level	Level III (observational studies and clinical trials without randomization).
Impact Summary	DLR improves image quality, reduces imaging times, and supports MRI accessibility by achieving high SNR on lower-field systems. Operational efficiency benefits are notable, but DLR may introduce artifacts and affect lesion visibility. Caution is advised in clinical use, with recommendations for ongoing validation.

Artificial Intelligence Applications for Workflow, Process Optimization and Predictive Analytics Letourneau-Guillon et al., 2020

Main Findings	This review examines AI applications in radiology workflow, highlighting areas such as scan protocoling, scheduling, worklist prioritization, image acquisition, and report generation. AI enhances efficiency by automating repetitive tasks, reducing errors, and supporting decision-making in patient management. Key benefits include optimized resource use, improved scheduling, and enhanced diagnostic workflow through automated prioritization of urgent cases. AI's role in improving patient safety and operational efficiency is emphasized.
Scientific Level	Advanced. This research is highly relevant for radiology departments, healthcare administrators, and AI developers.
Content Type	Systematic review of AI applications in workflow and process optimization in radiology.
Sample Size	Compilation of studies and trials across different radiology workflows, not specific to a single sample size.
Evidence Level	Level III (observational studies and expert opinions with significant real-world applicability).
Impact Summary	AI applications improve workflow efficiency, reduce turnaround time, and streamline radiology operations, supporting better patient management and resource utilization. By automating tasks such as protocoling and scheduling, AI allows radiologists to focus on higher-level interpretive tasks, enhancing productivity and reducing burnout risks.

Applications of Artificial Intelligence in the Radiology Roundtrip: Process Streamlining, Workflow Optimization, and Beyond - Kevin Pierre et al., 2023

Main Findings	This review discusses various AI applications that enhance workflow efficiency throughout the radiology process, from scan ordering and protocoling to scheduling and report generation. AI tools streamline operations by automating tasks like patient screening, exam scheduling, and protocoling, reducing human errors and enhancing overall efficiency. These applications improve radiology department productivity, optimize resource utilization, and support clinical decision-making, contributing to better patient management and satisfaction.
Scientific Level	Advanced. Relevant for radiologists, administrators, and AI developers, providing detailed insights and applicable findings for clinical workflow improvements.
Content Type	Systematic review of AI applications in radiology workflow optimization.
Sample Size	Compilation of various studies and real-world implementations; no specific patient sample size.
Evidence Level	Level III (observational studies and expert opinions with substantial clinical applicability).
Impact Summary	AI enhances workflow efficiency in radiology, allowing more accurate and timely processes. Automating routine tasks reduces radiologist workload, minimizes delays, and supports improved patient care by ensuring timely and accurate imaging workflows. These advancements have significant implications for operational productivity and patient satisfaction

<u>Optimization of Radiology Workflow with Artificial Intelligence</u> <u>Ranschaert et al., 2021</u>	
Main Findings	AI enhances radiology workflow by automating non-diagnostic tasks like scan protocolling, patient scheduling, and worklist prioritization. AI can identify inefficiencies and optimize resource allocation, reducing radiology department bottlenecks. This improves operational efficiency and patient flow while potentially decreasing wait times and costs. Integration challenges and regulatory requirements, however, limit widespread adoption.
Scientific Level	Advanced. Relevant for clinical radiologists, healthcare administrators, and policymakers, with applications shown in real-world settings.
Content Type	Systematic review of AI's role in optimizing radiology workflows and operational efficiency.
Sample Size	Compilation of various studies, no specific patient sample size, focused on workflow improvements.
Evidence Level	Level III (observational studies, operational analysis, and expert insights with practical clinical implications).
Impact Summary	AI contributes to workflow efficiency, reducing patient wait times and radiologist workload. Automated task management enhances productivity, with significant cost-saving potential for radiology departments. Integration and policy support are crucial for broader adoption.

<u>Prospective Evaluation of a Machine-Learning Prediction Model for Missed Radiology Appointments</u> <u>Rothenberg et al., 2022</u>	
Main Findings	This study evaluates a machine-learning model's ability to predict patient no-shows for radiology appointments. Using Gradient Boosted Regression Trees on 4.5 million historical appointments, the model achieved high accuracy in predicting no-shows retrospectively (AUC 0.93) and moderately in prospective testing (AUC 0.73). Key predictive factors included previous no-shows, appointment day and time, and interpreter needs. Prospective results highlight the need for ongoing model adaptation to maintain predictive power.
Scientific Level	Advanced. Relevant for healthcare administrators aiming to improve scheduling efficiency.
Content Type	Prospective evaluation of machine-learning models for operational efficiency in radiology scheduling.
Sample Size	Model trained on 4.5 million appointments with 631,386 no-shows; prospective test involved 2,264 scheduled exams.
Evidence Level	Level III (observational study with retrospective and prospective analysis).
Impact Summary	AI-based no-show prediction can improve resource utilization in radiology departments by enabling targeted interventions. The model requires continuous adjustment to address biases and external factors, such as changes in patient behavior post-COVID.

Identifying Opportunities for Workflow Automation in Health Care: Lessons Learned from Other Industries - Zayas-Cabán et al., 2021	
Main Findings	This study explores lessons from industries like finance and manufacturing to inform healthcare automation. Key findings include using automation to improve administrative workflows, such as scheduling, billing, and data processing, which can reduce manual workload, enhance productivity, and improve service quality. Effective automation in healthcare requires clear goal setting, stakeholder engagement, and ongoing monitoring to ensure performance aligns with intended outcomes. Privacy and bias in automated decision-making remain concerns in healthcare automation efforts.
Scientific Level	Intermediate. Relevant for healthcare administrators and IT policy makers.
Content Type	Review of automation applications across industries with recommendations for healthcare adoption.
Sample Size	Review of 123 articles across 11 industries, applied to healthcare context.
Evidence Level	Level III (expert opinions, observational findings from other industries).
Impact Summary	Workflow automation can streamline healthcare operations, increasing efficiency and accuracy in routine tasks. Adopting automation from other sectors requires adapting practices to fit healthcare's unique regulatory and operational landscape, particularly to maintain patient privacy and mitigate potential bias.

Bone and Soft Tissue Tumors: Horizons in Radiomics and Artificial Intelligence Richardson et al., 2022	
Main Findings	The study discusses AI and radiomics in bone and soft tissue tumor imaging, emphasizing noise reduction, improved contrast, and automated segmentation. AI applications in radiomics enable precise tumor classification, grading, and assessment of treatment response, supporting a shift towards "precision medicine." However, challenges remain in image segmentation, requiring standardized protocols for accurate results.
Scientific Level	Advanced. Relevant to radiologists and oncologists for clinical applications in MSK radiology.
Content Type	Review of AI and radiomics applications in imaging, tumor classification, and treatment monitoring.
Sample Size	Compilation of studies with varied sample sizes in musculoskeletal tumor imaging.
Evidence Level	Level III (observational studies, expert reviews, and trials with clinical implications).
Impact Summary	AI in radiomics enhances diagnostic precision and treatment assessment, particularly for bone and soft tissue tumors. Improvements in noise reduction and segmentation bolster diagnostic accuracy, though further standardization is needed to ensure reliable use in clinical settings.

<u>Changes in MRI Workflow of Multiple Sclerosis after Introduction of an AI-Software: A Qualitative Study - Rathmann et al., 2024</u>	
Main Findings	This study examined the impact of integrating AI-based software (mdbrain®) in the MRI workflow for multiple sclerosis (MS) patients. Key findings include reduced radiologist screen time, optimized workflow, and improved decision-making for contrast use. The AI software provided automated lesion quantification, making it easier to track MS progression. Interviewees noted significant time savings and improved accuracy in lesion analysis, although manual review is necessary for artifact-prone regions.
Scientific Level	Advanced. Relevant for clinical radiologists and healthcare administrators with detailed findings on workflow impact
Content Type	Qualitative study based on expert interviews and workflow analysis.
Sample Size	352 MS MRI exams analyzed annually, with in-depth qualitative input from 7 radiology professionals.
Evidence Level	Level III (observational, qualitative study with expert insights).
Impact Summary	AI integration in MS MRI workflows enhances operational efficiency and radiologist workload management, with faster lesion analysis and improved report communication. Artifact management remains a limitation, requiring manual review in certain regions.

<u>A Responsible Framework for Applying Artificial Intelligence on Medical Images and Signals at the Point-of-Care: the PACS-AI Platform</u> <u>Therault-Lauzier, P 2024</u>	
Main Findings	This paper introduces the PACS-AI platform, an open-source framework aimed at integrating AI models with the Picture Archive and Communication System (PACS) in healthcare. The platform addresses key challenges in AI deployment, such as data heterogeneity, cybersecurity, and interoperability, enabling real-time clinical applications of AI on medical images.
Scientific Level	Advanced, suitable for radiologists, cardiologists, and healthcare IT professionals.
Study Type	Framework proposal and preliminary application assessment.
Sample Size	Not directly applicable; discusses the platform's capabilities rather than specific quantitative study data.
Evidence Level	Level III (conceptual framework with early-stage application in healthcare settings, but without full clinical validation).
Impact Summary	This paper introduces the PACS-AI platform, an open-source framework aimed at integrating AI models with the Picture Archive and Communication System (PACS) in healthcare. The platform addresses key challenges in AI deployment, such as data heterogeneity, cybersecurity, and interoperability, enabling real-time clinical applications of AI on medical images.

Navigating Challenges

<u>Cybersecurity Considerations for Radiology Departments Involved with Artificial Intelligence</u> <u>Kelly et al., 2023</u>	
Main Findings	This review examines the potential of AI to support radiologists in image interpretation, workflow efficiency, and patient care. It highlights AI's role in automating tasks like lesion detection, image segmentation, and diagnosis, while also discussing ethical challenges, biases, and the importance of transparency. AI is positioned as an assistive tool rather than a replacement.
Scientific Level	Specialized, suitable for radiologists, medical imaging specialists, and AI researchers.
Study Type	Literature review summarizing recent advances, ethical considerations, and challenges in AI applications within radiology.
Sample Size	Review includes 34 studies related to AI in radiology.
Evidence Level	Level III (review based on observational studies and expert opinions).
Impact Summary	Improved workflow efficiency and diagnostic support, e.g., AI-assisted interpretation can reduce time and error in high-volume imaging environments.

Redefining Radiology: A Review of Artificial Intelligence Integration in Medical Imaging
Najjar, R., 2023

Main Findings	This comprehensive review explores the transformative impact of AI in radiology, emphasizing applications in image segmentation, diagnosis, and workflow optimization. It discusses how AI is changing diagnostic processes, enabling personalized medicine, and improving workflow efficiency. Key challenges include data quality, the "black box" problem, and ethical considerations.
Scientific Level	Highly specialized, suitable for radiologists, medical imaging specialists, and AI developers.
Study Type	Review of literature focusing on the historical progression, practical applications, challenges, and future directions of AI in radiology.
Sample Size	Review includes case studies and empirical evidence across various medical disciplines; no specific quantitative data.
Evidence Level	Level III (Review of observational studies and expert opinion without clinical trials).
Impact Summary	Significant improvements in diagnostic accuracy and workflow efficiency, e.g., reduction in interpretation time from days to hours in some cases.

Is Artificial Intelligence the New Friend for Radiologists? A Review Article Gampala et al., 2020	
Main Findings	This review addresses the increasing cybersecurity risks in radiology AI projects, driven by the integration of medical devices, data systems, and AI algorithms. It highlights the importance of cybersecurity protocols, offers guidance on protective measures, and discusses risk mitigation strategies such as regulatory compliance, auditability, and data de-identification.
Scientific Level	Highly specialized, suitable for radiologists, healthcare IT specialists, and cybersecurity experts.
Study Type	Literature review focused on cybersecurity challenges in radiology departments adopting AI.
Sample Size	Compilation of industry and academic references on healthcare cybersecurity.
Evidence Level	Level III (review based on observational data, expert insights, and industry standards).
Impact Summary	Enhanced security through protocols such as encryption, multi-factor authentication, and federated learning, with potential to reduce security breaches in healthcare AI systems.

<u>Analysing Barriers and Enablers for the Acceptance of Artificial Intelligence Innovations into Radiology Practice: A Scoping Review</u> <u>Eltawil et al., 2023</u>	
Main Findings	This scoping review investigates the barriers and enablers associated with adopting AI innovations in radiology from physicians' perspectives. Key barriers include lack of trust, limited knowledge, and perceived threats to professional autonomy. Enablers include high expectations of AI's potential to reduce diagnostic errors and improve efficiency and patient care quality.
Scientific Level	Specialized, suitable for radiologists, AI developers, and healthcare policymakers.
Study Type	Scoping review of studies assessing physician perspectives on AI acceptance in radiology.
Sample Size	12 primary studies were included, comprising qualitative, survey-based, and randomized controlled trial data.
Evidence Level	Level III (review of qualitative and observational studies with expert insights).
Impact Summary	Positive influence of AI in enhancing diagnostic accuracy, reducing radiologist workload, and improving patient outcomes, though limited by user trust and perceived role threats.

Applications and Challenges of Artificial Intelligence in Diagnostic and Interventional Radiology Waller, J al 2022

Main Findings	This review discusses AI applications in diagnostic and interventional radiology, including image analysis, diagnosis, and predictive modeling. Key benefits include improved workflow efficiency and diagnostic support, with challenges related to data quality, ethical issues, and the need for representative training datasets. The authors emphasize AI as an assistive tool, not a replacement.
Scientific Level	Advanced, suitable for radiologists, interventional radiologists, and AI developers.
Study Type	Literature review summarizing 21 recent studies on AI in diagnostic and interventional radiology.
Sample Size	Review includes 21 primary publications.
Evidence Level	Level III (review based on retrospective and observational studies without clinical trials).
Impact Summary	Increased efficiency in workflows, e.g., AI-assisted exams showed a 37% reduction in interpretation time and faster notifications to clinicians.