



ARTIFICIAL INTELLIGENCE IN MEDICAL IMAGING: KNOWLEDGE AND PERSPECTIVES OF SOUTH AFRICAN RADIOGRAPHERS

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Master of Health Sciences in Radiography in the Faculty of Health Sciences, Durban
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DECLARATION OF ORIGINALITY

This is to certify that this dissertation represents my work and not that of any other person unless explicitly acknowledged (including citations of published and unpublished sources). The work has not previously been submitted in any form to the Durban University of Technology or any other institution for assessment or any other purpose.

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_____**9/03/2026**_____
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_____**12/03/2026**_____
Date

DEDICATION

I would like to express my gratitude to God, the Almighty, for providing me with the strength and wisdom I needed to complete this study. I dedicate this dissertation to my parents, Professor E. Mutambara and Dr Alice Mutambara, who are my inspiration and who have supported me and encouraged me in my life pursuits.

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ABSTRACT

Background: This study focused on determining the perspectives of Radiographers in relation to the integration of AI into medical imaging. Artificial intelligence (AI) is the use of technology and computers to replicate intelligent behaviours and analytical thoughts that are similar to that of humans. Several studies indicate that medical imaging professionals, such as Radiologists and Radiographers, are seeing an increase in the use of AI applications in clinical settings. Diagnostic Radiographers are pivotal for the integration of AI systems into medical imaging as they serve as an interface between technology and patients. Although some studies have examined the perspectives of Radiographers on AI in some African countries, there is still no clear picture of the Radiographers' perspectives towards AI in the most technologically advanced country in Africa.

Aim of study: The study aimed to ascertain the knowledge and perspectives of South African Radiographers regarding the integration of AI in diagnostic imaging in order to provide unique recommendations to support the training of Radiographers.

Methodology: A quantitative cross-sectional research design was used. Non-probability purposive sampling was employed as it is the most appropriate approach for a content analysis inquiry. A self-administered questionnaire containing closed-ended questions was used to collect statistical data from Radiographers that met the requirements for participation. On completion of the questionnaires, the results were tabulated and graphically demonstrated. Data was analysed using the latest version 27 of SPSS (the Statistical Package for the Social Sciences).

Findings: SPSS version 27 was used to analyse the data and various statistical tests such as Descriptive statistics, the Analysis of Variance Model, the Binomial test, Pearson's correlation coefficient, One-sample t-test, Cronbach alpha and Independent samples t-test were adopted to analyse the data yielded by the collection tool. The

findings indicated that over 90 % of Radiographers in South Africa are aware of the concept of AI. The majority of Radiographers in South Africa have a positive attitude towards AI as there was significant agreement that AI is beneficial to the various aspects of diagnostic Radiography. While AI possesses many benefits, Radiographers also acknowledge the various barriers affecting the implementation of AI in the medical imaging profession.

Conclusion: It can be concluded that Radiographers recognize general AI concepts and are aware of some of AI's functional roles within the field but are unfamiliar with the more technical components of the technology. Therefore, the introduction of AI in the Radiography curriculum is pivotal to ensuring that Radiographers have a strong foundation for understanding AI. It was noted that Radiographers in South Africa believe that AI will have multiple benefits for their job performance. Inasmuch as AI is equipped with benefits for Radiographers, several barriers that hinder the implementation of AI in Radiography were also noted.

Keywords: South African Radiographers, Artificial Intelligence, acceptance of AI, automatic exposure control, medical imaging

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LIST OF ABBREVIATIONS

AEC	: Automatic Exposure Control
AI	: Artificial intelligence
ANOVA	: Analysis Of Variance Model
ASRT	: American Society of Radiologic Technologists
BHSC	: Bachelor of Health Sciences
DUT	: Durban University of Technology
EFRS	: The European Federation of Radiographer Societies
HOD	: Head of Department
HPCSA	: Health Professions Council of South Africa
IREC	: Institutional Research Committee
ISRRT	: International Society of Radiographers and Radiological Technologist
KZN	: KwaZulu-Natal
PhD	: Doctor of Philosophy
SA	: South Africa
SCoR	: Society and College of Radiographers
UK	: United Kingdom

DEFINITIONS OF TERMS

Artificial Intelligence: the use of technology and computers to replicate intelligent behaviours and analytical thoughts that are similar to that of humans.

Automatic exposure control: a radiographic density control system that automatically terminates the exposure when a specified radiation level is attained.

Computed Tomography: an imaging technique that uses X-rays to create detailed cross-sectional images of the body.

Computer-aided detection: computer algorithms and software that assist in detecting abnormalities in medical images.

Deep Learning: a sub-field of Artificial Intelligence that focuses on constructing large-scale neural network models capable of making accurate data-based decisions.

Flourosocopy: a medical imaging technique that uses continuous X-rays to produce real-time moving images.

General X-rays: a medical technique that uses ionizing radiation to create static images of the inside of the body.

Job Security: assurance that an employee will keep their job and not face involuntary termination due to external factors.

Machine Learning: a sub-field of computer science that gives computers the ability to learn without being explicitly programmed.

Magnetic Resonance Imaging: imaging technique that uses strong magnetic fields and radio waves to create detailed images of the body.

CHAPTER 1: OVERVIEW OF THE STUDY

1.1 INTRODUCTION AND BACKGROUND

Diagnostic radiography is an ever-evolving profession that combines advanced technology with patient care and safety. It stands out as one of the most tech-driven areas in healthcare, as Radiographers depend heavily on technological tools to produce diagnostic images and provide effective care. Without this technology, their role in patient management would not be possible (Hardy and Harvey 2020). One of the most recent technological advances is the use of artificial intelligence (AI), Lewis *et al.* (2019: 292) elaborate that artificial intelligence is gradually becoming a part of diagnostic radiography, playing a supportive role in several elements of the radiology workflow. It aids in tasks such as managing workflows, acquiring images, planning treatments, reconstructing data, enhancing images after processing, and improving overall image quality, all while contributing to more accurate diagnoses.

Artificial intelligence (AI) is the use of technology and computers to replicate intelligent behaviours and analytical thoughts that are similar to those of humans (Lu Yang 2019: 1). AI is useful in analysing medical data for insights that aid in diagnosis and improve patient experience. In the past, AI technologies were mainly limited to computer scientists due to limited processing power, insufficient understanding of neural networks, and a lack of data to test different theories, making them largely out of reach for the general public (Malamateniou *et al.*, 2021: 119). Nevertheless, AI is increasingly being integrated across various fields, including healthcare. Research by Lewis *et al.* (2019: 292) and Hardy and Harvey (2020: 20190840) highlights a growing presence of AI tools in clinical environments, particularly among medical imaging specialists like Radiologists and Radiographers. Ranschaert *et al.* (2019: 329) contend that this is happening without Radiographers receiving the education and training necessary to fully understand the advantages and risks of these applications.

Artificial intelligence (AI) has played a key role in imaging technology for decades, beginning with the implementation of automatic exposure control (AEC) in general radiography during the 1980s (Sterling 1988: 421). Söderberg and Gunnarsson (2010:

625) state that AEC is programmed to automatically terminate an exposure when enough quanta have reached the film to produce a diagnostic image. Although it did not involve diagnosing or interpreting images, this shift marked a transfer of decision-making from the Radiographer to the machine, demonstrating that the system could perform this task more precisely. This improvement ultimately benefited both radiology providers and patients by minimizing the need for repeat scans caused by incorrect exposure and by optimizing radiation doses during examinations (Hardy and Harvey 2020: 20190840).

Moreover, AI systems that provide comparable decision-making support for radiographic tasks are fundamentally similar to earlier technologies, as both must undergo clinical evaluation and receive Radiographer approval before being widely implemented. However, new AI systems can automate a wider variety of higher-level cognitive functions, which is a significant differentiator. Seeram and Kanade (2024: 105) note that in modalities such as computed tomography (CT) and magnetic resonance imaging (MRI), AI has played a significant role in automating image post-processing and optimizing radiation dose levels. Furthermore, AI significantly contributes to lowering radiation doses in CT scans by reconstructing high-quality images from noisy, low-dose input data. Similarly, studies by McCollough and Leng (2020: 113) and Harvey and Topol (2020: 1479) demonstrate that in MRI, real-time autonomous scan reconfiguration supported by AI-enabled technology leads to better image quality, reduced artefacts, and fewer repeat imaging sessions. Comparable AI applications have also been introduced in mammography, radiotherapy, ultrasound, projection radiography, and nuclear medicine (Malamateniou *et al.*, 2021: 58).

In South Africa, the adoption of AI-driven imaging technology is steadily growing, with systems increasingly capable of intelligently automating machine positioning for X-ray procedures. Automation combined with digital imaging within the X-ray room is capable of advancing the workflow whilst simultaneously gradually diminishing the role of the Radiographer in the X-ray room. Auto tracking, which is now embedded in the recent x-ray systems from industry leaders like GE Healthcare and Siemens Healthineers, enables the wall stand/ table tray to track and follow the movements of the ceiling-mounted tube stands (GE Healthcare 2021: 2). Additionally, auto positioning is another recent feature that is being embedded in X-ray systems. With

this capability, Block Imaging (2019) explains that the tube stand can be remotely adjusted from the control console. Furthermore, with auto-positioning, X-ray examinations are programmed into the X-ray room workstation, and once a protocol is selected, the correct positioning and angulation of the X-ray machine is achieved with just the push of a button.

Without a doubt, Radiographers' roles are changing as a result of AI's incorporation into medical imaging, with some critics arguing that it has led to a decline in their core skills and responsibilities. A meta-analysis by Lewis *et al.* (2019: 292) found that AI systems can diagnose problems just as accurately as medical practitioners. This suggests that AI can enhance workflow efficiency, generate high-quality images, improve image interpretation and segmentation, enable automated image registration, optimize radiation doses, and shorten scanning times. Diagnostic Radiographers play a crucial role in the integration of AI systems within medical imaging, acting as the key link between advanced technology and patient care. Despite the fact that some research has looked at how Radiographers in certain African nations view AI (Botwe *et al.* 2021: 861; Antwi *et al.* 2021: 1), there is still no clear picture of the perspectives that Radiographers have towards AI in the most technologically advanced country in Africa, namely South Africa.

As per the Global Innovation Index (2022), South Africa is ranked as the most technologically sophisticated country in Africa. Hence, the emergence of AI-equipped medical imaging equipment is most likely to be available in South Africa first, before it is accessible in low-resource countries in Africa. Therefore, it is important to understand the perspectives of Radiographers in an African country that is exposed to more AI imaging capabilities because the perspectives of Radiographers in low-resource African countries that are not technologically advanced cannot be generalized for a technologically advanced and fairly high-resourced country like South Africa. This study seeks to assess the understanding and perceptions of Radiographers working in South Africa concerning the integration of AI into their profession. The insights gained are expected to contribute to the development of future strategies and training programs that equip Radiographers with the necessary knowledge while addressing their concerns, an important foundation for the successful adoption of AI in radiology.

A brief overview of AI applications in various imaging modalities is provided above to contextualise the study. A comprehensive examination of the technical aspects of AI, including machine learning, deep learning, and modality-specific applications, is presented in Chapter 2, where the literature is critically analysed in greater depth.

1.2 PROBLEM STATEMENT

Radiography is fundamentally reliant on imaging technology, as both radiography and radiology would not exist without the ability to capture and interpret medical images. As noted by Al-Naser (2023: 162), artificial intelligence (AI) systems, which are designed to replicate cognitive functions for interpreting data and making decisions, have become increasingly common in the field. While this innovation has improved patient diagnosis and care, it has also influenced and reshaped radiographic procedures and the roles of Radiographers. However, this influence is not entirely new; the profession has continually evolved in response to technological advancements, with radiographic practices adapting to the capabilities and opportunities offered by emerging tools.

Historically, radiology and radiography have been early adopters of computer-assisted technologies (Doi 2007:198). However, existing literature has largely focused on Radiologists' roles, education, and diagnostic performance in relation to AI, with comparatively limited attention given to Radiographers as primary end-users of these technologies. Radiographers are central to the operationalization of AI systems in clinical settings, as they interact directly with imaging equipment, software platforms, and patients. Consequently, their knowledge, perceptions, and readiness to engage with AI are critical determinants of successful implementation.

Considering the diverse responsibilities Radiographers manage within cross-sectional imaging, AI is purposefully developed to significantly enhance and support their tasks and workflow. However, the tasks, duties, and responsibilities of Radiographers can potentially be drastically reduced if this level of automation were to be fully realized (Hardy and Harvey 2020). As a result, Coakley *et al.* (2022: 943) elaborate that while it is only natural for private and public hospitals to consider how implementing AI technologies might improve radiology department throughput and maximize efficiency,

it is equally crucial to fully comprehend and manage the perspectives of Radiographers. Radiographers play a vital role in the effective integration of AI systems in medical imaging, serving as a critical link between patients and the technology. Assessing Radiographers' knowledge and receptiveness to artificial intelligence is crucial prior to implementation, as it helps to understand end-users' perspectives and potential adaptability regarding its integration and function.

A comprehensive understanding of Radiographers' attitudes toward artificial intelligence in Africa remains limited, despite existing studies on the topic (Botwe *et al.* 2021: 861; Antwi *et al.* 2021: 260; Chivandire *et al.* 2022: 263). This gap is partly due to the absence of research focusing on the perspectives of South African Radiographers regarding AI implementation. Despite the rapid integration of artificial intelligence into diagnostic imaging departments, there is insufficient understanding of how this technological shift affects Radiographers as primary operators and end-users of imaging systems. Radiographers are directly responsible for image acquisition, workflow management, quality assurance, and patient interaction; therefore, AI implementation has practical implications for their daily responsibilities, required competencies, professional identity, and scope of practice. However, current research predominantly focuses on Radiologists' diagnostic performance and AI-assisted interpretation, with limited empirical evidence examining Radiographers' knowledge, preparedness, and perceptions of AI integration, particularly within the South African context.

This lack of radiography-specific evidence creates a professional gap, without understanding Radiographers' level of knowledge, attitudes, and readiness, AI technologies may be introduced without adequate training frameworks, policy guidance, or role clarification. Consequently, there is uncertainty regarding whether South African Radiographers are sufficiently prepared to engage with AI-enabled systems in a manner that supports safe practice, professional development, and effective patient care. Consequently, this study aims to conduct a quantitative analysis to explore South African Radiographers' opinions on the use of AI. The results of the dissertation will contribute insights for governance and development of policies related to AI adoption in the healthcare sector.

1.3 AIM

This study assesses the perspectives and knowledge of South African Radiographers concerning the integration of artificial intelligence in diagnostic imaging, intending to provide tailored recommendations to enhance Radiographers' training.

1.4 OBJECTIVES

- Assess the basic understanding of Radiographers regarding AI.
- To assess the willingness of Radiographers to accept the integration of AI into their profession.
- To evaluate the impact of AI on the job performance of Radiographers; and
- To assess the barriers to adopting AI in Radiography.

1.5 SIGNIFICANCE OF THE STUDY

According to Ahmed *et al.* (2018: 500) deep learning algorithms, a key component of artificial intelligence (AI), have made notable strides in image recognition and classification, facilitating precise and reliable disease diagnosis. Furthermore, due to its direct relevance to the duties and activities of a Radiologist, this area of artificial intelligence has been the subject of numerous research articles. However, discussions on how such technologies would affect Radiographers are frequently ignored.

Machine learning, which is a division of AI that allows computers to learn from data without explicit programming, has contributed to the extensive adoption of AI across various industries (Jordan and Mitchell 2015: 255). Geoff Hinton, known as "The Godfather of AI", asserted that there is no longer a need to train Radiologists and Radiographers due to the significant advancements and promising capabilities of AI technologies, particularly in deep learning applications (Hinton 2018: 1101). Hinton (2018: 1101) defines deep learning as the development of data representations with varying levels of abstraction, typically for image classification tasks using artificial neural networks composed of multiple processing layers. According to Geis (2019: 436), over the next five to ten years, it is anticipated that the number of specialists in the field will exceed demand, driven by rapid advancements in artificial intelligence. However, there are differing opinions on this projection. For example, in Joanna J. Bryson's 2020 presentation titled "The Role of Humans in an Age of Intelligent Machines," she highlights that AI applications in radiography have improved the quality

of work for Radiographers and have increased their professional value, rather than leading to job displacement. A 2019 study of members of the American Society of Radiologic Technologists highlighted that most respondents believed AI integration in the workplace significantly improved their workflow, functioned effectively, and complemented their traditional responsibilities (ASRT, 2019: 58).

The limited availability of data regarding South African Radiographers' perspectives on artificial intelligence and its implementation in routine clinical practice underscores the need for a dedicated investigation. As noted by Lai *et al.* (2020:18), the effective integration of artificial intelligence in healthcare relies on collaborative efforts and inclusive decision-making among multidisciplinary teams. Radiographers must be informed, ready, and supported to fully utilize AI as they are key stakeholders in its incorporation into medical imaging. This is expected to be a dynamic process that will ultimately help guarantee that implementation increases radiography efficiencies while prioritizing patient care and experience (Botwe *et al.*, 2021: 265). This justifies the need to have knowledge of how South African Radiographers currently view the incorporation of AI into their daily work. A similar study has been conducted at an African level, which consisted of respondents from 28 countries in Africa, including South Africa (Botwe *et al.*, 2021: 861). However, in this study, South African Radiographers only constituted 5% of the respondents across Africa, whilst other countries such as Nigeria and Tanzania constituted 25% and 19% of the response rate, respectively. Therefore, due to the limited response rate from South African Radiographers compared to other countries, these findings may not be directly generalizable to the South African radiography workforce. The sampling method employed in this study presented some limitations due to its lack of proportionality, leading to underrepresentation of countries with large populations and extensive Radiographer communities, while smaller countries or those with fewer Radiographers were disproportionately represented (Botwe *et al.*, 2021: 861).

An analysis of the literature strongly demonstrates that the author Botwe has contributed much relevant research that has added to the development of knowledge on the subject in Africa. Even though Botwe and colleagues conducted 2 studies investigating the perspectives of Radiographers towards AI in Africa, they still went on to conduct a Ghanaian-specific study on the matter, and the same should be done for

South Africa to get a clear view of a South African perspective rather than generalizing on studies done in Africa.

Based on a review of the existing literature, there appears to be a gap in research specifically exploring South African Radiographers' perspectives on the application of artificial intelligence in diagnostic imaging. Although some research has explored Radiographers' opinions on AI broadly, the viewpoints of the South African radiography workforce remain largely undocumented. This identified gap prompted the current study, which aims to comprehensively explore the perspectives of South African Radiographers regarding the integration of AI into radiology imaging. Additionally, the study intends to develop practical recommendations to enhance Radiographer's training, ensuring they are well-equipped to deliver high-quality care with the assistance of artificial intelligence. The findings are also intended to inform policy development to support the effective implementation of AI within South Africa's healthcare system.

1.6 STRUCTURE OF THE DISSERTATION

Table 1: structure of the dissertation

Chapter 1: Introduction	Addresses the background, aim, justification, and primary objectives related to Radiographers in South Africa.
Chapter 2: Literature Review	This chapter offers a thorough review of the existing literature relevant to the topic.
Chapter 3: Theoretical framework	The elements of the theoretical framework supporting the study are covered in this chapter.
Chapter 4: Methodology	Details of the study's design and methodology, which employed a quantitative cross-sectional approach.
Chapter 5: Findings	Presents and analyzes the data utilizing appropriate methods, such as graphical representations.
Chapter 6: Discussion of Findings	Discusses the findings in the context of relevant literature.

Chapter 7: Conclusion, limitations, and recommendations	Addresses the study's limitations and offers recommendations for various stakeholders.
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1.7 SUMMARY OF THE CHAPTER

The chapter presents the problem statement and contextual background of this study. Following an overview of the study's objectives and purpose, the significance of the research is addressed. The subsequent chapter reviews relevant literature that supports and validates the study.

CHAPTER 2: LITERATURE REVIEW

2.1 INTRODUCTION

According to Polit and Beck (2014: 89), a literature review offers scholars the context for understanding existing knowledge on a topic and sheds light on the motivation for the new study. This chapter is focused on a review of extant literature to assess the perspectives of Radiographers on the integration of AI in their profession globally, in Africa, and in South Africa. The literature review serves to highlight findings from relevant studies and identify existing gaps necessary to address potential concerns of Radiographers. The chapter delineates the theoretical frameworks, terminology, methodologies, and variables pertinent to the phenomenon under investigation.

2.2 PROCESS OF SOURCING RELEVANT LITERATURE

A comprehensive online review of the existing literature was undertaken to elucidate the perspectives of Radiographers regarding the integration of artificial intelligence within their professional practice. The preliminary search focused specifically on the viewpoints of Radiographers in South Africa, subsequently expanding to include perspectives across Africa and internationally on other continents. The literature included in this chapter was retrieved from various scholarly databases and search engines, notably Google Scholar and the Durban University of Technology (DUT) online library. A search strategy incorporating Boolean "AND" and "OR" operators was utilized to retrieve scholarly articles from multiple electronic databases, namely PubMed, ScienceDirect, Google Scholar, and Elsevier Radiography, without imposing any temporal limitations. Keywords such as "artificial intelligence", "machine learning", "deep learning", "Radiography", "medical imaging", "diagnostic imaging", "computed tomography", "magnetic resonance imaging", "fluoroscopy", and "knowledge of Radiographers towards AI" were used. Vendors included in the study search were Siemens Healthineers (Erlangen, Germany), General Electric (GE Healthcare, Chicago, IL) and Philips (Amsterdam, NL). Keywords, namely "artificial intelligence", "ethics", "Privacy" and "healthcare", were used to gather resources on AI ethics.

2.3 FUNDAMENTALS OF AI

2.3.1 Definition of AI

Artificial Intelligence is defined by Joiner (2018: 124) as the field of study and advancement in computer systems capable of carrying out tasks typically associated with human intelligence, for example, visual cognition, speech interpretation, decision-making and language translation. Oleboya and toluyani (2018: 587) elucidate that in a professional context, the term "artificial intelligence" is commonly used to describe when a machine imitates "cognitive" functions that humans typically associate with the human mind, such as "learning" and "problem-solving". Additionally, AI draws from the complexities of the human brain to contribute to the development of more advanced computer systems.

The primary objectives of AI research revolve around critical areas such as reasoning, knowledge acquisition, planning, learning, communication through natural language processing, perception and the capability to manipulate objects and move (Russell 2010: 48). As per Ting *et al.* (2018: 539), diverse methodologies are employed in the domain of Artificial Intelligence, including statistical techniques, computational intelligence, and conventional symbolic AI. Panayides *et al.* (2020: 1837) state that AI incorporates a wide array of tools, including search and mathematical optimization variations, logic, probability-based methods and economics. Furthermore, AI is a multidisciplinary field that draws from a wide range of disciplines, including mathematics, computer science, psychological research, the discipline of linguistic philosophy, neurology, and many more.

2.3.2 Machine Learning

Machine Learning constitutes a subfield within the discipline of computer science that gives "computers the ability to learn without being explicitly programmed" (Samuel, 1959: 4). Based on the study of computational learning theory within artificial intelligence and the analysis of pattern recognition, Mahesh (2020: 381) states that machine learning delves into the examination and creation of algorithms capable of acquiring knowledge from data and making predictions. Jordan and Mitchell (2015: 255) elucidate that these algorithms surpass the limitations of rigid program instructions by generating data-based forecasts or decisions through the development of models based on sample inputs. According to Wang (2016: 164), data is utilized to

train machine learning (ML) systems in order to identify patterns and relationships. Additionally, there are several types of machine learning algorithms, such as reinforcement learning, supervised learning, and unsupervised learning. Mahesh (2020: 381) reinforces that these algorithms can enhance their efficiency in performing specific tasks when exposed to more data. In the field of Radiology, machine learning has made significant advancements, revolutionizing the process of collecting and assessing medical images.

2.3.3 Deep Learning

Deep Learning is a sub-field of artificial intelligence that focuses on constructing large-scale neural network models capable of making accurate data-based decisions (Kelleher, 2019: 1). Moreover, this approach proves particularly valuable when dealing with intricate datasets and abundant information sources. The application of deep learning is widespread across online enterprises and upscale consumer electronics. For instance, Kelleher (2019: 1) explains that Facebook employs deep learning technology to analyze textual content derived from online communications. Moreover, deep learning is utilized by major technology companies such as Google, Baidu and Microsoft for various purposes, such as image search and machine translation. As an example, deep learning has become the prevailing technique for facial and speech recognition on digital cameras, and it is now commonly integrated into smartphones (Kelleher, 2019: 2).

Recent advancements in AI research, along with the abundance of available digital data for algorithm training and the availability of powerful computational resources, have allowed deep learning algorithms to outperform humans in specific tasks. This marks a significant improvement compared to earlier AI methods that produced sub-par results. Processing medical images and providing health condition diagnoses rely on deep learning, which plays a crucial role in the field of healthcare. Decision-making is a fundamental aspect of life and while using intuition or gut feeling is one approach, LeCun *et al.* (2015: 436) argue that utilizing relevant data to inform judgments is the most effective method. Additionally, deep learning enables decisions to be based on data as it allows for the identification and extraction of patterns from extensive datasets that accurately correspond to intricate inputs, ultimately leading to well-informed decisions. The development of high-performance parallel computing technologies utilizing graphics processing units (GPUs), coupled with the availability of large

datasets, has significantly advanced the field of deep learning in computer vision (Ting *et al.*, 2019: 167). Furthermore, this technology shows considerable potential for analyzing both unstructured data (such as text and images) and organized data (such as databases and tables) within the healthcare sector. Over the past decade, deep learning algorithms have increasingly facilitated the analysis of medical images across various organs and imaging modalities. Tasks traditionally performed by Radiologists, including lesion detection, segmentation, classification, and monitoring, may become more efficient through the automation capabilities of these systems (Gosh *et al.*, 2019 32). Deep learning has demonstrated significant success in the field of abdominal radiology, effectively supporting a range of tasks related to different organs and medical conditions.

2.3.4 Relationship between Machine Learning and Deep Learning

Artificial intelligence encompasses both machine learning and deep learning, with deep learning being a sub-component of machine learning (refer to Figure 1). These three elements have transformed the radiology industry by automating numerous time-consuming procedures performed by Radiologists and Radiographers. According to Kohli *et al.* (2017: 754), deep learning algorithms utilize neural networks with multiple layers to autonomously acquire complex patterns and representations from data. They constitute a subset of machine learning algorithms. In contrast to conventional machine learning, Erickson *et al.* (2017: 505) argue that deep learning has transformed the field of artificial intelligence by incorporating extra layers into the algorithmic model architecture to enhance decision-making capabilities. Deep learning has gained significant popularity due to its exceptional performance in various tasks, especially when dealing with unstructured input data such as photos, audio and text. Machine learning and deep learning are both essential components of artificial intelligence, each having distinct use cases and applications depending on the specific problem and its characteristics.

Image pre-processing involves utilizing machine learning (ML) and deep learning (DL) algorithms to enhance unprocessed signals or reconstructed images. Sun *et al.* (2016: 10) confirms that these methods have various practical applications, such as reconstructing images from sparse MRI data; reducing noise and artifacts; improving resolution; and handling image collection and reconstruction tasks. Moreover, machine learning (ML) and deep learning (DL) models in the field of Radiology are highly

valuable as they enhance image recognition and diagnosis capabilities. Yang *et al.* (2018: 1348) point out that these models are capable of efficiently categorizing medical images to identify and locate specific abnormalities, lesions, or cancers. This ability aids in the early identification of health issues and aids in devising appropriate treatment plans. Notably, Higaki *et al.* (2019: 73) state that an ML analysis of brain magnetic resonance imaging (MRI) displays superior sensitivity compared to a human reader. Consequently, Christ *et al.* (2017: 39) acknowledge that it can accurately detect tissue alterations that serve as early indications of an ischemic stroke within a limited time-frame following the manifestation of symptoms. Moreover, ML and DL models utilize image analysis techniques to accurately determine the volume of a lesion or organ. This involves analyzing pixel intensity, texture, and edges to effectively segment tissues. For example, in the case of lesion segmentation, the contour of metastases in patients with liver metastases can be outlined. Prasad *et al.* (2012: 416) adds that this allows for the extraction of the largest diameter in both the long and short axes, enabling the subsequent monitoring of chemotherapy response. Additionally, it facilitates the computation of tumor volumetry to estimate the volume of the future liver remnant.

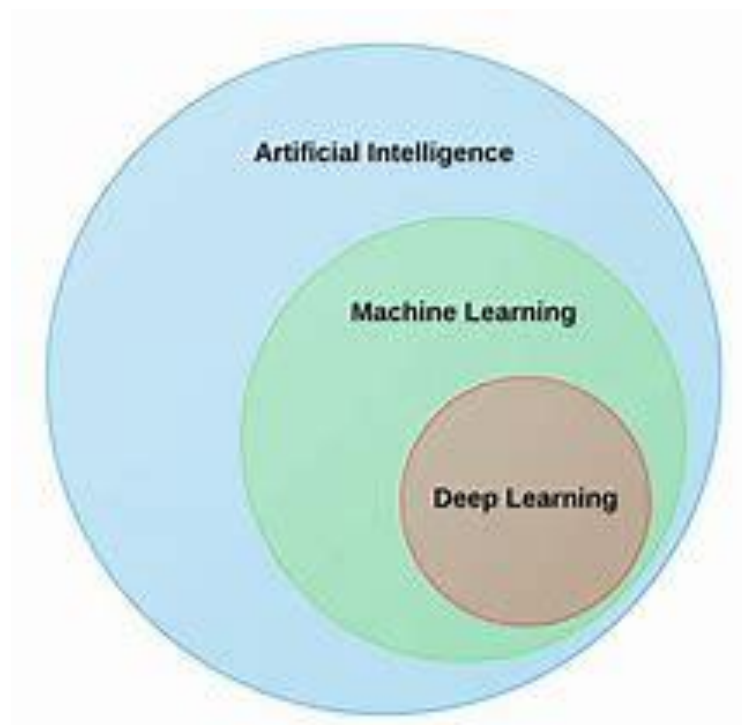


Figure 1: Relationship between Artificial Intelligence, Machine Learning and Deep Learning (Prasad *et al.* 2012: 416)

2.4 APPLICATIONS OF AI IN RADIOGRAPHY

Artificial intelligence has demonstrated significant advancements in the field of medical imaging, primarily in its application for image processing. Ting *et al.* (2018: 539) state that AI can analyze various medical images such as X-rays, mammograms, and ultrasounds, as well as images from CT and MRI scans. By delivering quantitative data, it greatly assists in the identification and diagnosis of abnormalities, including fractures and tumors.

With the introduction of Computer Aided Analysis (CAD) and Automated Exposure Control (AEC) in the 1960s, the concept of automation in radiology began to gain momentum. Computer-aided diagnosis (CAD) emerged as a valuable tool for clinical professionals, providing support in addition to AI. It facilitates tasks such as picture processing, picture feature analysis, and data classification (Doi, 2007: 198). Giger and Suzuki (2008: 359) elucidate that CAD has significantly enhanced the accuracy of breast cancer detection in mammograms, as well as aiding in the differential diagnosis of lung nodules and interstitial lung disease on CT scans. Chan *et al.* (2020: 281) argue that the primary limitation of CAD lies in its inability to achieve the same level of "intelligence" as deep learning algorithms.

Automatic Exposure Control (AEC), on the other hand, is a radiographic density control system that automatically terminates the exposure when a specified radiation level is attained (Söderberg and Gunnarsson, 2010: 625). Kalra *et al.* (2005: 267) add that the latest systems not only regulate exposure time, but also adjust kVp and mA. Additionally, the primary aim of AEC is to consistently produce top-notch radiographs while minimizing technical limitations for the Radiographer. AEC is an integral part of imaging equipment and finds widespread usage across all imaging modalities.

Although the evaluation of AI in relation to interpreting medical images is the main subject of numerous articles, there are various other ways in which AI is applied in the field of Radiography. Patient positioning, image capture, treatment planning, workflows and reconstruction processes across different modalities are just a few examples of areas where AI-enabled automation has had a diverse impact on Radiography (Hardy and Harvey, 2020: 44). While there is constant progress in technological advancements in medical imaging equipment, the clinical integration of AI has introduced new approaches to optimize and refine the diagnostic imaging workflow.

2.4.1 General Radiography

Frequently, general radiography is the initial approach used to address clinical inquiries. However, accepting radiographic images of inadequate diagnostic quality can greatly compromise the standard of care. This may necessitate additional radiographs, prolong the diagnosis process, jeopardize patient safety, and increase treatment expenses (Kjelle and Chilinga, 2022: 36). Given the prevalence of chest radiographs in hospital settings, there has been a push to develop AI-enabled equipment in this medical field.

According to Saade *et al.* (2021: 304), despite sub-optimal radiographic technique and image quality, diagnostic Radiographers may choose not to repeat mobile chest exams and instead provide radiographs of inferior diagnostic quality for reporting. Additionally, critical studies are often concealed within extensive worklists without any indications that the patient is at an elevated risk. To assess anteroposterior chest radiographs, GE has developed Critical Care Suite 2.0™, a collection of artificial intelligence algorithms integrated into mobile X-ray equipment (General Electric Company, 2021). According to GE, these algorithms have the capability to determine the position of the endotracheal tube, detect pneumothorax, and prioritize investigations based on AI findings. Furthermore, the system possesses the capability to automatically rotate radiographs, detect anatomical cut-off points, assess for under-exposure and over-exposure, and offer suggestions to Radiographers when needed. Jaka *et al.* (2023: 436) add that these features for evaluating images greatly assist Radiographers in rendering judgments on the diagnostic suitability of radiographic images. Furthermore, vital discoveries resulting from studies incorporating AI are promptly recognized and given priority, ensuring that they are promptly addressed by Radiologists.

To enhance Radiographers decision-making capabilities, Philips has integrated the Radiology Smart Assistant™, an artificial intelligence-enabled solution (Philips, 2022). According to Philips, this technology enables the real-time analysis of erect postero-anterior chest radiographic images at the point of acquisition, specifically focusing on collimation, rotation and inspiration. Results of a recent study have shown that implementing AI-based picture analysis in postero-anterior chest examinations resulted in a 28% increase in properly collimated images, a 34% reduction in unnecessary exposure, and a notable 30% improvement in departmental productivity (Poggernborg *et al.*, 2021: 654). According to Philips (2022), the radiology Smart

AssistantTM prompts the Radiographer to provide a justification when there is a disagreement between the Radiographer and AI regarding the analysis of an image that falls below standards. Jaka *et al.* (2023: 436) believes that this feature proves valuable in assessing the progress of Radiographers over time or conducting audits on the performance and workload of the diagnostic imaging department. Radiographers can easily access individual performance statistics and the number of studies in their department that meet positioning standards.

In addition, Siemens Healthineers has developed the YSIO X.preeTM ceiling-mounted X-ray system, equipped with the myExam 3D Camera to enhance image acquisition efficiency (Siemens, 2021). Utilizing an embedded AI algorithm, the system can identify the thorax and adjust collimation even when patients are fully clothed. This automated process not only optimizes radiation dosage but also grants Radiologists additional time to dedicate to patient care (Siemens, 2021).

2.4.2 Computed Tomography

Wide detector computed tomography (CT) scanners offer reduced scan times, but incorrect patient positioning by Radiographers can lead to varying dose reference levels for specific anatomical regions and therapeutic objectives (Paulo *et al.*, 2020:11). Ishita *et al.* (2022:151) mention numerous studies indicating that patient positioning away from the isocenter has negative implications for organ dose and image quality. Radiographers may encounter challenges in accurately positioning the patient at the isocenter of the gantry. According to Jaka *et al.* (2023: 437), factors such as human error, workload pressure, patient size and presentation contribute to issues related to dosage and picture quality. To address this, Singh *et al.* (2017: 497) explain that modern CT scanners utilize a ceiling-mounted 3D camera that utilizes deep learning (DL) technology to gather information about the patient's shape, contours, position (head or feet first), height and width. By automatically positioning patients at the isocenter, this technology enables the detection of improper patient placement and alerts Radiographers to the issue. Compared to human experts, AI demonstrates superior performance in this specific task, resulting in the improved reliability of radiation output, higher image quality and faster scan times (Booij *et al.*, 2021: 131).

To accurately determine the relevant anatomy and designate the scanning area for the upcoming CT scan, localizer radiographs are utilized. According to Schwartz *et al.*

(2018: 49), variances amongst operators may lead to inconsistent interpretations of the scanning range, excessive scanning of irrelevant areas, the omission of critical anatomy, and unnecessarily high radiation exposure for patients. Salimi *et al.* (2021: 162) elucidate that advanced workflows employ deep learning technology to accurately identify specific anatomical regions from localizers and select the optimal scan range centered around the required anatomical coverage. Siemens FAST Integrated WorkflowTM, Philips CT Precise SuiteTM and GE's RevolutionTM Maxima are some examples of AI-enhanced CT systems (Siemens, 2021; Philips, 2021; General Electric Company, 2022).

The rapid scan speeds and high spatial resolution of CT are widely acknowledged, although this comes at the cost of increased radiation exposure (Kubo *et al.*, 2014: 1953). Agostini *et al.* (2020: 365) explain that efforts have been made to reduce radiation in chest CT patients through specific techniques, but this often leads to a compromise in image quality. Research has shown that deep learning-based reconstruction outperforms iterative reconstruction in denoising low-dose chest CT images and enhancing their spatial resolution (Klug *et al.*, 2022: 509). Similar conclusions have been drawn in abdominal imaging. The first image reconstruction technique that utilizes deep learning to generate high-quality CT images from low-dose scans is known as TrueFidelityTM (General Electric Company, 2019).

2.4.3 Magnetic Resonance Imaging

According to Bash (2022: 197), the development of AI-based DL image reconstruction techniques has been driven by the need for shorter MRI scan times while maintaining high diagnostic image quality and benefits such as signal-to-noise ratio and artifact reduction. GE and Philips have successfully implemented DL image reconstruction, resulting in sharper images and scan time reductions of up to 50% and 66% respectively (General Electric Company, 2021; Philips, 2020). Siemens Healthineers has also introduced Deep ResolveTM functionality to their MRI scanners, enabling a scan duration reduction of up to 70% (Siemens 2020). Additionally, when used alongside Simultaneous Multi-Slice technology, scan times can be further accelerated by up to 80%. For example, DL imaging now takes less than two minutes, significantly faster than the ten minutes needed for a knee MRI on a three-Tesla machine.

To streamline manual labor and eliminate inconsistencies caused by human operators, advancements have been made in the automation of MRI processes using artificial intelligence (AI). Zhan (2011: 2087) argues that research conducted in the early 2000s regarding automated scan slice positioning is relevant to current practices. Furthermore, hospitals and doctors currently differ in their protocol selection, but AI is now capable of automating this process as well. This includes providing recommendations for patient positioning, coil and scan parameter selection, and even automated breathing instructions to ensure consistent timing when required. For example, GE's AIRTM Workflow, Philips' SmartWorkflow, and Siemens' myExam CompanionTM are some notable AI-powered solutions in this field (Siemens, 2020; General Electric company, 2021; Philips, 2020).

2.4.4 Fluoroscopy

The radiation dose received by patients and staff during fluoroscopy-guided procedures is greatly influenced by the Radiographer. In extreme cases, individuals may suffer tissue damage from excessive exposure, such as hair loss, skin redness or skin ulcers (Liao *et al.* 2020: 447). As a result, Mahesh *et al.* (2014: 431) suggest that fluoroscopy operators must prioritize the radiation protection of both their patients and employees. This includes reducing the use of magnification; lowering the height of the X-ray detector; using lower fluoroscopy frames and pulse rates whenever possible; and adjusting collimation for the specific anatomical area being targeted. For fluoroscopic gastrointestinal endoscopy and cardiac interventional treatments, an automated approach has been developed. To efficiently visualize the relevant anatomy and procedural activity without compromising image quality, a fluoroscopy system equipped with artificial intelligence (AI) capabilities, developed by Omega Medical Imaging, is utilized (Omega Medical Solutions, 2020). Bang *et al.* (2020: 555) explain that by utilizing deep learning technology, this AI-enabled system significantly reduces patient and staff radiation dose by over 60% compared to traditional methods. It is feasible to expect increased automation in all imaging methods and expanded automation capabilities due to the current use of AI in clinical applications. In the medical imaging field, there are various AI-powered systems accessible.

According to Hardy and Harvey (2020), numerous manual processes that were traditionally performed before an examination, during patient positioning, during imaging protocol selection, during image capture, during image interpretation, during

post-processing and even equipment maintenance, can now be automated. This advancement is advantageous for imaging experts. Radiographers should acquaint themselves with the new technology and demonstrate their readiness to actively participate in the development, utilization and integration of AI-powered solutions.

2.5 GLOBAL CONTEXT

In recent years, Radiographers have increasingly incorporated automated technologies into their work. However, some may argue that this has resulted in a decline in their core skills, responsibility and independence in decision-making (Malamateniou *et al.*, 2021: 58). The implementation of digitalization and automation has brought about efficiency and productivity improvements in imaging departments. Various studies have been conducted to assess the perceptions of Radiographers globally towards the use of artificial intelligence (AI) in medical imaging, which has resulted in a combination of cautiousness and enthusiasm. Nevertheless, the integration of AI into clinical practice is already progressing successfully.

The UK has consistently been a leader in advancing the role of Radiographers, with consultants reporting Radiographers being recognized as highly skilled practitioners. A study conducted in the UK investigated Radiographers' perspectives on artificial intelligence (AI) and revealed that most respondents believed that the introduction of AI would significantly impact their daily clinical practice and reduce their workload (Rainey *et al.*, 2022: 347). This aligns with the results of a worldwide survey conducted by Akudjedu *et al.* (2023: 104) which revealed that Radiographers are optimistic that AI will enhance their job performance. Akudjedu *et al.* (2023: 104) suggest that the information conveyed through literature and the efforts of businesses developing AI solutions can influence this perception.

Research conducted in various European countries by Coakley *et al.* (2022: 943) found that Radiographers generally have a positive view of the utilization of artificial intelligence (AI). However, concerns exist amongst Radiographers regarding potential inaccuracies, job displacement and reductions in compensation that may be caused by AI. These prompts the question of whether AI has the potential to completely replace Radiographers in the future, or if it will serve to improve their work. Despite these concerns, AI has the potential to enhance the practices of Radiographers and expand their responsibilities.

A survey conducted by Abuzaid *et al.* (2021: 83) involved 34 Radiologists and 119 Radiographers in the United Arab Emirates to evaluate their perspectives on integrating AI into clinical practice. The findings indicated that the staff members demonstrated a favorable and receptive attitude towards adopting AI. However, it was observed that 17% of respondents had limited knowledge regarding AI, while 40% acquired knowledge through self-learning. Additionally, 73% expressed difficulties in accessing training programs designed to bridge the knowledge gap amongst staff members.

Internationally, artificial intelligence is already making waves in clinical practice across various settings, including diagnostic imaging in healthcare facilities. This impact is predicted by Hudson and Heales (2022: 44) to continue growing in the future. Moreover, a notable example can be found in certain mammography screening centres in the United Kingdom, where validated AI technologies are supplementing Radiologists' reports. Additionally, a recent study by Lauritzen *et al.* (2021: 67) demonstrated the potential of AI in population-based breast screening. Through the use of AI, Radiologists were able to significantly reduce their workload by over 60% whilst simultaneously lowering false-positive results by more than 25%. Consequently, the integration of AI-enhanced breast imaging alongside specialized healthcare professionals offers the promise of more effective, efficient, and patient-focused treatment. In response to the increased use of chest imaging tests during the COVID-19 epidemic, Wang *et al.* (2020: 19549) state that several AI methods have been enhanced for identifying and managing the virus. Mollura *et al.* (2020: 397) posit that these applications have been particularly beneficial in resource-limited environments and radiotherapy treatment planning workflows.

Radiographers are increasingly gaining knowledge regarding the applications, potential risks, and benefits of artificial intelligence technologies, as well as their implications for future training, research objectives, and professional practice. Regarding the impact of AI on radiography, statements have been issued by the European Federation of Radiography Societies (EFRS), the American Society of Radiologic Technologists (ASRT), the International Society of Radiographers and Radiological Technologists (ISRRT), and the Society and College of Radiographers (SCoR) in the United Kingdom. Radiologists and Radiographers should actively engage in the planning, development, implementation, utilization, and assessment of

artificial intelligence applications in medical imaging and radiation therapy. This is underscored in a joint statement from ISRRT and EFRS (2020: 93), highlighting the importance of prioritizing technological advancements when addressing complex clinical challenges.

To ensure the optimal integration of AI in medical safety, clinical imaging and radiation therapy, it is crucial to provide effective training for the current and future workforce. The Society and College of Radiographers AI working group has also provided valuable recommendations for radiography clinical practice, education, research and building important relationships (Malamateniou, 2021: 1192). These partnerships are essential for the smooth and secure implementation of AI tools within medical imaging teams.

Synthesising the global literature on Radiographers' AI perspectives reveals several important patterns. First, despite geographic and healthcare system differences, Radiographers consistently express positive attitudes toward AI integration, suggesting that optimism about AI's potential may be a universal professional response rather than a context-specific phenomenon. Second, the concerns raised about job security, skill erosion, and training adequacy are remarkably consistent across studies from the UK (Rainey *et al.*, 2022), Europe (Coakley *et al.*, 2022), the UAE (Abuzaid *et al.*, 2021), and North America (ASRT, 2020). This consistency indicates that AI triggers similar professional anxieties regardless of local implementation status. Third, a significant gap between general AI awareness and technical understanding appears universal, with Radiographers across multiple studies reporting familiarity with AI concepts but limited knowledge of specific algorithms or applications. This gap has important implications for education and training, suggesting that curricula must move beyond conceptual introductions to provide practical, technical competency. Fourth, the predominance of cross-sectional survey designs in this literature limits understanding of how attitudes evolve, highlighting the need for longitudinal research tracking Radiographers' perspectives before, during, and after AI implementation.

2. 6 THE AFRICAN AND SOUTH AFRICAN CONTEXTS

The African literature on Radiographers' AI perspectives presents a complex picture of optimism tempered by significant contextual challenges. Studies across the continent consistently report positive attitudes toward AI's potential benefits, including improved patient outcomes and enhanced practice efficiency (Botwe *et al.*, 2021; Chivandire *et al.*, 2022; Antwi *et al.*, 2021). However, this enthusiasm is accompanied by acute awareness of barriers that are particularly pronounced in low-resource settings. Unlike their counterparts in high-income countries, African Radiographers must contend with fundamental infrastructural limitations including unreliable electricity, inadequate internet connectivity, and outdated equipment that may render AI implementation impossible regardless of professional willingness (Waho, 2020: 48; Wuni *et al.*, 2021: 69). This tension between aspiration and reality creates a unique professional context that distinguishes the African experience from the global literature discussed in Section 2.5.

The utilization of digital radiology and AI has been limited in Africa due to cost and perceived complexity. According to Daniel *et al.* (2020: 513), many African nations face challenges in infrastructure, the availability of skilled imaging professionals, data rights frameworks, and public policies related to AI. Additionally, issues with water, energy, and telecommunications have hindered the widespread adoption of AI technologies, resulting in their predominance in the private sector. However, there is potential to more widely utilize these technologies in public hospitals, where the necessary equipment may be available.

Numerous research studies have been conducted in African countries to explore Radiographers' perspectives on artificial intelligence (AI). In Zimbabwe, Radiographers responded positively to a study examining their perceptions of the potential benefits of AI (Chivandire *et al.*, 2022: 263). This finding aligns with research by Botwe *et al.* (2021: 861) in Africa, in which most respondents anticipated that AI would enhance patient outcomes, improve radiographic practice, and facilitate prompt diagnoses by strengthening quality assurance measures. In a study by Botwe *et al.* (2021: 260) in Ghana, it was found that Radiographers in the country were optimistic about the possible advantages of artificial intelligence in medical imaging. However, the study also highlighted several challenges that need to be addressed, namely

decision-making, cyber security, data protection and the risk of AI-related mistakes. Additionally, constraints such as limited technical expertise, high costs of equipment, and cybersecurity concerns have been recognized as a possible obstacle to Ghana's adoption of AI in medical imaging. Waho (2020: 48) also mentioned that many devices in low-resource countries are still analog and in poor working condition. Furthermore, traditional radiography methods with darkroom processing are still widely used in many African nations. Given these circumstances, it is virtually impossible to incorporate AI into clinical radiography practice. In many public hospitals in Africa, radiographs are typically printed on paper as part of the clinical treatment process due to the absence of electronic patient records. Consequently, Wuni *et al.* (2021: 69) explain that these facilities face difficulties in implementing AI technology without investing in the required infrastructure. Furthermore, it is worth noting that even in the few hospitals equipped with completely digitized systems, electronic health records are not interconnected with other hospitals.

Inadequate technological expertise and personnel training; insufficient data rights frameworks; government regulations; the expenses associated with installing and maintaining AI equipment; concerns about potential job loss; and challenges with internet connectivity have all been previously acknowledged in the African context study by Botwe *et al.* (2021: 681). However, there is an increasing level of support, particularly in resource-limited environments, for the utilization of AI technology in essential aspects of imaging. A study by Botwe *et al.* (2021: 681) conducted in 28 countries in Africa found that Radiographers in Africa have favorable opinions about the use of AI in radiology. However, there were serious worries about employment stability when it came to the use of AI in radiology. This difference in opinion amongst the panelists, as pointed out by Chivandire *et al.* (2022: 263), is not unexpected given the extensive discussions surrounding the potential mechanization of professions and the potential displacement of human workers by AI. However, it is worth considering the outcome that occurred with the introduction of digital radiography, which rendered darkroom assistants obsolete in many African countries. As with previous pioneering and transformative technologies, there may be several challenges to address before artificial intelligence can be effectively integrated into medical imaging practices in Africa. Key challenges to the successful use of AI include insufficient funding,

expertise, support infrastructure, and regulatory frameworks; it is important for stakeholders to address these areas accordingly (Botwe *et al.*, 2021: 682).

Although many of the challenges discussed are particularly pronounced in low- and middle-income countries due to infrastructural limitations, financial constraints, and workforce shortages, it is important to recognise that high-income countries also face significant barriers in implementing artificial intelligence in radiography. Studies from high-income settings report challenges related to data governance, algorithmic bias, medico-legal liability, integration of AI into existing clinical workflows, interoperability with hospital information systems, and resistance to change among healthcare professionals. Furthermore, concerns regarding overreliance on AI, transparency of algorithms, and ethical accountability remain global issues rather than context-specific problems. However, the key distinction lies in the magnitude and nature of these challenges. In high-income countries, barriers are often related to regulation, optimisation, and governance of AI systems, whereas in low-income countries, fundamental constraints such as infrastructure, funding, digital literacy, and access to large annotated datasets pose more structural limitations. Recognising that AI implementation challenges are both globally shared and contextually differentiated strengthens the understanding that equitable adoption requires tailored strategies rather than uniform solutions.

The Africa study at large conducted by Botwe *et al.* (2021: 687) included 51 Radiographers practicing in South Africa, constituting 5% of the respondents. This is the only study that sought to solicit the perspectives of Radiographers practicing in South Africa towards AI. However, the findings from this study cannot be generalized to South Africa nor be considered as the final perspectives of Radiographers in South Africa as the low number of respondents does not represent Radiographers in South Africa at large. Moreover, with South Africa being one of the most technologically advanced countries in Africa, a much clearer perspective of Radiographers practicing in South Africa is needed as findings from low-resourced African countries cannot be generalized to a highly developed country like South Africa. According to the researcher's knowledge and the literature reviewed, there is no existing literature specifically exploring the perspectives of South African Radiographers on the integration of AI in diagnostic imaging. The perspectives of Radiographers in South Africa remain largely undocumented, despite existing research exploring

Radiographers' attitudes towards artificial intelligence. This gap in knowledge prompted the current study, which aimed to thoroughly investigate South African Radiographers' opinions on the use of AI in diagnostic imaging.

2.7. ETHICS OF ARTIFICIAL INTELLIGENCE IN HEALTHCARE

The use of AI applications in healthcare has greatly impacted various aspects of the medical field, such as medical imaging, electronic medical records, laboratory diagnosis and treatment, new drug discovery, preventive and precision medicine, biological extensive data analysis, process efficiency and data management for health organizations (Morley *et al.*, 2020: 65). However, this scientific sector must address multiple ethical and legal issues. Murphy *et al.* (2021: 7) explain that traditionally, healthcare decisions were made by humans, hence, the implementation of intelligent computers in decision-making processes raises concerns regarding accountability, transparency, consent, and privacy.

According to Amisha (2019: 2328), in the realm of modern technology, transparency emerges as a significant challenge to address. Particularly in the context of image analysis utilizing deep learning algorithms, Varkey (2021:18) states that the interpretation and explanation of such AI algorithms pose practical difficulties. Farhud and Zokaei (2021: 4) explain that medical professionals, typically knowledgeable about the workings of deep learning algorithms, may struggle to provide a clear explanation behind a diagnosis. Moreover, in the process of diagnosing and treating patients, AI systems are bound to make errors, making it intricate to establish accountability.

Machine learning algorithms in healthcare may also be susceptible to algorithmic bias, potentially leading to higher risk predictions for certain races or genders, despite these factors not being the true causes of the disease (Miller and Brown 2018: 129). According to Morley *et al.* (2020: 65), in the era of AI, the significance and interpretation of radiography data related to its value, ownership, usage and accessibility has evolved. However, Naik *et al.* (2020: 478) argue that it is important to note that AI is a complex technology that may contain inherent biases and potential risks. The extensive adoption of AI-based intelligent and autonomous robots in radiology carries a higher likelihood of errors that could have significant consequences, elevate systemic risks, and amplify complex ethical and societal dilemmas (Schonberger, 2019: 171).

2.7.1 Ethical Considerations Of Artificial Intelligence

The trust associated with the collection, management and evaluation of data is a fundamental aspect of data ethics in AI in Radiology (Char *et al.*, 2018: 981). Important considerations include obtaining informed consent, ensuring privacy and data protection, addressing issues of data ownership, maintaining impartiality, promoting transparency, facilitating knowledge transfer to all individuals regardless of their data handling capabilities, and granting ethical and rational access rights to data (Davenport and Kalakota, 2018: 94). These concerns play a critical role in the field of data ethics. According to Mittelstad (2016: 303), the reliability of the data can be assessed by comprehensively examining its scope and details, the range of information it covers, its accuracy in reflecting real-world scenarios, and any indications of partiality or inconsistencies. Geis *et al.* (2019: 329) add that it is important to acknowledge that all datasets possess some degree of partiality.

Furthermore, these biases can arise from various factors and may either favor or disadvantage specific sub-groups within a population based on characteristics such as gender, sexual orientation, ethnicity, social class or economic status. In the field of Radiology, it is important to be mindful of potential biases that may arise due to comorbidities, technical issues, and variations in scanning methodologies (Geis *et al.*, 2019: 329). These biases can impact the accuracy of AI models used in evaluations. Therefore, it is crucial to thoroughly study and understand these biases in order to minimize their influence.

2.7.2 AI In Relation To The Protection Of Personal Information Act In South Africa

Respecting privacy as a fundamental value and right is an integral aspect of ethical AI, which entails ensuring data security and safeguarding. In South Africa, the Protection of Personal Information Act (POPIA) offers a balanced framework that upholds the rights to privacy protection, information access, and freedom of expression (POPI Act, 2013). This is particularly crucial as AI relies on substantial personal biometric data and information to achieve optimal performance within the healthcare sector. However, Jobin *et al.* (2019: 389) argue that it is worth noting that POPIA may not fully address the distinct challenges and intricacies posed by the integration of AI in healthcare. Check (2018) explains that large technology corporations will require significant quantities of patient and personal data to effectively utilize algorithms in the era of big

data. However, it is important to note that even after de-identification, there remains a risk of re-identification for this data.

Recent research has highlighted the potential for computational methods to re-identify individuals within health data repositories maintained by both public and private organizations. For instance, one study demonstrated that an algorithm could re-identify approximately 69.8% of children and 85.6% of adults in a physical activity cohort, despite efforts to de-identify data through the removal of sensitive health information and data aggregation (Nal *et al.*, 2018). Adetayo and Andrea (2023: 1) acknowledge that there is a necessity for updated data legislation that upholds the value and right to privacy by addressing the significant obstacle of re-identification risk. Furthermore, given the rapid advancement of technology, it is imperative to employ a creative and multidisciplinary approach to fill the existing gaps in supervision and regulation.

When working with AI systems, one of the challenges involves ensuring that appropriate consent models are used to obtain authorization for the use of personal health data (Tobin and Jubran, 2022: 2). Adetayo and Andrea (2023: 1) elucidate that it is crucial to address the issue of patients' awareness regarding the potential uses of their data and the risks associated with re-identification as these factors are essential for obtaining meaningful permission. Additionally, as AI systems continue to evolve and perform more advanced processes, obtaining consent may become increasingly challenging. To obtain informed consent, it is necessary to provide a detailed explanation of the procedures enabled by AI. Additionally, it is crucial to address any concerns or doubts that individuals may have about this technology. Therefore, Adetayo and Andrea (2023: 1) suggest that further investigation is needed to identify the most effective approaches for sharing relevant information and providing appropriate warnings about these advanced technologies in the respective fields of use.

2.7.3 Ethics Of Algorithms And Trained Models

While AI is highly proficient in categorization tasks, it is necessary to acknowledge that AI products are computer programs created, developed and managed by individuals rather than actual individuals. Concepts like equality and fairness are not inherent to AI. It is the responsibility of humans to address these concerns as they must anticipate

the potential for AI models to behave improperly or be misused, and proactively take measures to prevent unethical consequences, preferably in advance.

To foster trust amongst patients and healthcare professionals in AI, Geis *et al.* (2019) advise that it is essential that the decision-making process is conducted with a high level of transparency. Furthermore, it is crucial to understand the rationale behind the results produced by an algorithm and the process it follows to arrive at a specific decision. For transparency, it is necessary for a model to be visible and comprehensible to external observers (Geis *et al.* 2019). Gilpin *et al.* (2018: 287), on the other hand, argue that excessive transparency may potentially reveal confidential information or make it more susceptible to malicious attacks. Furthermore, a broad interpretation of transparency could also compromise privacy by unveiling private data that was initially hidden in the underlying datasets. While there may be differing views regarding the extent of technical information necessary for transparency, it is important to communicate to the public how data will be used by users to develop autonomous or intelligent tools.

Explainability is the ability to effectively communicate the decision-making process of a model in a manner that is easily understood by individuals (Schoenberger 2019: 171). According to Floridi and Taddeo (2016: 374), it aims to provide insight into why a model made a particular choice and the conditions under which it performs successfully or fails. Furthermore, understanding the technical aspects of algorithm development and how results are presented to users are both integral parts of explainability. In other areas of AI, adversarial attacks are commonly acknowledged, and the Radiology AI community is gradually becoming aware of them as well (O Neil *et al.* 2016: 98). Whilst there may be potential solutions, the field of Radiology currently lacks sufficient protection against such attacks. Therefore, it is crucial to acknowledge and address this deficiency.

2.8. JOB SECURITY

Job security emerges as one of the most contested themes in the AI and radiography literature, with studies reporting divergent findings that reflect both genuine professional uncertainty and the influence of contextual factors. The concept of job insecurity is defined as a "sense of powerlessness to maintain desired continuity in a threatened job situation" (Nam, 2019: 155). Davy *et al.* (1997: 323) have historically

accompanied technological transitions, from the industrial revolution to the digital age. AI's emergence in the 1980s elicited both negative sentiments regarding job security and positive expectations of expanded opportunities (Chao and Kozlowski, 1986: 70), a duality that persists in contemporary radiography research.

Geographic variation significantly shapes perceptions of job security. In African contexts, where the historical precedent of darkroom assistants becoming obsolete during digitalisation remains within professional memory, job security concerns are particularly pronounced. Botwe *et al.*'s (2021) continent-wide study found that 61.3% of African Radiographers feared job displacement, while Chivandire *et al.* (2022: 263) documented similar anxieties in Zimbabwe. In contrast, studies from North America report more optimistic outlooks, with the ASRT (2020) emphasising that Radiographer staffing levels are expected to remain stable. This geographic divergence may reflect differences in labour protections, professional scope, and exposure to AI. Radiographers with direct AI experience may feel more secure than those speculating about future impacts.

Studies across the continent consistently report positive attitudes toward AI's potential benefits, including improved patient outcomes and enhanced practice efficiency (Botwe *et al.*, 2021; Chivandire *et al.*, 2022; Antwi *et al.*, 2021). However, this enthusiasm is accompanied by acute awareness of barriers that are particularly pronounced in low-resource settings. Unlike their counterparts in high-income countries, African Radiographers must contend with fundamental infrastructural limitations including unreliable electricity, inadequate internet connectivity, and outdated equipment that may render AI implementation impossible regardless of professional willingness (Waho, 2020: 48; Wuni *et al.*, 2021: 69). This tension between aspiration and reality creates a unique professional context that distinguishes the African experience from the global literature discussed in Section 2.5.

The literature also reveals a tension between those who view AI as a threat and those who see it as an opportunity. Davenport and Ronanki (2018: 108) argue that AI's primary objective is not job displacement but task automation, suggesting that fears of widespread unemployment may be overstated. This perspective is supported by research showing that knowledge-based professionals, including those in research and development, do not view AI as a threat because they believe it incapable of

performing tasks requiring creativity or emotions (Ili and Lichtenthaler, 2017: 21). However, executives in industries such as retail and machinery express greater concern about AI-related job losses, indicating that perceptions vary by sector.

For Radiographers specifically, the evidence is mixed. Akudjedu *et al.* (2023: 104) found that 40% of respondents believed AI enhances professional attractiveness, yet the same study documented concerns about skill erosion due to over-reliance on AI-driven technologies. This ambivalence is echoed in Abuzaid *et al.*'s (2021: 83) Middle Eastern study, in which Radiographers and Radiologists expressed significant concerns about job security. These findings suggest that job security anxieties coexist with recognition of AI's benefits, creating a complex psychological landscape for technology acceptance.

Theoretical frameworks help explain these divergent findings. Technological displacement theory (Frey and Osborne, 2017) predicts that occupations involving routine, predictable tasks are most vulnerable to automation, which would seemingly position aspects of radiography at risk. However, augmentation theory offers an alternative lens, suggesting that AI will complement rather than replace human workers by automating specific tasks while enhancing human decision-making. Radiographers who implicitly adopt a displacement lens may experience greater anxiety, while those who view AI as augmentative may anticipate role enhancement. This theoretical distinction has practical implications: how professional bodies and educators frame AI as a replacement or an augmentation may significantly influence Radiographers' perceptions of job security and, consequently, their willingness to embrace the technology.

2.9. JOB SATISFACTION AND EMPLOYABILITY

Job satisfaction is defined as a positive emotional state that arises from the evaluation of one's job or job experiences (Robbins and Coulter, 1997: 87). Additionally, the attitudes of employees towards their work are indicative of their level of satisfaction. When tasks undergo changes, and the possibility of layoff arises, employees may experience doubt about their self-worth and value. These circumstances can have a detrimental impact on their self-esteem and overall sense of fulfillment in life, according to Reinardy (2012: 54). Irrespective of the nature of the job, Axtell *et al.* (2002: 217) state that employees benefit from exposure to technology and the challenges

associated with implementing advanced systems. Moreover, this exposure enhances job satisfaction by enabling the evolution of job responsibilities. However, Axtell *et al.* (2002: 217) argue further that some employees may have reservations about such adjustments as they believe they limit career progression and reduce opportunities for job rotation and teamwork. Furthermore, research indicates that incorporating gamified job designs can enhance operational efficiency, motivation, and job satisfaction within industrial businesses.

Employability refers to possessing the knowledge, skills and abilities necessary to meet the evolving needs of employers and customers, thereby enabling individuals to achieve their potential and goals in the workplace (CBI, 1991: 1). In a technology-driven era where automation is replacing human labor in various fields, it is crucial to have a well-trained workforce that can keep up with technological advancements.

According to the World Economic Forum (2018), there will always be a significant demand for emotional and cognitive skills such as coordination, critical thinking, and complex problem-solving. The ability to exhibit "soft skills", including emotional support, is highly valued and goes beyond simply completing tasks. Soft skills, such as creativity, empathy, sound judgment, and the ability to motivate and inspire others, are qualities that are uniquely human and should be nurtured. As noted by Kolbjørnsrud *et al.* (2016), the ability to think creatively and embrace experimentation is essential to keeping pace with advancements in the field of AI. In addition, the development of strong interpersonal skills such as coaching, teamwork, social networking, and people development will be critical for achieving success in the next five years. Kolbjørnsrud *et al.* (2016) explain that this is because technology has not yet mastered the ability to effectively respond to human beings' emotional needs. Employees should demonstrate flexibility, empathy, a goal-oriented mindset, and motivation to effectively address the needs of others and maintain employability in the modern workplace (Suarda *et al.* 2017). Furthermore, they must be proficient in utilizing technology to achieve desired outcomes. According to Plastino and Purdy (2018: 16), staying up to date with technology and adjusting one's behavior accordingly is crucial for remaining marketable in the workplace. The findings of a study by Bhargava *et al.* (2020: 106) indicate that while respondents had confidence in their skills, enhancing and updating those skills would boost their confidence in their ability to find and maintain employment, leading to greater job stability and satisfaction.

2.10. SUMMARY OF THE CHAPTER

A thorough analysis of the relevant literature for the study is provided in this chapter. It offers an overview of Radiographers' perspectives on the application of artificial intelligence in their profession on a global scale. In addition to addressing key concerns such as job security and employability identified in the literature, the chapter also discusses the ethical considerations associated with AI in healthcare. The subsequent chapter outlines the theoretical framework guiding this study.

CHAPTER 3: THEORETICAL FRAMEWORK

3.1. INTRODUCTION

The relevant literature informing this study was examined in the previous chapter. This chapter focuses on the theoretical framework that underpins the research. As it is based on established theory within the field, the theoretical framework is a fundamental element of the study (Adom, Hussein, and Agyem, 2018: 438). Kivunja (2018: 44) emphasizes that the theoretical framework comprises theories advanced by experts in the field of study, a structure that supports or holds the theory of a research study. This research study is grounded in the Technology Acceptance Model (TAM) developed by Fred D. Davis in 1989.

3.2 TECHNOLOGY ACCEPTANCE MODEL

The acceptance or rejection of technology remains a topic of discussion, particularly given its rapid development in information and communication technologies (ICT) and its impact on individuals' personal and professional lives. Over the years, the scientific community has developed numerous theories and models to understand technology acceptance and effective utilization. One such model, Davis's Technology Acceptance Model (TAM), has gained significant traction as the primary framework for analyzing the factors influencing user acceptance of technology (Marangunić and Granić, 2015: 81).

Davis developed the Technology Acceptance Model (TAM) in 1985, which has now become one of the most influential extensions of Ajzen and Fishbein's Theory of Reasoned Action in academic literature (Lee *et al.*, 2003: 752). Davis (1989: 319) explains that TAM was developed in response to concerns about employees' failure to use available information technology tools effectively. According to Davis (1985), the first step in expanding the use of information systems is to enhance employees' acceptance of information technology. Davis derived the TAM by adapting the Theory of Reasoned Action, a comprehensive theory in social psychology that has proven effective in explaining various behaviors such as exercising and voting (Fishbein and Ajzen, 1977).

A comprehensive understanding of the evolution and emergence of TAM requires a brief overview of the theories and models that preceded and influenced it. The

increasing prevalence of technology in daily life has highlighted the significance of understanding the factors that impact individuals' acceptance or rejection of technology. Marangunić and Granić (2015: 81) acknowledge that psychological theories have laid the groundwork for explaining and predicting these choices. TAM is built on the theories of Reasoned Action (TRA) (Ajzen, 1980) and Planned Behavior (TPB) (Ajzen, 1985: 11). Ajzen developed theories that can effectively anticipate and understand behavior and attitudes by recognizing that people are rational beings who systematically use available information.

3.2.1 Theory of Reasoned Action

Social psychologists Martin Fishbein and Icek Ajzen developed the Theory of Reasoned Action (TRA) in the late 1960s. Fishbein first introduced it in a study conducted in 1967 and later expanded upon it in their 1975 book titled "Belief, Attitude, Intention and Behavior: An Introduction to Theory and Research" (Fishbein and Ajzen 1977). According to Hale (2002: 259), this theory provides a valuable framework for understanding and predicting human social behavior, particularly attitudes and intentions. The Theory of Reasoned Action (TRA) suggests that behavior is primarily predicted by behavioral intentions rather than attitudes. According to the theoretical framework proposed by Ajzen and Fishbein, one can determine an individual's actual behavior by considering their previous intentions and beliefs towards that behavior (Ajzen, 1980).

As the TRA became more widely used in social research, its limitations and drawbacks became apparent. Marangunić and Granić (2015: 83) argue that one of the main obstacles is individuals who perceive themselves as having limited control over their actions and mindset. Ajzen (1985) suggested that there is a spectrum of control between behaviors and attitudes, ranging from little control to significant control. To address these findings, Ajzen (1985) introduced a third element to the theory. This additional component is known as perceived behavioral control. The addition of this element has led to a newer theory, the Theory of Planned Behavior. The Theory of Planned Behavior (TPB), an extension of TRA developed by Ajzen and Fishbein, emerged as a consequence of the Theory of Reasoned Action, which served as the foundation for other concepts. According to Marangunić and Granić (2015: 83), the concept of perceived behavioral control was introduced by TPB to elucidate how external stimuli and limitations influence behavior.

3.2.2 Theory of Planned Behaviour

Icek Ajzen is the primary contributor to the development of the Theory of Planned Behavior (TPB), which builds upon the previous Theory of Reasoned Action (TRA). Published in 1985 with the title "From Intentions to Actions: A Theory of Planned Behavior", Ajzen's work established the TPB (Ajzen, 1985). According to Ajzen (1985), the TPB builds on the TRA by incorporating an additional element, perceived behavioral control. Moreover, this extension recognizes that individuals' behavior can be affected by external variables or constraints beyond their control, in addition to their attitudes and subjective norms. Marangunić and Granić (2015: 85) argue that the TPB model addresses the limitations of the TRA study conducted by Ajzen and Fishbein, including its inability to account for behaviors over which individuals have only partial control. The primary focus of TPB is the individual's intention to perform a specific behavior. Mathieson (1991: 73) states that the individual's intention is influenced by their attitude towards the activity, subjective norms regarding the behavior, and beliefs about their capability to successfully engage in the desired behavior.

According to Ajzen (1985), an attitude towards conduct refers to the evaluation, whether positive or negative, of engaging in a particular behavior. Additionally, beliefs shape attitudes, while norms are influenced by normative beliefs and the desire to conform. Moreover, perceptions about an individual's opportunities and resources to participate in a behavior influence their perceived behavioral control. Ajzen (1991: 179) notes that there is a direct relationship between behavioral achievement and perceived behavioral control in the Theory of Planned Behavior (TPB). When two individuals possess the same level of intention to act, the one with a higher confidence in their abilities is likely to achieve greater success compared to the one with lower confidence.

Marangunić and Granić (2015: 85) postulate that the theory focuses on predicting and understanding the motivating factors that influence behavior that are not under voluntary control, and determining the most effective strategies and environments for implementing behavior modification techniques. One of the main limitations of TPB, as noted by Marangunić and Granić (2015: 86), is that the theory is only applicable in situations where an individual's behavior is not within their conscious control. The theory does not account for unconscious motivations and assumes that individuals make logical and rational decisions based on available information. Additional

challenges include the lack of consideration for factors such as personality and demographic variables, as well as the assumption that perceived behavioral control accurately reflects actual behavioral control, which may not always be the case (Mathieson, 2001: 86).

Both the TRA (Theory of Reasoned Action) and the TPB (Theory of Planned Behavior) provided useful frameworks for predicting and understanding an individual's actual behavior, despite some limitations. However, challenges arose in relation to adapting these models to specific contexts, such as when users needed to give their approval for an information system. According to Marangunić and Granić (2015: 86), many research projects struggled to develop reliable measures for system acceptance or rejection. To address this issue, Fred Davis adapted the concepts of reasoned action and planned behavior to create the Technology Acceptance Model (TAM) theory. The objective of TAM was to establish a reliable model that could accurately predict how any given technology would be adopted and used in the real world.

Davis (1986) considered that utilizing a system is a distinct behavior, and thus models such as the Theory of Reasoned Action (TRA) and Theory of Planned Behavior (TPB) would be suitable for explaining and forecasting this behavior. However, Davis made two noteworthy adjustments to the TRA and TPB models. Firstly, he focused solely on an individual's attitude towards the activity instead of taking subjective norms into account when predicting actual behavior. Secondly, he found that a user's attitude towards utilizing a system could be predicted by two different beliefs: perceived usefulness and perceived ease of use (Davis, 1986).

3.2.3 Emergence of TAM

The original conceptual model for technological acceptance was proposed by Fred Davis in 1985 (Davis, 1986), whereby he suggested that the actual usage of a system can be understood by considering user motivation, which is influenced by an external stimulus consisting of the characteristics and capabilities of the system. Davis (1986) further developed his conceptual model to create the Technology Acceptance Model (TAM) to explain user motivation. The TAM identifies three factors that can explain why a user is motivated to adopt a technology, namely perceived ease of use, perceived usefulness, and attitude towards technology. Davis (1986) hypothesized that a user's attitude toward the system plays a significant role in determining whether they will use

it. The user's attitude was found to be influenced by two main factors: the perceived usefulness and the perceived ease of use. It was observed that the perceived ease of use had a direct impact on the perceived usefulness. Davis (1986) defined perceived usefulness as the degree to which a person believes that using the particular system would enhance his or her job performance, whereas perceived ease of use was defined as the degree to which a person believes that using the particular system would be free of effort. A more elaborate definition to differentiate between the two terms is defined by Holden and Karsh (2010: 159) as follows:

- I. **Perceived Ease of Use (PEOU):** This refers to the user's perception of the effort required to use a particular technology. If a user believes that a technology is easy to use, they are more likely to accept and adopt it.
- II. **Perceived Usefulness (PU):** This represents the user's perception of the degree to which technology enhances their job performance or facilitates achieving specific goals. If a user believes that a technology is useful, they are more likely to accept and use it.

The constructs of Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) influence an end-user's perceptions of a technology, which subsequently predicts their attitude towards the technology. This in turn predicts the likelihood of its acceptance, as stated by Sharp (2006: 3). To validate the Technology Acceptance Model (TAM), Davis (1989) conducted several studies using system utilization as the dependent variable and PEOU and PU as two independent variables. His findings revealed a significant correlation between self-reported current usage and self-predicted future consumption, as well as PU.

3.3 EXTENSION OF TAM TO TAM2

Davis and colleagues (1989: 319) conducted a study that found that attitude did not fully explain the relationship between perceived utility and reported ease of use. Based on these findings, they proposed a simplified version of the Technology Acceptance Model (TAM) that removed the attitude component (Davis, 1989: 319). In later developments of the TAM, a new variable called 'behavioral intention' was introduced, and its perceived utility directly affected it (Davis *et al.* 1989: 982). According to Davis and his colleagues, there are instances where a person may develop a strong intention to use a system without forming an attitude, as long as they perceive the system as

helpful. In these situations, the TAM may need to be adjusted. Marangunić and Granić (2015: 91) elaborate that the findings regarding the direct impact of perceived usefulness on actual system use can be clarified by removing the attitude construct and incorporating the behavioral intention construct. At the same time, any unexplained direct influence found from the system features on the attitude variable was addressed by eliminating the attitude variable. An important modification made to the original TAM was the inclusion of other variables, known as external variables, that could influence an individual's perception of the system. Venkatesh and Davis (1996: 451) explained that these external variables typically include factors such as the implementation process, user participation design, user training, and system features.

Davis enhanced his model in subsequent experimental phases, incorporating additional variables and modifying the initial correlations. Similarly, other studies have utilized TAM and proposed several additional factors. Consequently, TAM has become a prominent model for forecasting and describing system usage over time. TAM is referenced in the majority of studies exploring user acceptance of technology (Lee *et al.* 2003: 752). However, some academics argue that TAM may have attracted a disproportionate amount of superficial research, diverting attention from the actual challenge of technology acceptance (Chuttur, 2009: 1). Based on the consistent findings of Davis (1989: 319) and Davis *et al.* (1989: 982), it has been established that perceived usefulness plays a significant role in determining the intention to use. To further explore the factors influencing perceived usefulness, Venkatesh and Davis (2000: 186) introduced an extended model called TAM 2 (refer to Figure 2). The objective of TAM 2 was to identify and understand the various factors that impact perceived usefulness. These variables included:

- **subjective norm:** the influence of others on the user's decision to use or not to use the technology;
- **image:** the desire of the user to maintain a favorable standing amongst others;
- **job relevance:** the degree to which the technology was applicable;
- **output quality:** the extent to which the technology adequately performed the required tasks; and
- **result demonstrability:** the production of tangible results.

Furthermore, experience and voluntariness were included as moderating factors of the subjective norm.

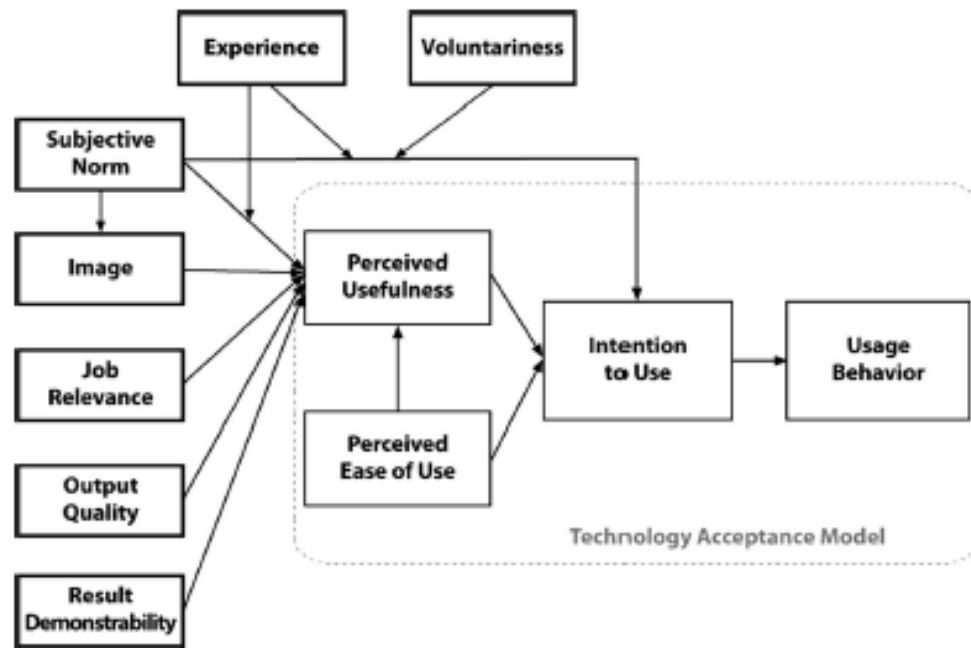


Figure 2: Technology acceptance model 2 (TAM 2) (Davis 1989: 319).

3.4 APPLICATION OF THE TECHNOLOGY ACCEPTANCE MODEL TO THE STUDY

The study aims to assess the knowledge and perspectives of South African Radiographers regarding the integration of AI in diagnostic imaging to provide unique recommendations to support the training of Radiographers in their readiness to provide quality patient care using AI. To do so, it is imperative to explore Radiographers' attitudes, beliefs, and intentions concerning the adoption and use of artificial intelligence (AI) in the field of medical imaging. The Technology Acceptance Model (TAM 2) provides a relevant theoretical framework for understanding the factors influencing the acceptance of AI technology amongst Radiographers in this context. The components of TAM 2 relate to the study in the following ways:

- I. **Perceived Ease of Use (PEOU):** Radiographers' attitudes towards the ease of integrating AI into their daily workflow are a critical factor in analyzing their perceptions. Radiographers' perceptions of how easy or difficult the integration of AI will be in their daily workflow and how it influences their acceptance. Questions about the user-friendliness of AI systems, ease of learning, and adaptability to current practices fall under this category. Factors such as user-

friendly interfaces, training programs, and technical support can impact perceived ease of use. PEOU is particularly relevant to Objective 4 (barriers to adoption) because perceived complexity and difficulty are significant obstacles to technology acceptance. Even if Radiographers recognize AI's usefulness (PU), they may resist adoption if they believe it will be too difficult to use (PEOU).

- II. **Perceived Usefulness (PU):** Radiographers' beliefs about the benefits of AI in improving their job performance, diagnostic accuracy, or overall efficiency in their day-to-day tasks will influence their perspectives towards AI. Assessing how Radiographers perceive AI's usefulness in enhancing patient care and the quality of medical imaging is crucial.
- III. **Subjective Norms:** this involves the influence of social factors on Radiographers' attitudes towards AI integration. Understanding the perceptions of colleagues, supervisors, or other relevant stakeholders and how their opinions shape the Radiographers' views on AI falls under subjective norms. Social factors play a role in the endorsement or discouragement of the use of AI in the radiography profession.
- IV. **External Variables:** in the context of the study, external variables may include organizational support, access to necessary resources, and the overall infrastructure for AI implementation in the healthcare institution. These external factors can significantly impact Radiographers' perspectives of AI. These factors can impact both perceived ease of use and perceived usefulness.

The Technology Acceptance Model 2 is highly suitable for the study as it can systematically analyze the factors influencing Radiographers' perspectives towards the integration of AI technology, providing insights that can aid in the development of high-quality strategies for the successful implementation and integration of AI in the field of medical imaging.

3.5 APPLICATION OF TAM2 TO STUDY DESIGN

The theoretical framework guided not only the development of research objectives but also the design of the questionnaire and the interpretation of findings. The questionnaire was structured to capture all TAM2 constructs:

- Section A (Demographics): Captures external variables that may moderate technology acceptance (sector, geographical location, years of experience, qualification)
- Section B (Awareness): Measures external variables related to knowledge and understanding of AI
- Section C (Benefits): Operationalises Perceived Usefulness (PU) through multiple items
- Section D1 (Attitudes): Captures attitude toward using technology, which mediates the relationship between beliefs and intention
- Section D2 (Perceptions): Includes items that measure PEOU (D2.3) and other beliefs about AI
- Section E (Barriers): Captures external variables and PEOU-related constraints that impede adoption

3.6 SUMMARY OF THE CHAPTER

The components of the theoretical framework that underpin the study are discussed in detail in this chapter. The relation of the theoretical framework to the study was discussed. The preceding chapter presents the research design and methods used to collect data that allow an accurate description of the perspectives of Radiographers on AI.

CHAPTER 4: RESEARCH METHODOLOGY AND DESIGN

4.1 INTRODUCTION

This chapter outlines the methodology of the research study, including the research type and design, research protocols, data collection tools, sampling procedures, ethical considerations, and the statistical analysis methods employed. The quantitative methodology, along with the positivist paradigm, was used for the study. The population under study was diagnostic Radiographers in the research setting of South Africa. The purposive sampling technique is discussed, as well as the inclusion and exclusion criteria for the study. In addition, the process of data collection, ethical considerations, and data analysis are described in greater detail.

Creswell (2009: 22) defines research designs as the strategies and processes for studies that encompass the decisions from general assumptions to complete techniques of data collection and analysis. Furthermore, when describing the research design, Maxine and Peter (2014: 74) state that the researcher specifies the how, when, and where of the way data was gathered and analyzed in the investigation. A quantitative cross-sectional research design was used for this study. Quantitative research sets out to gather data using measurements and analyzes this data for trends and relationships to answer research questions (Bloomfield and Fisher, 2019: 27). Polit and Beck (2012: 10) elaborate that quantitative research uses specific and narrow (closed-ended) questions, collects numerical data, and analyzes the data using statistics in an unbiased and objective manner. Spector (2019: 125) states that a cross-sectional design is ideal when assessing the attitudes and knowledge amongst healthcare personnel. Moreover, a cross-sectional study design allows for the simultaneous collection of data from a population.

A cross-sectional study is defined as observational research that analyses the data of variables collected at one given point in time across a sample population (Zheng, 2015: 66). This design was deemed appropriate for the study as the quantitative cross-sectional design allows for data to be collected from multiple respondents at a single point in time. Furthermore, this study design is cost-effective for the budget of the study. Data obtained from this design is quantifiable, and all the variables utilize scales that have been developed from the literature.

4.2 RESEARCH DESIGN

According to Creswell (2009: 22), research designs are the plans and procedures for investigations that include choices ranging from broad hypotheses to comprehensive methods of gathering and analyzing data. Furthermore, when describing the research design, Maxine and Peter (2014: 74) state that the researcher specifies the how, when, and where of the way data was gathered and analyzed in the investigation.

Quantitative research sets out to gather data using measurements and analyzes this data for trends and relationships to answer research questions (Bloomfield and Fisher 2019: 27). Polit and Beck (2012: 10) elaborate that quantitative research uses specific and narrow (closed-ended) questions, collects numerical data, and analyzes the data using statistics in an unbiased and objective manner. Spector (2019: 125) states that a cross-sectional design is ideal when assessing attitudes and knowledge amongst healthcare personnel. This design was deemed appropriate for the study as the quantitative cross-sectional design allows for data to be collected from multiple respondents at a single point in time. Furthermore, data obtained from this design is quantifiable, and all the variables utilize scales that have been developed from the literature.

4.3 RESEARCH PARADIGM

A research paradigm is understood as a basic set of beliefs that guide action (Guba and Lincoln 1994: 105). The term 'paradigm' was first coined by American philosopher Thomas Kuhn to refer to a philosophical way of thinking (Kuhn, 1962: 10). Rashid *et al.* (2019) acknowledge that a research paradigm acts as a frame of reference for one's study as it is used to draw conclusions and develop findings about the phenomenon. The research paradigm explains the type of research being conducted. It influences what should be studied, how it should be studied, and how the results of the study should be interpreted. Moreover, it has significant implications for every decision made in the research process (Kivunja and Kuyini, 2017:26). Although there are numerous paradigms that structure and organize modern healthcare research, they are all essentially philosophical and encompass the following common elements: epistemology, ontology, methodology and axiology (Guba and Lincoln, 1994: 110;

Kaushik and Walsh, 2019: 1). This study drew from the positivism paradigm. The positivist paradigm maintains the belief that reality is out there to be studied, captured, and understood. The positivist paradigm asserts that real events can be observed empirically and explained with logical analysis (Creswell and Plano-Clark, 2018: 88)

Elements of this paradigm are briefly explained below:

- **Ontology:** Ontology is the philosophical study of the nature of existence or reality (Kivunja *et al.* 2017: 26). Furthermore, ontology refers to the assumptions that scholars make to be certain that something is real or makes sense, or the very essence or nature of the social incidents they are examining (Creswell and Plano-Clark, 2018: 88). Crotty (1998: 18) states that ontology scrutinizes one's fundamental belief system as a researcher about the nature of being and existence. It aids one to conceptualize the nature and form of reality, and what one believes can be known about that reality. The reality of the current study is that there is an increasing emergence of AI in the medical imaging field, and there is scarce information regarding the perspectives of South African Radiographers on the integration of AI in medical imaging.
- **Epistemology:** In academic enquiry, epistemology is used to define how one gains knowledge of what one knows. It emphasises the nature of human knowledge and comprehension that researchers can obtain to be able to extend, widen, and develop the frontiers of knowledge in their fields (Kivunja *et al.*, 2017: 27; Creswell and Plano-Clark, 2018: 88). Epistemology is essential because it supports the researcher to instill the faith put into data. In this study, the perspectives of Radiographers were extracted from Radiographers across South Africa. Closed-ended questionnaires were used to bring about this reality.
- **Axiology:** refers to the role of ethical concerns that must be considered when planning a study. It includes outlining, assessing, and understanding concepts of wrong and right behaviours concerning the study. Furthermore, axiology ponders on what value to attribute to the different facets of an inquiry, the respondents, the data, and the listeners to whom one shall report the results of one's study (Kivunja *et al.*, 2017: 28). The study follows all ethical considerations as required by the institutional research ethics committee.

- **Methodology:** refers to the design of the research, methods, procedures, and techniques used in a study that is well pre-arranged to examine something. It is the process of conducting research (Creswell and Plano-Clark, 2018: 88). Overall, the methodology articulates the reason and course of the systematic processes followed in carrying out a study to advance knowledge about a research problem. It comprises the assumptions made, limitations faced, and how they were minimized or mitigated (Kivunja *et al.*, 2017: 28). A quantitative research design was used for the study as it has a platform that allows for a wider accessibility of respondents, which was ideal in this study as it ensured the accuracy and objectivity of the phenomenon being studied.

4.4 STUDY SETTING

A research setting is an environment in which research is carried out and where data is collected (Roberts and Priest, 2010: 48). The questionnaire was open to all Radiographers across the country of South Africa. According to International Citizens Insurance, there are over 600 hospitals in South Africa, with roughly 400 being public hospitals and 200 being private hospitals. South Africa's healthcare system is rated as the best healthcare system in Africa, ranking 50th out of 89 countries in the 2023 Global Healthcare Index (Business Insider Africa, 2023). South Africa has a two-tier healthcare system, a public and private healthcare system, due to major differences in funding, support, and resources. There is a major difference between the two systems. Public healthcare is used by 84% of the population. However, many public hospitals are underfunded, leading to long waiting times, dilapidated equipment, and overcrowding. On the other hand, private hospitals offer state-of-the-art equipment along with top specialist doctors. The use of medical imaging systems is prevalent in both public and private hospitals in South Africa.

Data was collected across all 9 provinces of South Africa from diagnostic Radiographers practicing in both public and private facilities. According to Kabongo, Nel and Pitcher (2015: 3), the full range of diagnostic imaging modalities is available in both the public and private sectors in just three of South Africa's eleven provinces: KwaZulu-Natal, Gauteng, and Western Cape Province. In general, Mpumalanga has the fewest provincial resources, while Gauteng has the most. At 34.8 units per million, general radiography is the most widely available modality. With the smallest difference in units per million between the provinces with the least and best resources (1:2.3) and between the public and private sectors (1:5.3), this modality is also the most geographically equitable.



Figure 3: Map of South Africa showing the different provinces (Omatayo *et al.*, 2020: 4)

4.5 STUDY POPULATION

A research population can be defined as the entirety of all subjects that comply with a set of criteria, covering the entire group of people that are of interest to the investigator and to whom the research results can be generalized (Maxine and Peter 2014: 18). The research population for this study comprised diagnostic Radiographers across South Africa. At the time of data collection, the number of Radiographers accredited by the South African Health Professions Council was not clearly indicated, as there was no information on such figures on the HPCSA online database. However, a study conducted by Mkhize *et al.* (2022: 271) discussing the temporal trends in the South African diagnostic radiology workforce from 2002- 2019 demonstrated that 7242 Radiographers were registered with HPCSA in 2019. Moreover, the average annual increase is 277 Radiographers each year. Therefore, for the year 2024, it can be estimated that roughly 8627 Radiographers were registered with the Health Professions Council of South Africa.

	2002 (n (%))	2019 (n (%))	Total increase (n)	Average annual increase (n)	Total % increase	Average annual % increase
All imaging personnel						
Radiographers	2,540 (82)	7,242 (83)	4,702	277	185	10
Radiologists	506 (16)	1,007 (12)	501	29	99	6
Sonographers	49 (2)	504 (6)	455	27	906	50
Total	3,095	8,753	5,658	333	183	10

Figure 4: South African diagnostic imaging personnel by calendar year, demographics, and provincial profile (Mkhize *et al.*, 2022: 271)

4.5.1 Inclusion Criteria

- Diagnostic Radiographers registered with the Health Professions Council (HPCSA) as an independent practitioner or completing community service.
- Respondents should be willing and able to provide informed consent to participate in the study.

- Respondents should be 18 years or older.

4.5.2 Exclusion Criteria

- Sonographers, Radiation Therapists, and Nuclear medicine Radiographers registered with the HPCSA as independent practitioners, or completing community service.
- Student Radiographers.
- Any person who failed/refused to sign the consent form.

4.6 SAMPLING TECHNIQUE AND SAMPLE SIZE

Sampling refers to the decisions that the researcher makes in relation to where and from whom data is gathered to answer the research questions (Ravitch and Carl 2016: 157). Polit and Beck (2012: 10) elaborate that sampling is the act, process, or technique of selecting a representative part of a population, called a sample, to determine the parameters or characteristics of the whole population. The goal of sampling is to determine a population's characteristics by directly observing only a portion of the population (Polit and Beck, 2012: 10). This step of the study involved selecting respondents from the population, where the researcher intended to use established methods of selection to obtain a group of respondents who were characteristic of the population. This was important to translate the results of the study into general observations or assumptions about the population (Mouton, 1996:123).

Non-probability purposive sampling was employed since it is the best method for a content analysis investigation. Vehovar, Toepoer, and Steinmetz (2016: 329) highlight that this sampling method entails the researcher using his/her expertise to select a sample that is most useful to the purpose of the research. The minimum number of respondents was calculated based on a formula for cross-sectional studies to determine the sample size with a 90% confidence level and a 5% margin of error. Using the estimated population of 8,627 diagnostic Radiographers registered with HPCSA in 2024 (extrapolated from Mkhize *et al.*, 2022: 271), the sample size was calculated as follows:

$$n = \frac{Z^2 \times p \times (1-p)}{e^2}$$

Where:

- $Z = 1.645$ (Z-score for 90% confidence level)
- $p = 0.5$ (maximum variability assumed)
- $e = 0.05$ (margin of error of 5%)

This calculation yielded a minimum required sample size of **$n = 264$** respondents.

While purposive sampling is more commonly associated with qualitative research, it is widely accepted in quantitative survey research when the following conditions are met (Etikan, Musa and Alkassim, 2016: 2):

- The research aims to obtain in-depth information from a specific, well-defined population
- Probability sampling is not feasible due to the absence of a complete sampling frame
- The sample characteristics are clearly defined through inclusion and exclusion criteria
- The sample size is calculated to ensure statistical power
- The findings are interpreted with appropriate acknowledgment of limitations regarding generalisability

In this study, purposive sampling was appropriate because the target population, diagnostic Radiographers registered with the HPCSA, is a defined professional group; however, a complete, accessible sampling frame with current contact details does not exist. Under these circumstances, purposive sampling combined with a calculated sample size and transparent reporting of recruitment methods provides a rigorous approach to data collection (Sharma, 2017: 751).

4.7 DATA COLLECTION PROCESS AND METHODS

Data collection is the process of gathering evidence from significant sources that could answer the research problem and assess the outcomes (Terrell, 2016: 45). Before commencing the study, the researcher obtained ethics clearance from the DUT's Institutional Research Committee (IREC 184/23). The questionnaire (Appendix C) was developed on Google Forms, and in order to access Radiographers in all provinces,

the survey link was shared across social media platforms, namely Facebook, LinkedIn, and WhatsApp. Data was collected over 3 months, with regular reminders being sent out to maximize the response rate. The primary recruitment strategy involved sharing the survey link across professional social media platforms frequented by Radiographers, namely:

- **Facebook:** Posts were made in several closed professional groups for South African Radiographers, including "South African Radiographers," "Radiography in SA," and provincial radiography groups. Group administrators were contacted for permission prior to posting.
- **LinkedIn:** The survey link was shared on the researcher's professional profile and in relevant healthcare professional groups.
- **WhatsApp:** The survey link was circulated through professional WhatsApp groups for Radiographers in various provinces and healthcare facilities.

While the initial recruitment plan relied on social media, the researcher recognised the limitations of this approach, including algorithm visibility, potential for low response rates, and difficulty reaching Radiographers in certain regions. Therefore, additional recruitment measures were employed to ensure the target sample size was achieved. The researcher shared the survey link with former classmates, colleagues, and professional contacts, requesting them to complete the survey and forward it to other eligible Radiographers within their professional networks. This approach combines purposive sampling with elements of snowball sampling, as respondents were asked to identify and refer other potential respondents who met the inclusion criteria (Naderifar, Goli, and Ghaljaie, 2017: 2).

Despite these efforts, by the initial closing date, 223 responses had been received. To achieve the calculated sample size of 264, the data collection period was extended by an additional 4 weeks. During this extension, the researcher continued to circulate the survey link with renewed reminders, emphasising the importance of achieving the target sample for statistical validity.

A letter of information (Appendix A), together with informed consent (Appendix B) for the study, was shared with the respondents before the questionnaire (Appendix C) was answered. These were directly displayed as soon as a potential participant clicked on

the link. A self-administered questionnaire containing closed-ended questions was used to collect statistical data from Radiographers who met the requirements for participation. The questionnaire was chosen as a suitable method for data collection as it is cost-effective and allows for large-scale data collection. The questionnaire was composed of five parts: the first part gathered the socio-demographic information of the respondents, including gender, age, qualification, clinical experience, HPCSA registration status, sector of employment, and geographical setting. The Radiographers' awareness, attitudes, benefits, and barriers to adopting AI in radiography were captured using multiple responses, and an attitudinal five-point Likert scale was used to measure respondents' responses to cover the rationale for the study. To ensure the reliability of the survey instrument, the questions must be clear and concise, and to do so, the researcher avoided asking the following types of questions (Pearlman and Stacks, 2001: 233-250):

- **Double-barreled questions:** these are questions that are essentially asking about two different attributes whilst requiring a single answer.
- **Confusing questions:** these are questions that are poorly worded or written in an illogical manner.
- **Negative questions:** these are questions in which a 'no' represents a positive response, whilst a 'yes' indicates a negative answer.
- **Ambiguous questions:** these are questions in which the topic a question asks about is too broad to provide a specific answer that is useful to the question.
- **Assumptive questions:** these are questions that assume that the respondent has prior knowledge of the topic being asked.

The questionnaire consisted of the following sections:

- Demographics.
- Awareness of AI Concepts and applications in radiography.
- Benefits of AI in radiography.
- Attitudes and perceptions of Radiographers towards AI.
- Barriers to adopting AI in radiography.

4.8 RELIABILITY AND VALIDITY

Reliability: Reliability, as defined by Polit and Beck (2010: 452), refers to the accuracy and consistency of the data collected in a study, which is directly related to the methods used to assess the research variables. Creswell and Creswell (2018: 154) further describe reliability as the internal consistency and reproducibility of the data collection instrument. For the items on the measurement scale to establish appropriate correlations, they must effectively measure the same underlying construct. According to Litwin (1995), there are three ways to assess reliability, namely:

- Test-retest reliability
- Alternate-form reliability and
- Internal consistency reliability.

To ensure reliability for the study, alternate form reliability was used to confirm reliability by using differently worded questions to measure the same attribute. Questions were reworded in more than one way, not changing the meaning of the question. This ensured reliability as one aspect was measured in two separate questions, thereby confirming the reliability of the respondents' answers (Litwin 1995).

Validity: Validity, as described by De Vos *et al.* (2011: 96), refers to the degree to which an instrument accurately assesses the intended questions and their precision. Hesse-Biber (2010: 86) elaborates that a data instrument evaluates the accuracy of scientific findings, while validity pertains to the thoroughness and soundness of the reasoning underpinning the study's conclusions. According to Litwin (1995), there are four ways to assess validity, namely:

- Face validity
- Content validity
- Criterion validity
- Construct validity

The questionnaire was validated by the criteria of face, construct, and content validity. Polit and Beck (2010: 379) state that when a measurement instrument accurately assesses the attribute it is designed to measure, it is considered to have face validity.

This was achieved by submitting the questionnaire to a statistician for evaluation. Verifying the relationship between variables is referred to as construct validity (Teddlie and Tashakkori, 2009: 339). The primary objective of this form of validity is to evaluate whether the data collection instrument accurately measures the intended constructs. Understanding and analyzing the construct or variable is an essential initial step in the process of construct validation (Teddlie and Tashakkori, 2009: 339). The data collection tool was developed with the research objectives in mind and structured to capture the necessary information. To ensure that the application of construct validity was appropriate for statistical analysis, the researcher sought advice from a qualified statistician. Content validity refers to whether items measure the content they are intended to measure (Polit and Beck, 2010: 336). To ensure content validity, the questions in the questionnaire aligned with the concepts that had been developed through the wide range of literature outlined in Chapter 2.

4.9 PILOT STUDY

A pilot study, sometimes named a feasibility study, is a test run done in preparation for the comprehensive inquiry. It can also be used in the specific pre-testing of research instruments, including questionnaires (Polit and Beck, 2014: 196; Terrell, 2016: 41). Thabane *et al.* (2010:25) point out that pilot studies are an important part of the process of determining the viability of a study that is intended to be conducted on a larger scale. In the current study, a pilot study was carried out to test the questionnaire in order to refine it, as well as test its usability and any problematic or ambiguous areas or questions that needed to be addressed. Piloting the questionnaire also gave the researcher an indication of the average time taken to complete the questionnaire.

The questionnaire was administered to 9 diagnostic Radiographers across the 9 provinces of South Africa who met the inclusion criteria for piloting purposes only. These respondents were not included in the full-scale study. The researcher scouted for 9 Radiographers to participate in the study by creating an invitation poster (Appendix C) with the researcher's contact details, which was circulated on radiography social media platforms. The first 9 Radiographers who met the inclusion criteria were sent a link to the Google Forms survey via WhatsApp. A letter of information (Appendix A), together with informed consent (Appendix B) for the pilot study, was displayed on the online survey, which respondents had to confirm reading and give consent to participate in the study before proceeding to answer the

questionnaire (Appendix C). Five Radiographers employed in private hospitals and 4 Radiographers employed in public hospitals were selected. This diverse group of 9 Radiographers allowed the researcher to capture various perspectives. Ethical approval was obtained from relevant research ethics committees and institutional reviews to ensure that the study met ethical standards. Data was collected as the 9 respondents completed the survey; the feasibility of the data collection method was analysed; and the researcher identified any issues and challenges that arose. After collecting data from the respondents, the results were analysed, and the researcher gathered feedback from the respondents about their experiences. This aided in refining the survey questionnaire to ensure clarity and relevance. The respondents were thanked for their contribution as they completed the questionnaire. Based on the insights gained from the pilot study, necessary adjustments were made to improve the effectiveness of the study. Once the pilot study was complete, recruitment for the full study commenced.

4.10 DATA ANALYSIS

Kudyba (2014: 230) defines data analysis as the process of gathering unprocessed data and processing it into meaningful information that can be utilised to facilitate informed decision-making. Following the completion of the questionnaire, the results were compiled and analysed using SPSS version 27 (Statistical Package for the Social Sciences). Both descriptive and inferential statistical methods were employed, with test selection guided by the research objectives, the nature of the collected data, and the assumptions underlying each approach.

4.10.1 Descriptive Statistics

Descriptive statistics were used to summarise the sample's demographic characteristics and to provide an overview of responses across all sections. Frequencies, percentages, means, and standard deviations were calculated for categorical and continuous variables as appropriate (Vetter, 2017: 1797). Data are presented using tables and graphs to facilitate interpretation.

4.10.2 Inferential Statistics: Test Selection and Justification

The selection of inferential statistical tests was guided by three considerations: (1) the research objective being addressed, (2) the level of measurement of the variables (nominal, ordinal, or continuous), and (3) the assumptions underlying each test. The following tests were employed:

4.10.2.1 Binomial Test

A binomial test was used to address Objective 1 (assessing basic understanding of AI). This test is appropriate when data are dichotomous (two categories) and the researcher wishes to determine whether the observed proportion differs significantly from a hypothesised value (Springer, 2008: 47). In this study, awareness questions in Section B required Yes/No responses, and the binomial test was used to determine whether the proportion of Radiographers aware of each AI concept differed significantly from chance (50%). A $p\text{-value} < 0.05$ was considered statistically significant (Dahiru, 2008: 21).

4.10.2.2 Chi-Square Goodness-of-Fit Test

The chi-square goodness-of-fit test was also applied to Objective 1 data, specifically for questions where respondents rated their awareness on a four-point scale (from "never heard of it" to "know a lot about it"). This test determines whether the observed frequency distribution across response categories differs significantly from what would be expected by chance (Albrecht, 1980: 149; Hollander, 1992: 458). A significant result indicates that certain response options were selected more frequently than others, providing insight into the distribution of awareness levels.

4.10.2.3 One-Sample t-test

The one-sample t-test was used to address Objectives 2, 3, and 4, where respondents responded to Likert-scale questions (1 = strongly disagree to 5 = strongly agree). This test determines whether the mean score for a sample differs significantly from a specified test value (Ross et al., 2017: 9). Following the approach used in similar radiography AI studies (e.g., Botwe et al., 2021), the neutral midpoint of 3.5 was selected as the test value. A mean significantly greater than 3.5 indicates agreement with a statement, while a mean significantly less than 3.5 indicates disagreement. This test was appropriate because Likert-scale data, when aggregated across multiple

items, can be treated as approximately continuous, and the one-sample t-test is robust to moderate violations of normality with sample sizes above 30 (Pallant, 2016: 215).

4.10.2.4 Independent Samples t-test

The independent-samples t-test was used to compare mean scores between two independent groups, addressing all four objectives for which group comparisons were relevant. This test is appropriate when comparing a continuous dependent variable across two categories of an independent variable (Pallant, 2016: 265). In this study, it was used to compare:

- Awareness levels between private and government sector Radiographers (Objective 1)
- Attitudes and perceptions between urban and rural Radiographers (Objective 2)
- Benefit perceptions between sectors and locations (Objective 3)
- Barrier perceptions between sectors and locations (Objective 4)

The test assumes approximately normal distribution of the dependent variable in each group and homogeneity of variances, which was assessed using Levene's test. Where the homogeneity assumption was violated, adjusted t-values (Welch's test) were reported.

4.10.2.5 Analysis of Variance (ANOVA)

One-way ANOVA was used to compare mean scores across more than two groups, primarily for Objective 1 (awareness across qualification levels) and Objective 4 (barrier perceptions across qualification levels). ANOVA extends the t-test to situations with three or more groups, testing whether there are significant differences among group means while controlling the Type I error rate (Pallant, 2016: 275). When the overall ANOVA was significant, post-hoc tests (Tukey's HSD or Games-Howell) were conducted to identify which specific groups differed. Tukey's HSD was used when homogeneity of variances was assumed; Games-Howell was used when variances were unequal.

4.10.2.6 Welch Test

The Welch test was employed as an alternative to ANOVA when the assumption of homogeneity of variances was violated, particularly for awareness of AI applications across qualification levels (see Section 5.5.2.2). The Welch test is more robust than standard ANOVA when group variances are unequal and is recommended when sample sizes differ across groups (Field, 2018: 526).

4.10.2.7 Spearman's Rank Correlation Coefficient

Spearman's correlation was used to examine relationships between continuous variables, specifically between years of experience and awareness levels (Objective 1), age and benefit perceptions (Objective 3), and age/experience and barrier perceptions (Objective 4). Spearman's rho was chosen over Pearson's correlation because:

- Some variables (e.g., awareness scores) were not normally distributed
- Spearman assesses monotonic relationships without assuming linearity
- Spearman is appropriate for ordinal data or continuous data that violate normality assumptions (Ali, 2022: 3249; Pallant, 2016: 146)

Correlation coefficients (rho) were interpreted as follows: small = 0.10-0.29, medium = 0.30-0.49, large = 0.50-1.00 (Cohen, 1988).

4.10.2.8 Factor Analysis

Factor analysis with promax rotation was conducted to identify underlying structures within the questionnaire items and to create composite variables for further analysis. This technique was appropriate because:

- It reduces data dimensionality by grouping related items into factors
- It confirms whether items theorised to measure the same construct (e.g., benefits of AI) actually load together empirically
- It enables creation of reliable composite variables for subsequent statistical testing (Taber, 2018: 1273)

The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy (> 0.7) and Bartlett's test of sphericity ($p < 0.05$) were used to confirm that the data were suitable for factor analysis.

4.10.2.9 Cronbach's Alpha

Cronbach's alpha was calculated for each factor identified through factor analysis to assess internal consistency reliability. Alpha values above 0.7 were considered acceptable, indicating that items within each factor consistently measured the same underlying construct (Taber, 2018: 1273). Composite variables were created by averaging item scores within each factor, providing more reliable measures than individual items.

4.11 ETHICAL CONSIDERATIONS

According to the Declaration of Helsinki, a researcher must consider the legal, ethical, and regulatory values and principles for research involving human subjects in their states, as well as applicable international values and principles (Kong and West, 2013: 3). The fundamental ethical principle is not to cause any type of harm to research respondents. Letters of permission were requested from the DUT IREC to ensure that ethics were maintained (Appendix D). Gatekeepers' permission was not required for this study, as the study did not require access to the database of any institution or organization. Furthermore, a similar study conducted across Africa did not require gatekeepers' permission, as neither do not require access to the database of any healthcare institutions or the radiography representative council. The letter of information (Appendix A), which provided a concise synopsis of the study and highlighted the advantages and disadvantages of the study, was given to the prospective respondents. Consent (Appendix B) was requested before respondents could commence completing the online survey.

During this research process, the researcher upheld the four main principles of ethics, namely justice, beneficence, non-maleficence, and autonomy (Jahn, 2011: 225). Regarding non-maleficence, the questionnaire was designed to ensure that respondents were not exposed to any private information or data that could be used against them, thereby minimizing potential harm. The responses were collected anonymously to protect confidentiality. Respondents were provided with a confidential and non-intimidating environment that encouraged honest and voluntary participation.

In addition, the study fully respected respondents' autonomy. Respondents retained the right to withdraw from the study at any point without penalty, and all did so voluntarily. As participation was voluntary and there were no direct incentives, the study adhered to principles of fairness and equity. Respondents could request the deletion of their data or be excused from the study without facing any negative consequences. All collected data was handled with strict confidentiality, with access limited to the researcher via a password-protected computer. The data will be securely maintained for five years before being permanently deleted by the researcher.

4.12 SUMMARY OF THE CHAPTER

The selection of research design and methodology was defined and justified in this chapter. A quantitative cross-sectional study upholding the positivist paradigm was conducted. Non-probability sampling was used to select diagnostic Radiographers across South Africa. The inclusion and exclusion criteria were discussed, as were the methods used to process the data. The findings generated from the data analysis are addressed in the following chapter.

CHAPTER 5: PRESENTATION OF THE FINDINGS

5.1 INTRODUCTION

In exploring the integration of artificial intelligence (AI) into medical imaging, understanding the perspectives of South African Radiographers is essential for assessing both the practical implications and the broader acceptance of this technological advancement. This chapter presents the results obtained from the comprehensive study that was conducted across South Africa to analyse the perspectives of South African Radiographers on the integration of artificial intelligence into medical imaging. The study was driven by 4 main objectives, namely i) to assess the basic understanding of Radiographers regarding AI; ii) to assess the willingness of Radiographers to accept the integration of AI in medical imaging; iii) to evaluate the impact of AI on the job performance of Radiographers; and iv) to assess the barriers to adopting AI in radiography to provide unique recommendations that support the training of Radiographers.

An online questionnaire was the primary tool used to collect data across South Africa and proved to be an efficient tool, as many respondents across the country could be easily accessed. The data obtained from the online questionnaire were analysed using SPSS version 27. This chapter includes both descriptive and inferential statistics, which are presented simultaneously based on the study objectives. The aim of descriptive statistics is to summarise categorical and numerical data in an informative way, both numerically and graphically (Green *et al.*, 2023: 723). In inferential statistics, data is analysed from a sample to make inferences (deductions) and generalize the results to the population (Salas-Parra *et al.*, 2023: 195). Descriptive statistics were presented in the form of tables and graphs, and inferential statistics were interpreted using p-values. Goodman (1993: 137) elaborates that p-values can range between 0 and 1.

5.2 STATISTICAL TESTS

To determine whether the data collected was significant, statistical tests were conducted. Parab and Bhalerao (2010: 187) state that these are mathematical tools

for analysing quantitative data generated in a research study. Various statistical tests may be applied to examine the collected data. A set of statistical techniques was adopted to extract information and provide accurate findings for this study. Descriptive tests, binomial tests, one-sample *t*-tests, independent sample *t*-tests, Chi-square goodness-of-fit tests, and Spearman's correlation tests were conducted. These tests were prepared to determine the perspectives of Radiographers in South Africa on the integration of AI into their profession.

5.2.1 Descriptive Statistics

Descriptive statistics included the mean, mode, and standard deviations, where required. According to Vetter (2017: 1797), it also concentrates on the central tendency or dispersion of the data. Furthermore, descriptive statistics consist of univariate or bivariate data. In this study, univariate data refers to data dependent on a single factor, such as testing for knowledge, whereas bivariate data tries to link two variables by finding an association or correlation between them, such as the age and the knowledge of Radiographers. An example of this would be: Did the age of Radiographers affect their level of knowledge of AI?. The information collected from the data is presented in the form of tables and graphs for the different sections of the questionnaire, thus making it convenient to note the distribution of frequencies.

5.2.2 Binomial Test

A binomial test is a parametric hypothesis test that applies when the population can be divided into two classes: each observation of this population will belong to one or the other of these two categories (Springer, 2008: 47). This test helped determine the differences in knowledge and awareness of AI concepts and applications in radiography, and each response to each question produced a p-value. A p-value is defined by Dahiru (2008: 21) as the probability under the assumption of no effect or no difference of obtaining a result equal to or more extreme than what was observed. The P stands for probability and measures how likely it is that any observed difference between groups is due to chance. Goodman (1993: 137) elaborates that being a probability, P can take any value between 0 and 1. Values close to 0 indicate that the observed difference is unlikely to be due to chance, whereas a p-value close to 1 suggests no difference between the groups other than due to chance. Thus, Dahiru (2008: 21) acknowledges that it is common in medical journals to see adjectives such

as “highly significant” or “very significant” after quoting the p-value, depending on how close to zero the value is. A p-value between 0.00 and 0.05 in SPSS is considered significant.

5.2.3 One-Sample *t*-test

The One-sample *t*-test determines whether a mean score is significantly different from a scalar value (Ross *et al.*, 2017: 9). The one-sample *t*-test may be used to determine if the population average or mean gives a different value to what the assumed value may be (Ross *et al.*, 2017: 9). This type of test was selected to determine if the average agreement/disagreement scores differ significantly from the neutral or central score. In this study, the central score was 3.5 for the sections on benefits, applications of AI, attitudes, perceptions, and barriers to adoption. Values close to 3.5 would indicate little significance, whereas significant disagreement would be seen by values < 3.5, and significant agreement may be seen by values >3.5.

5.2.4 Independent Sample *t*-test

The Independent sample *t*-test compares two independent groups of cases. The test is used to determine if there is a significant difference in the mean scores of the two different groups (Pallant, 2016: 265). The test was used in this study to analyse differences between the benefits of AI and work geographical location. Results demonstrating a p-value < 0.05 were considered significant.

5.2.5 Chi-Square goodness-of-fit test

The Chi-square goodness-of-fit test is a statistical hypothesis test used to determine whether a variable is likely to come from a specified distribution or not (Albercht, 1980: 149). It is often used to evaluate whether sample data is representative of the full population. Hollander (1992: 458) elaborates that the analysis is done to determine if any of the response options is selected significantly more than the others. This test was used for the section on the awareness of AI concepts and applications in radiography.

5.2.6 Spearman's Correlation Test

Spearman's rank correlation coefficient is a method of testing the strength and direction (positive or negative) of the correlation (relationship or connection) between two variables (Ali, 2022: 3249). It measures how ordinal variables or rank orders are

related. This was used to correlate age and experience with different variables from the questionnaire, such as barriers to implementation and awareness of applications and concepts.

5.3 DATA COLLECTION TOOL

The data collection tool was in the form of an online questionnaire uploaded on Google Forms. The questionnaire was self-developed and was verified using a pilot study. The questionnaire consisted of 5 sections as follows:

- Section A: Demographics.
- Section B: Awareness of AI concepts and applications in radiography.
- Section C: Benefits of AI applications in radiography.
- Section D: Attitudes and perceptions of Radiographers towards AI.
- Section E: Barriers to adopting AI in radiography.

5.4 DEMOGRAPHICS

Demographics refer to socio-economic and physical information about a population group (Connelly, 2013: 269). This includes age, ethnicity, sex, income, etc. (Connelly, 2013: 269). Researchers cannot surmise that there are differences or no differences between groups of respondents if demographics are not included in the study (Hammer, 2020: 261). This segment details the socio-demographic characteristics of the respondents. A total of 265 (n=265) Radiographers across South Africa participated in the study. The personal and work-related demographics of the respondents are described below.

5.4.1 Personal Demographics

The sample consisted of 162 (61.1%) females and 103 (38.9%) males. The majority of the respondents were between the ages of 35-44 years old (n=80), with 43% (n=114) having a Bachelor of technology degree in radiography and 36.2% (n=96) of the respondents having a bachelor's degree in radiography. Figure 5 demonstrates a summary of the personal demographics of the respondents.

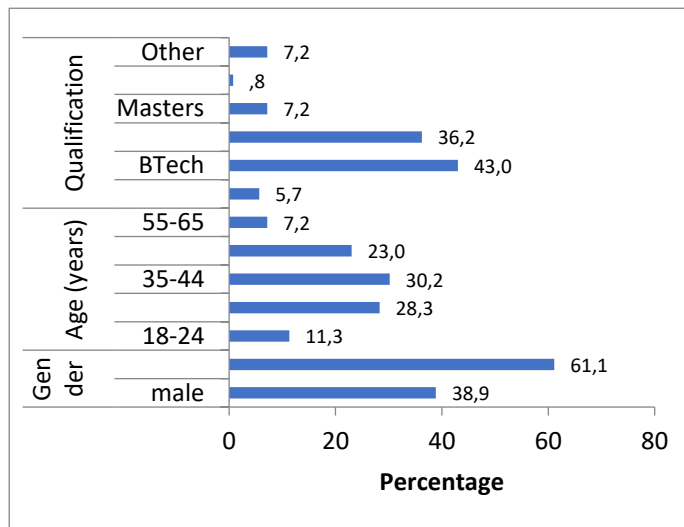


Figure 5: Summary of the gender, age, and qualifications of the respondents

5.4.2 Work-Related Demographics

The majority of respondents were Radiographers working in the KwaZulu-Natal province (n=56). Approximately 71.7% of the respondents had work experience of more than 5 years, with 35.1% of the respondents falling between the years of work experience range of greater than 10 years but less than 20 years. Approximately 69.8% of the respondents were Radiographers working in the government health sector, and 30.2% of the respondents were working in the private health sector. Eighty percent (80%) of the Radiographers worked in urban areas, and 20% worked in rural areas. Figure 6 demonstrates a summary of the province, years of work experience, sector, and location of the respondents. When asked which imaging modalities the respondents use in their workplaces, 87% of the respondents used general X-rays, and 61.5% used computed tomography. Figure 7 demonstrates a summary of the imaging modalities used by the respondents in their workplace.

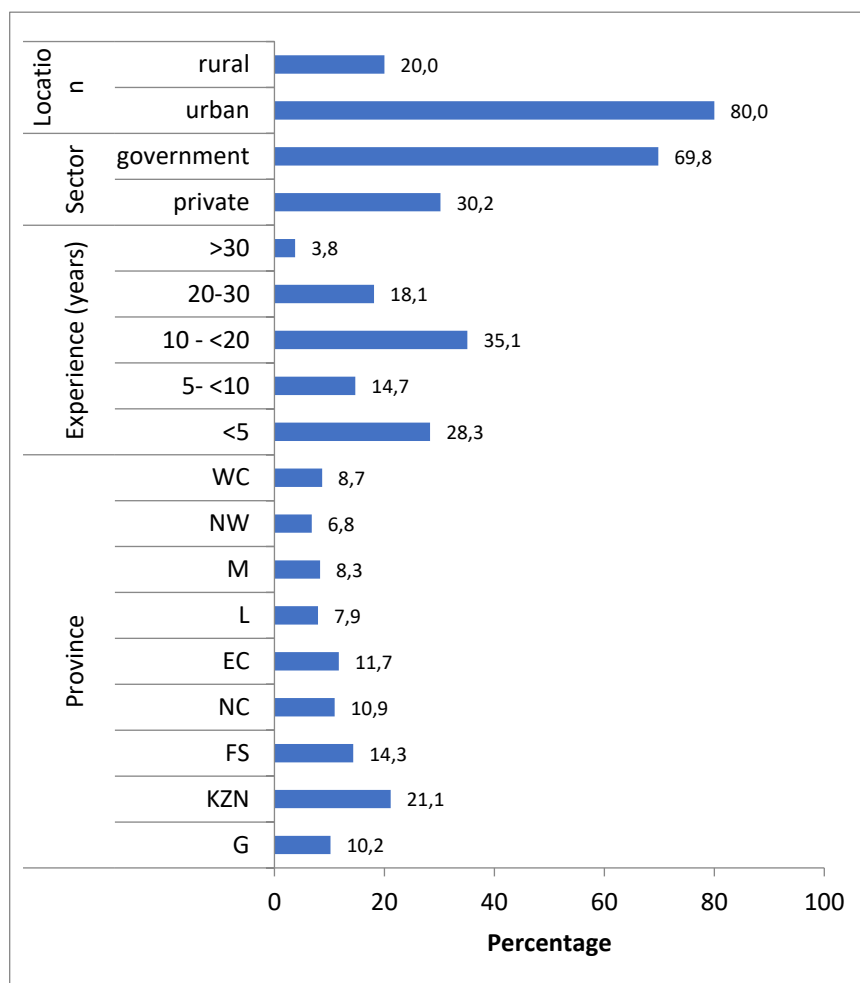


Figure 6: Summary of the province, years of work experience, sector, and working location of the respondents

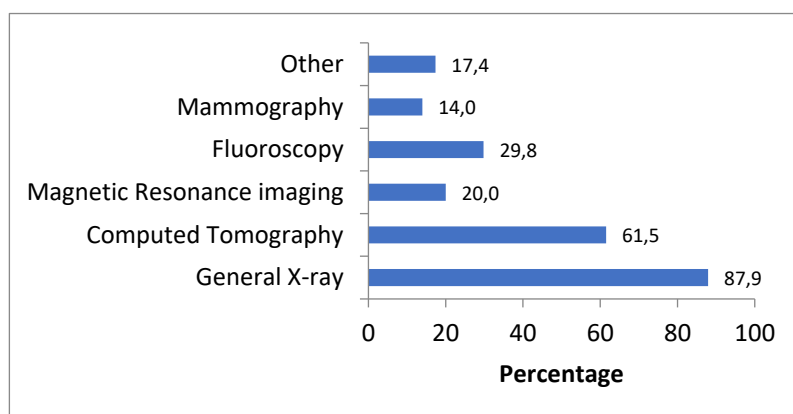


Figure 7: Summary of the imaging modalities used by the respondents in their workplace

5.5 AWARENESS OF AI CONCEPTS AND APPLICATIONS IN RADIOGRAPHY

Section B of the questionnaire asked respondents if they were aware of certain AI concepts and applications in radiography. Awareness and understanding of AI concepts and system applications are essential for Radiographers as they are the key players in medical imaging and are increasingly encountering artificial intelligence (AI) in their field. Noting the level of awareness of AI concepts and applications amongst Radiographers is pivotal in identifying gaps in knowledge and understanding. This is an important aspect to consider, especially when fulfilling the fourth objective of the study, which is to develop unique recommendations that support the training of Radiographers by ensuring that they are knowledgeable and their concerns are addressed.

The data collected is demonstrated using a table (Table 2) consisting of nine questions (items), frequency (number of responses), the Chi-square (X^2), and the p-value. The p-value is defined as a measurement to confirm a theory against the data collected (Beers 2022: 1). It measures the probability of attaining the perceived results. The lower the p-value, the greater the statistical significance. A p-value of 0.05 or lower is generally considered statistically significant (Beers, 2022:1). Furthermore, Beers (2022: 1) elaborates that this simply means that with a confidence level of 95%, the specific result applies to the entire population, not just the sample. A high p-value signifies that the result is only applicable to the sample and not the entire population. In SPSS, a p-value given as .000 is very small and is reported as $P < .001$; a p-value of .017, for example, is reported as $p = .017$.

Table 2: Summary of the response frequency of the awareness of AI concepts and applications

Item	Responses as Frequency (%)				χ^2	p-value
	I have never heard of it	I have heard of it but know nothing about it	I have heard of it and know a bit about it	I have heard of it and know a lot about it		
Artificial intelligence (concept)	1 (0.4)	15 (5.7)	131 (49.4)	118 (44.5)	207.619	<.001
Machine learning (concept)	40 (15.1)	50 (18.9)	126 (47.5)	49 (18.5)	72.766	<.001
Computer aided detection (concept)	4 (1.5)	28 (10.6)	134 (50.6)	99 (37.4)	166.049	<.001
Deep Learning (concept)	60 (22.6)	54 (20.4)	103 (38.9)	48 (18.1)	28.268	<.001
Automatic exposure control (concept)	2 (0.8)	9 (3.4)	130 (49.1)	124 (46.8)	223.468	<.001
Radiology smart assistance (application)	66 (24.9)	84 (31.7)	85 (32.1)	30 (11.3)	29.898	<.001
CT ceiling mounted 3D camera (application)	82 (30.9)	100 (31.7)	61 (23.0)	22 (8.3)	50.909	<.001
Deep Resolve TM (Application)	140 (52.8)	78 (29.4)	40 (15.1)	7 (2.6)	147.574	<.001
True Fidelity TM (application)	167 (63.0)	56 (21.1)	38 (14.3)	4 (1.5)	225.340	<.001

When respondents were asked to determine their level of awareness of AI concepts and applications related to radiography, various responses were received. Significant responses were received from this section. A significant 93.9% knew about the concept of AI, with 44.5% having heard of AI and knowing a lot about it. A significant 66% of the respondents knew of the concept of machine learning, with 47.5% having heard of the term but having minimal knowledge of the concept. Similarly, the same was noted for the concepts of computer-aided detection, deep learning, and automatic exposure control. The majority of the respondents, 88%, knew about the concept of computer-aided detection. Moreover, 50.6% of those respondents knew of the concept of computer-aided detection, but they did not have much knowledge about the concept. With deep learning, a significant 57% knew of the concept, but 38.9% had minimal knowledge about the concept. A predominant percentage, 95.9%, of the respondents

knew of the concept of automatic exposure control, but 49.1% had minimal knowledge of the concept.

Respondents were asked about their level of awareness regarding four AI applications in various imaging modalities of radiography. Radiology smart assistance is used in general radiography; CT ceiling-mounted 3D camera and True Fidelity TM are used in computed tomography; and Deep Resolve TM is used in magnetic resonance imaging, respectively. The majority of respondents had little to no knowledge about these applications. A significant 56.6% had little to no knowledge of the Radiology Smart assistance application, with 31.7% of the respondents having heard of the application but not knowing anything about it. Similarly, the majority of the respondents, 62.6%, had little to no knowledge about the CT ceiling-mounted 3D camera application, with 31.7% of the respondents having heard of the application but not having any other knowledge about it. A large percentage of the respondents had little to no knowledge of the Deep Resolve and True Fidelity applications. Moreover, 82.2% of the respondents hardly had any knowledge of the Deep Resolve application, with 52.8% not knowing the application at all, as they had never heard of it. Similarly, 84.1% of the respondents hardly had any knowledge of the True Fidelity application, with 63% having never heard of the application before. These results are illustrated in Figure 8.

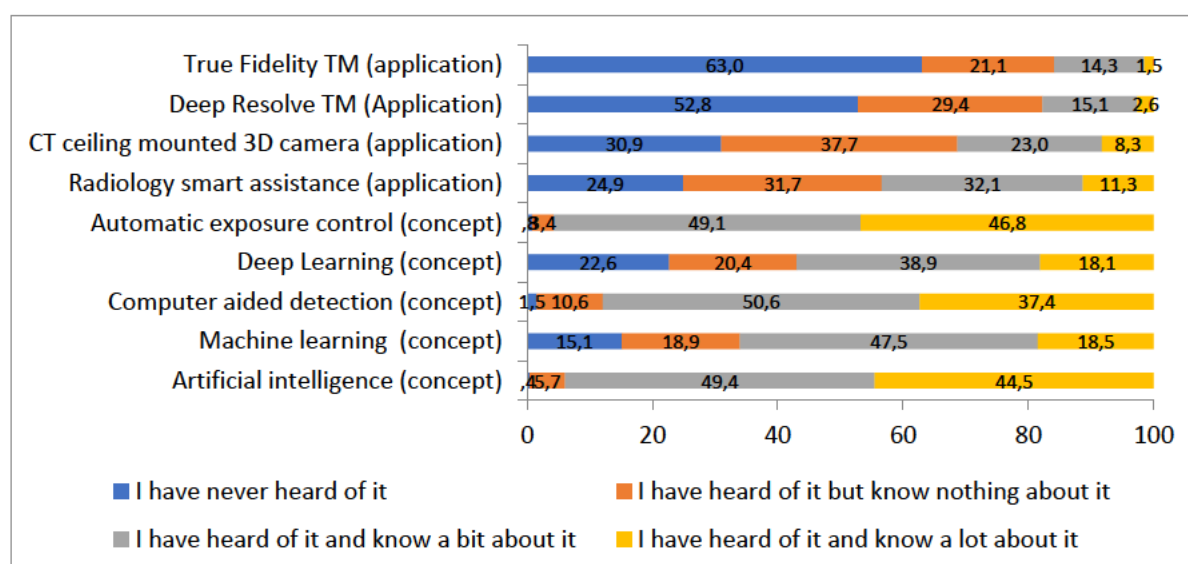


Figure 8: Awareness levels (%) of AI concepts and applications amongst Radiographers in South Africa

5.5.1 Factor Analysis for Awareness of Applications and Concepts

Factor analysis with promax rotation was applied to these 9 items. Two factors were extracted, which account for 55.29% of the variance in the data. A Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO) of .856 and a significant Bartlett's test indicate that the data was adequate for successful and reliable extraction. Rotation converged in 3 iterations. The details of the extracted factors are demonstrated below in Table 3.

Table 3: Composition of factors and reliability-awareness (composite variables)

Factor	Construct	Variance extracted	Cronbach's alpha
1	Awareness of applications (AWARE_APP)	45.14	.791
2	Awareness of concepts (AWARE_CON)	10.15	.866

The composite variables created by averaging the agreement scores for every item in each variable are credible, and the Cronbach's alpha values (.791 and .866) obtained show that there is strong internal consistency among the items on each component.

5.5.2 Analysis of the composite variables of the awareness of AI concepts and applications in radiography

These composite variables were analysed using a binomial statistical test in which data is tested to determine if a significant proportion falls above or below 2.5 (the midpoint of the scale). The results from this test highlighted that a significant 81% are neither aware nor have any knowledge about radiography AI applications, $p < .001$; and a significant 81% have at least some knowledge of radiography AI concepts, $p < .001$.

5.5.2.1 Bivariate analysis

Bivariate analysis was done to test if there were any differences in the composite variables across the demographics. There were no significant differences in any variables across genders or provinces. However, there was a positive correlation

between the years of experience and level of awareness of AI applications, $\rho=.165$, $p=.007$. This means that more years of working experience are associated with more awareness of Radiography AI applications.

5.5.2.2 ANOVA and Welch test

For comparison of the level of awareness with qualification, two different tests were conducted based on the conditions met. An Analysis of Variance (ANOVA) Model test and the Welch test were conducted. The ANOVA test is used for several independent samples, and it compares more than two groups of cases simultaneously to establish if there are relationships between the groups (Pallant, 2016: 275). The ANOVA test was used to compare the awareness of AI concepts with levels of qualifications. From the ANOVA test, there was a significant difference in awareness and knowledge of AI concepts across qualifications, $F(5, 259) = 8.397$, $p<.001$. Tukey's post hoc analysis shows that those with a master's qualification have significantly more awareness and knowledge than those with a diploma ($p<.001$), BTech ($p=.004$), or degree ($p=.003$). Those with an 'other' qualification have significantly more awareness and knowledge than those with a diploma ($p<.001$), BTech ($p=.002$), or degree ($p=.002$); while those with a PhD have significantly more awareness and knowledge than those with a diploma ($p=.018$).

A Welch test was also conducted, and results from the test highlighted that there is a significant difference in the awareness and knowledge of AI applications in radiography [Welch (5; 10.451) = 12.835, $p<.001$]. Results from a Games-Howell post hoc test indicate that knowledge and awareness are significantly higher for those with a BTech than those with a diploma ($p=.014$); for those with a masters than those with a diploma ($p=.001$) or a degree ($p=.011$); and for those with an 'other' qualification than for those with a diploma ($p<.001$), BTech ($p=.014$) or degree ($p=.001$).

5.5.2.3 Independent sample t-test

Independent sample t-tests demonstrated that there is significantly more awareness and knowledge of AI concepts and applications amongst those employed in the private sector than in the government sector, $t(263) = 4.850$, $p<.001$. Additionally, there is also a higher level of awareness and knowledge of AI concepts and applications amongst

those who work in urban areas as compared to those who work in rural areas, $t(263) = 4.367, p < .001$.

5.6 BENEFITS OF AI APPLICATIONS IN RADIOGRAPHY

For this section, respondents were asked fifteen questions (items) to determine their level of agreement or disagreement regarding the benefits of AI. To ascertain if there was a substantial agreement or disagreement with the assertions, a one-sample t-test was used for these questions. This test determines if the average agreement score deviates considerably from the central value of 3.5. If there is a significant difference, $p < .05$, a mean score of >3.5 indicates significant agreement, and a mean score of <3.5 indicates significant disagreement. Nothing further is mentioned regarding the results if it is not significant ($p > .05$), which indicates that there is neither considerable agreement nor significant disagreement. The results from the one-sample t-test are summarised in Figure 9.

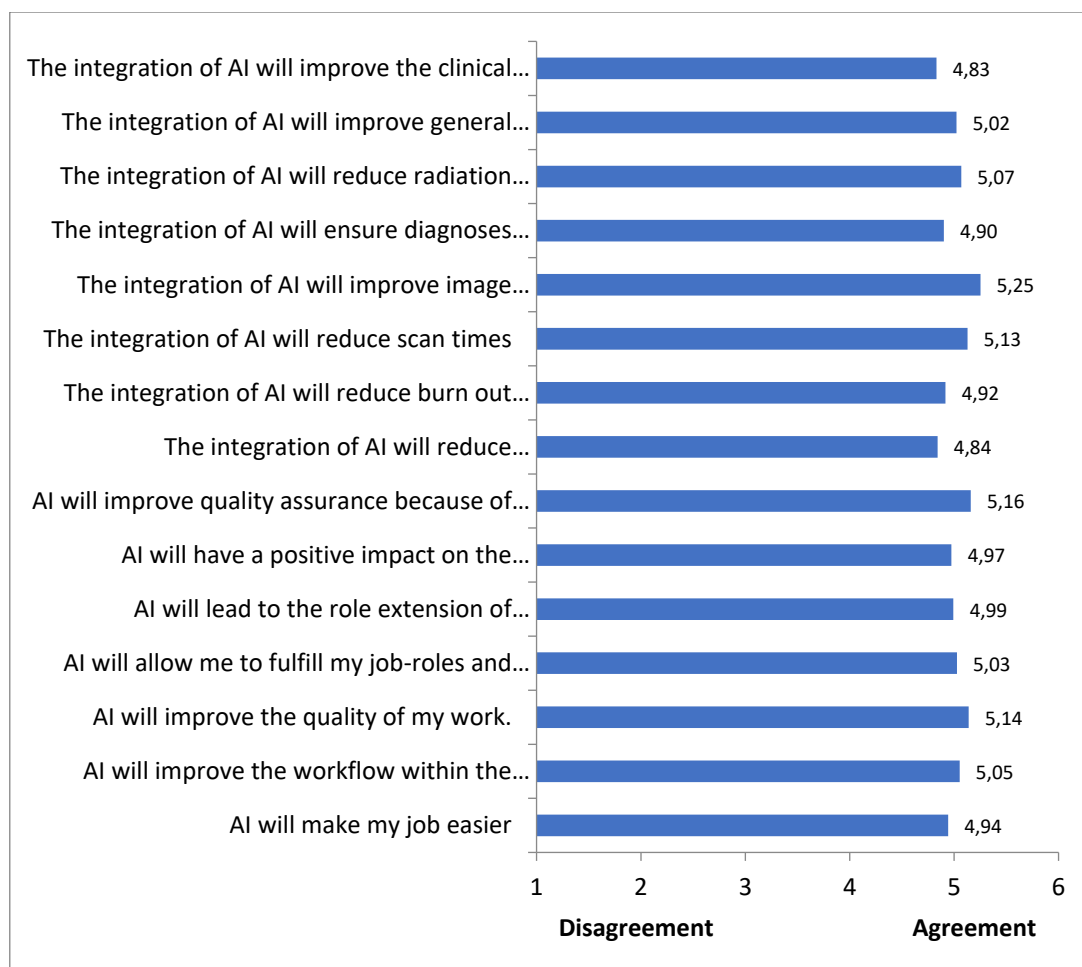


Figure 9: demonstrates the level of agreement and disagreement regarding the benefits of AI to radiography

There is significant agreement that AI will have the following benefits for radiography

- i. AI will make the job easier.
- ii. AI will improve the workflow of the Radiology department.
- iii. AI will improve the quality of Radiographers' work.
- iv. AI will allow Radiographers to fulfil their job roles and responsibilities.
- v. AI will lead to the role extension of Radiographers.
- vi. AI will have a positive impact on Radiography.
- vii. AI will improve the quality assurance because of its efficiency in diagnosis
- viii. The integration of AI will reduce occupational stress amongst Radiographers in SA.
- ix. The integration of AI will reduce burnout amongst Radiographers in SA.
- x. The integration of AI will reduce scan times.
- xi. The integration of AI will improve image post-processing.
- xii. The integration of AI will ensure diagnoses are accurate.
- xiii. The integration of AI will reduce radiation doses to patients.
- xiv. The integration of AI will improve general radiography practice.
- xv. The integration of AI will improve the clinical care of patients.

While all the benefits show significant agreement, the ability to improve image post-processing, improve quality assurance, improve quality of work, reduce scan times, and reduce radiation dose were perceived as the five most beneficial aspects of AI.

5.6.1 Factor Analysis for the Benefits of Integration

For these 15 items, factor analysis using Promax rotation was used. 67.68% of the variation in the data can be explained by the single component that was extracted. The data was sufficient for a successful and dependable extraction, as shown by a significant Bartlett's test and a Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO) of .943. Table 4 illustrates the specifics of the characteristics that were extracted.

Table 4: Composition of factors and reliability of the benefits of AI integration (composite variables)

Factor	Construct	Items included	Variance extracted	Cronbach's alpha
1	Benefits of integration (BEN_INT)	C1.1 – C1.15	67.68	.968

The composite variable created by averaging the agreement scores for each item in the variable is credible, and the Cronbach's alpha values obtained (67.68) show that there is strong internal consistency among the items on the factor. Respondents were also asked to indicate their level of agreement or disagreement regarding the clinical areas in which AI would be beneficial. There is a significant agreement that AI is beneficial to all the clinical areas of Radiography, namely general X-rays, computed tomography, magnetic resonance imaging, theatre Radiography, interventional Radiography, mammography, picture archiving systems, and radiology information systems. While all the benefits show significant agreement, application to magnetic resonance imaging, computed tomography, interventional radiography, mammography, and fluoroscopy were ranked as the top five clinical areas in which AI would be beneficial. A summary of these results is depicted in Figure 10.

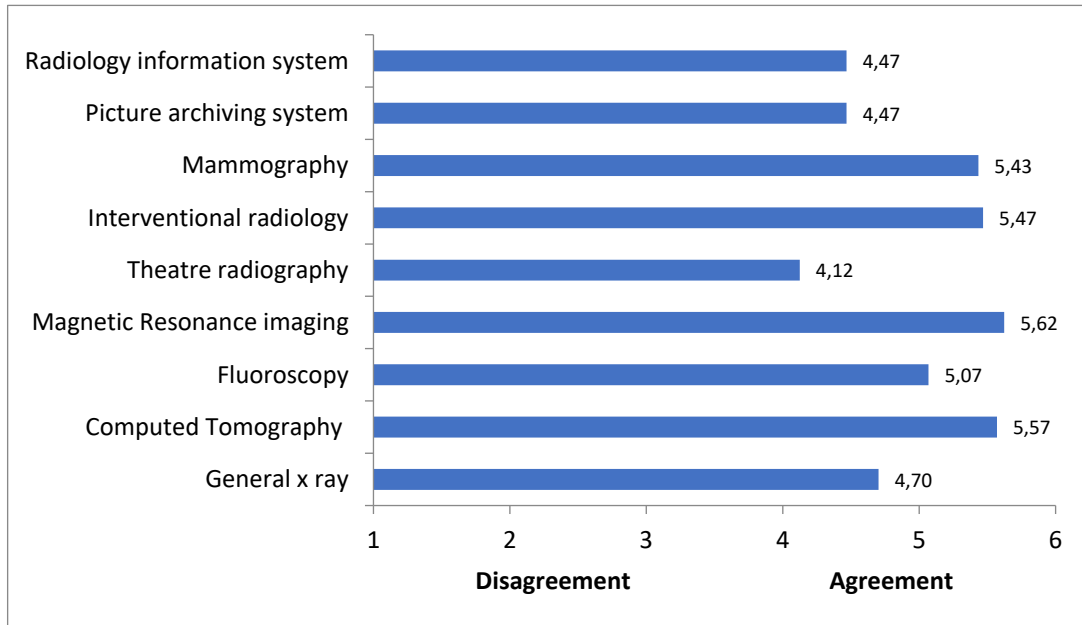


Figure 10: summarises the benefits of integrating AI applications into Radiography clinical areas

5.6.2 Factor Analysis for Benefits of Application

Factor analysis with Promax rotation was applied to these 9 items. Two factors were extracted, which account for 66.14% of the variance in the data. A Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO) of .842 and a significant Bartlett's test indicate that the data was adequate for successful and reliable extraction. Rotation converged in 3 iterations. Details of the extracted factors are shown in Table 5.

Table 5: Composition of factors and reliability – Benefits: Application (composite variables)

Factor	Construct	Items included	Variance extracted	Cronbach's alpha
1	Benefits of application 1 (BEN_APP_1)	CT, fluoroscopy, MRI, interventional Radiography, mammography	52.89	.867
2	Benefits of application 2 (BEN_APP_2)	General x-rays, theatre Radiography, PACS, RIS	13.25	.886

The composite variables created by averaging the agreement scores for every item in each variable are credible, and the Cronbach's alpha values (.867 and .886) obtained indicate that there is strong internal consistency among the items on each component.

5.6.3 Analysis of the composite variables of the benefits of AI applications

The composite variables from the constructs of benefits of integration (BEN_INT), benefits of application 1 (BEN_APP_1), and benefits of application 2 (BEN_APP_2) were analysed using a one-sample t-test. A one-sample t-test is used to determine if the population average or mean gives a different value to what the assumed value (Ross *et al.*, 2017: 9). From this test, there was significant agreement that AI is beneficial when integrated into radiography and when applied to the different clinical areas of radiography, $p < .001$.

5.6.3.1 Bivariate analysis

Bivariate analysis was done to determine whether there are any differences in the three composite variables across some of the demographics. There were no significant differences in any of the three composite variables across gender or province. However, there was a negative correlation between the age of respondents and BEN_APP_2, $\rho = -.159$, $p = .009$. The higher the age, the greater the disagreement that AI is beneficial to general radiography, theatre radiography, picture archiving systems, and radiology information systems.

5.6.3.2 ANOVA test

For the analysis of the benefits of AI with qualification, an Analysis of Variance (ANOVA) Model test was conducted. The ANOVA test highlighted that there is a significant difference in the perceived benefits of AI (BEN_APP_2) across qualifications, $p < .001$. Tukey's post hoc analysis shows that those with a master's degree significantly agree that AI is beneficial in general radiography, theatre radiography, picture archiving systems, and radiology information systems, compared with those with a diploma ($p = .029$).

5.6.3.3 Independent sample t-test

Independent sample t-tests were conducted, and they highlighted that there is significantly more agreement amongst Radiographers practicing in the private sector

and urban areas than Radiographers in the government sector and rural areas that AI is beneficial to the clinical areas of radiography.

5.7 ATTITUDES AND PERCEPTIONS OF RADIOGRAPHERS TOWARDS AI

For this section, respondents were asked to determine their level of agreement or disagreement with statements that would be evaluated to ascertain their attitudes and perceptions toward the integration of AI into the medical imaging field. These questions were categorized into 2 separate sections. Section D1 was based on attitudes, and Section D2 focused on perceptions.

5.7.1 Attitude

Seven questions (items) were asked to determine the attitudes of Radiographers toward the integration of AI into their field. To ascertain if there was a substantial agreement or disagreement with the assertions, a one-sample t-test was used. This test determines if the average agreement score deviates considerably from the central value of 3.5. A mean score of >3.5 denotes considerable agreement, a mean score of <3.5 denotes strong disagreement, and a significant difference $p < .05$. Nothing further is mentioned regarding the results if it is not significant ($p > .05$), which indicates that there is neither considerable agreement nor significant disagreement. The results from the one-sample t-test are summarised in Figure 11.

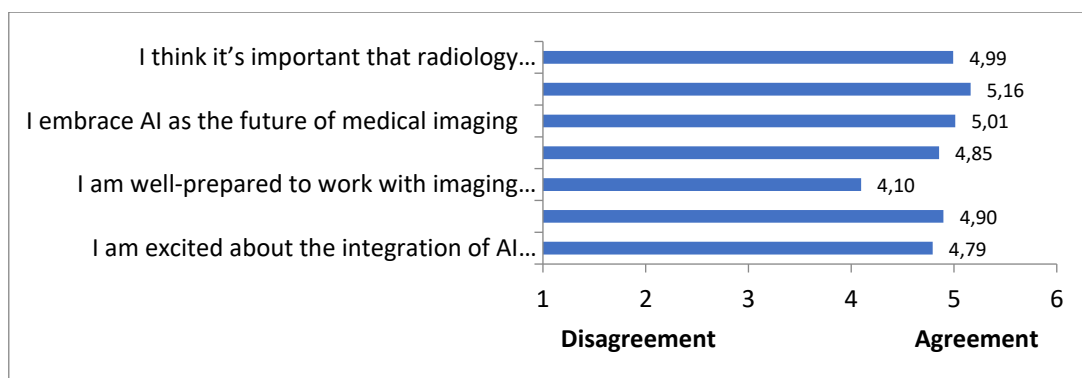


Figure 11: Summarises the attitudes of Radiographers in SA

From the results, it is clear that SA Radiographers have positive attitudes toward the integration of AI into medical imaging, as there is significant agreement amongst Radiographers that:

- They are excited about the integration of AI within diagnostic radiography.

- They are willing to accept the changes that come with AI.
- They are well prepared to work with imaging that has AI.
- They believe that equipment that has AI is easy to use.
- They embrace AI as the future of medical imaging.
- They are willing to undergo further education or training to be able to embrace these emerging AI trends in medical imaging.
- They think it is important that radiology departments start planning for the integration of AI into medical imaging.

5.7.1.1 Factor Analysis for Attitude

Seven items were subjected to factor analysis using promax rotation. 78.05% of the variation in the data can be explained by the single component that was extracted. The data was sufficient for a successful and dependable extraction, as shown by a significant Bartlett's test and a Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO) of .935. The extracted factor and the item loadings are summarised in 6.

Table 6: Composition of factors and reliability - Attitudes

Factor	Construct	Items included	Variance extracted	Cronbach's alpha
1	Attitude (ATT)	D1.1 – D1.7	78.05	.958

The composite variable created by averaging the agreement scores for each item in the variable is credible, and the Cronbach's alpha values (.958) show that there is strong internal consistency among the items on the factor.

5.7.2 Perceptions

Nine questions (items) were asked to determine the perceptions of Radiographers toward the integration of AI into their field. To ascertain if there was a substantial agreement or disagreement with the assertions, a one-sample t-test was used. This test determines if the average agreement score deviates considerably from the central value of 3.5. A mean score of >3.5 denotes considerable agreement, a mean score of <3.5 denotes strong disagreement, and a significant difference $p < .05$. Nothing further is mentioned regarding the results if it is not significant ($p > .05$), which indicates that

there is neither considerable agreement nor significant disagreement. The results from the one-sample t-test are summarised in Figure 12.

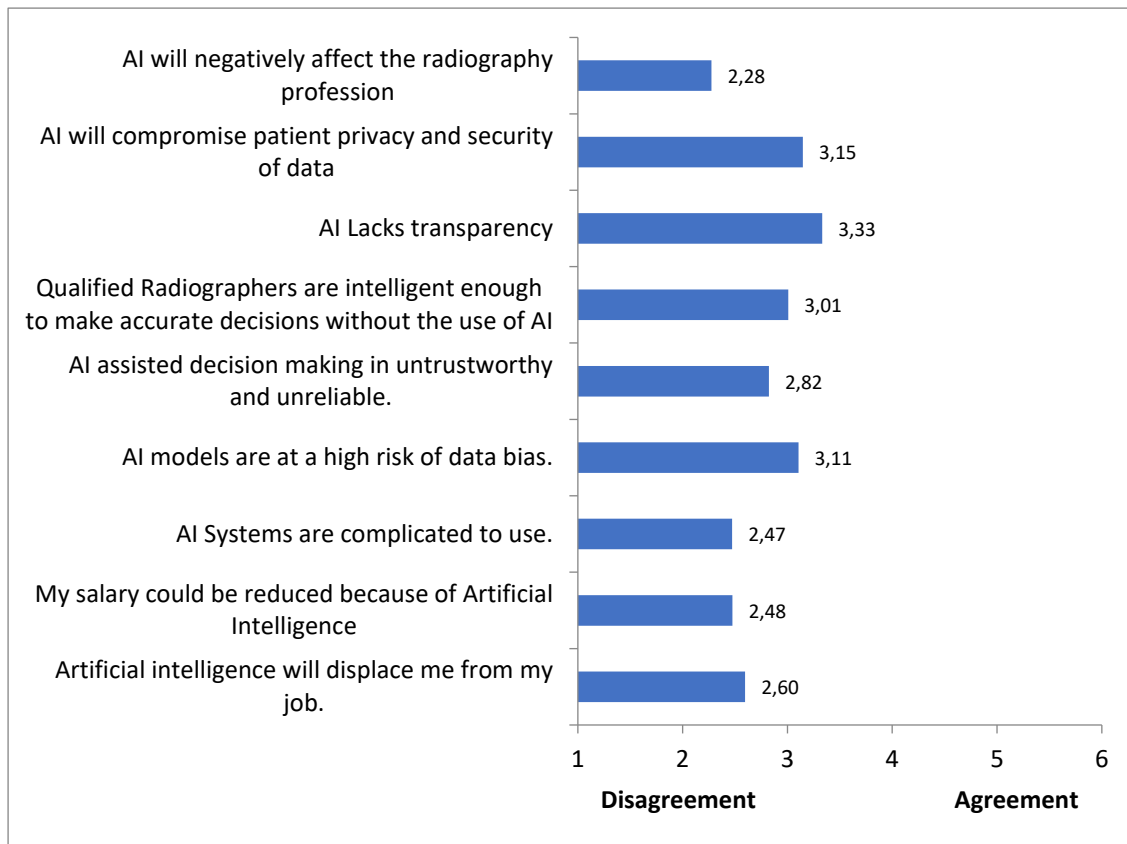


Figure 12: Summary of the perceptions of Radiographers towards the integration of AI in the medical imaging field in SA.

From the results, Radiographers have positive perceptions towards the integration of AI into medical imaging as there is significant disagreement that:

- AI will displace Radiographers from their jobs.
- Salaries could be reduced because of AI.
- AI systems are complicated to use.
- AI models are at high risk of data bias.
- AI-assisted decision-making is untrustworthy and unreliable.
- Qualified Radiographers are intelligent enough to make accurate decisions without the use of AI.
- AI will compromise patient privacy and the security of data.
- AI will negatively affect the radiography profession.

While the majority of the statements showed significant disagreement, statement D7, which states the AI lacks transparency, was not significant. It had neither significant agreement nor significant disagreement.

5.7.2.1 Factor analysis for perceptions

These nine items were subjected to factor analysis using promax rotation. 75.58% of the variation in the data can be explained by the single component that was retrieved. The data was sufficient for a successful and dependable extraction, as shown by a significant Bartlett's test and a Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO) of .950. Table 7 summarizes the item loadings and the extracted factor.

Table 7: Composition of factors and reliability – perceptions (composite variables)

Factor	Construct	Items included	Variance extracted	Cronbach's alpha
1	Perceptions (PER)	D2.1 – D2.9	75.58	.964

The composite variable created by averaging the agreement scores for each item in the variable is credible, and the Cronbach's alpha values (.964) show that there is strong internal consistency among the items on the factor.

5.7.3 Analysis of the composite variable for the attitudes and perceptions of Radiographers towards AI.

The composite variables from the constructs of attitude (ATT) and perceptions (PER) were analysed using a one-sample t-test. This test yielded results that indicate significant agreement that Radiographers have a positive attitude towards AI, and there is significant disagreement that Radiographers have negative perceptions of AI.

5.7.3.1 Bivariate analysis

Bivariate analysis was done to determine if there are any differences in these composite variables across some of the demographics. There were no significant differences in any of these variables across gender, province, age and experience. However, a Welch test was conducted and there was a significant difference in the attitudes and perceptions of Radiographers towards the integration of AI into medical imaging. Results from the Games-Howell post hoc test indicate that there are significantly more positive attitudes for those with masters than those with a diploma ($p=.020$) or a B-Tech ($p=.001$) and for those with an 'other' qualification than those with a B-Tech ($p=.011$). Furthermore, the Games-Howell post hoc test highlighted that there are significantly more positive perceptions amongst Radiographers with diplomas than those with a master's ($p=.046$) or those with a PhD ($p=.040$) and those with an 'other' qualification ($p=.019$).

5.7.3.2 Independent sample t-test

Independent sample tests were conducted, and they demonstrated differences in the attitudes and perceptions of Radiographers across geographical locations and working sectors. Radiographers employed in the private sector had more positive attitudes than those employed in the government sector, and Radiographers employed in the government sector had more negative perceptions than those in the private sector. Additionally, Radiographers in urban areas had more positive attitudes than those in rural areas, and Radiographers in rural areas had more negative perceptions than those in urban areas.

5.8 BARRIERS TO ADOPTING AI IN RADIOGRAPHY

In this section, respondents were asked to determine their level of agreement or disagreement with statements that could be barriers to the implementation of AI in radiography. Fourteen questions (items) were asked. For these items, a one-sample t-test was conducted to determine if there was significant agreement or disagreement with the statements. The results from the one-sample t-test are demonstrated in Figure 13.

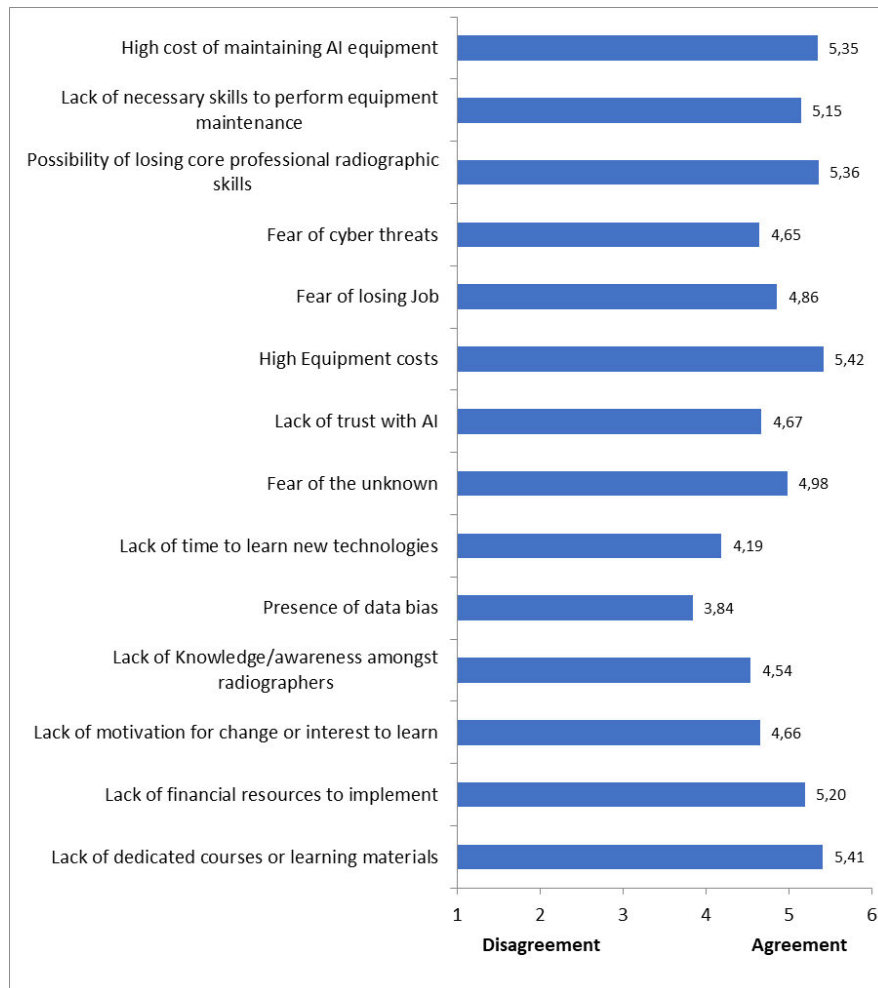


Figure 13: Summary of the one-sample t-test for the barriers to adopting AI in Radiography

The results from the one-sample t-test indicate that Radiographers in SA perceive the following as a barrier to the successful implementation of AI in Radiography:

- Lack of dedicated courses or learning materials.
- Lack of financial resources to implement.
- Lack of motivation for change or interest in learning.
- Lack of knowledge/awareness among Radiographers.
- Presence of data bias.
- Lack of time to learn new technologies.
- Fear of the unknown.
- Lack of trust in AI.
- High equipment costs.
- Fear of losing a job.

- Fear of cyber threats.
- Possibility of losing core professional radiographic skills.
- Lack of necessary skills to perform equipment maintenance.
- High cost of maintaining AI equipment.

While significant agreement with the barriers to the implementation of AI in radiography was noted, high equipment cost; a lack of dedicated courses or learning materials; the possibility of losing core professional radiographic skills; a lack of financial resources to implement; and the high cost of maintaining AI equipment were ranked as the top five worst barriers to the implementation of AI by Radiographers in SA.

5.8.1 Factor Analysis for Barriers

Factor analysis with promax rotation was applied to these 14 items. E6 (lack of time to learn new technologies) was removed from the analysis because it loaded strongly onto multiple factors. Three factors were extracted, which account for 47.56% of the variance in the data. A Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO) of .837 and a significant Bartlett's test indicate that the data was adequate for successful and reliable extraction. Rotation converged in 5 iterations. The extracted factor and the item loadings are summarised in Table 8

Table 5.8: Composition of factors and reliability – Barriers (composite variables)

Factor	Construct	Items included	Variance extracted	Cronbach's alpha
1	Fear/distrust (BARR_FEAR)	E5, E7, E8 E10, E11	32.19	.817
2	Resources (BARR_RES)	E1, E2, E9, E12-E14	8.84	.777
3	Employee participation (BARR_EMP)	E3, E4	6.52	.774

The composite variables created by averaging the agreement scores for every item in each variable are credible, and the Cronbach's alpha values (.817,.777, and.774)

demonstrate that there is strong internal consistency among the items on each component.

5.8.2 Analysis of the composite variables for the barriers to adopting AI into Radiography

The composite variables from the constructs of barriers associated with fear (BARR_FEAR), barriers associated with resources (BARR_RES) and barriers associated with employee participation (BARR_EMP) were analysed using a one-sample test. This test yielded results that indicate significant agreement amongst Radiographers in SA that barriers exist in all three barrier groupings/constructs.

5.8.2.1 Bivariate analysis

Bivariate analysis was conducted to test if there are any differences in these composite variables across demographics. No significant differences were noted in these variables across gender or province. However, there is a positive correlation between age and agreement that resources are a barrier to adopting AI in radiography, and older Radiographers are associated with more agreement. Similarly, there is a positive correlation between age, experience and the agreement that fear is a barrier to adopting AI. Older Radiographers and Radiographers with more years of experience are associated with more agreement that fear amongst Radiographers is a barrier to implementing AI.

5.8.2.2 ANOVA test

For comparison of the barriers of AI with qualification, an Analysis of Variance (ANOVA) Model test was conducted. The ANOVA test highlighted that there is a significant difference in the barriers of fear (BARR_FEAR) across qualifications, ($p=.569$). Tukey's post hoc analysis shows that those with a diploma qualification are in more agreement that fear is a barrier in adopting AI in SA than those with a master's degree ($p=.025$) and those with 'other' qualifications ($p=.038$).

5.8.2.3 Independent sample t-test

Independent sample t-tests across the working sector and geographical location demonstrated the following results.

- Radiographers employed in the government sector are more in agreement that fear is a barrier to adopting AI than Radiographers employed in the private sector.
- Radiographers employed in the government sector are more in agreement that a lack of resources is a barrier to adopting AI than Radiographers employed in the private sector.
- Radiographers employed in the government sector are more in agreement that employee participation is a barrier to adopting AI than Radiographers employed in the private sector.
- Radiographers employed in rural areas are more in agreement that fear is a barrier to adopting AI than Radiographers employed in urban areas.
- Radiographers employed in rural areas are more in agreement that a lack of resources is a barrier to adopting AI than Radiographers employed in urban areas.
- Radiographers employed in rural areas are more in agreement that employee participation is a barrier to adopting AI than Radiographers employed in urban areas.

5.9 SUMMARY OF THE CHAPTER

This chapter presents the findings obtained from the study. Over 90 % of Radiographers in South Africa are aware of the concept of AI. The majority of Radiographers in South Africa have a positive attitude towards AI as there is significant agreement that AI is beneficial to the various aspects of diagnostic radiography. While AI possesses many benefits, Radiographers also acknowledge the various barriers that hinder the implementation of AI in the radiography profession. The significance of these results will be discussed in the following chapter.

CHAPTER 6: DISCUSSION OF THE FINDINGS

6.1 INTRODUCTION

The previous chapter presented the findings of the study. These findings are discussed based on an analysis of the data and the subsequent interpretation of the perceptions of Radiographers in South Africa on the integration of AI into medical imaging. The chapter has been structured to provide a summary of the response rate, followed by a discussion of the results for the various sections of the questionnaire that were developed from the objectives of the study. The study findings are interpreted and discussed by contrasting the observed similarities and differences with those of the literature presented in Chapter 2. Lastly, the chapter reconciles the findings with the theoretical framework of the study discussed in Chapter 3.

6.2 RESPONSE RATE

Survey response rates are essential to evaluate any research as they reflect the quality of the survey (Frey, 2018: 10). The response rate is calculated by dividing the number of valid responses by the total number of eligible respondents in the selected sample, then multiplying by 100 to express it as a percentage (Fincham, 2008: 2). This calculation enables a precise assessment of non-responses within a study. According to Brick and Williams (2013: 36), it is important to acknowledge that a high non-response rate can increase the risk of bias in the study's final estimates. The final response rate for this study was 265 respondents, which made up 72.28%. This response rate was higher when compared to a similar study conducted by Botwe *et al.* (2021: 687) with a similar aim. The study by Botwe *et al.* only constituted 51 Radiographers across South Africa, which made up only 5% of the respondents of the study. Another study conducted in Ghana by Botwe *et al.* (2021: 268) had a response rate of 64.5 %. A similar study conducted across Nordic countries by Pedersen (2024: 776) had a high response rate above 90% (n=586), so did a similar study by Aldhafeeri (2022: 178) in Saudi Arabia (n=562). The response rate for this study is significantly higher than previous studies that investigated the perspectives of Radiographers in SA on the integration of AI into medical imaging.

6.3 SOCIO-DEMOGRAPHIC FACTORS OF THE RESPONDENTS

All the study respondents were Radiographers practicing in South Africa. They worked across all 9 provinces of South Africa, had different years of clinical experience, and used various imaging modalities. All the Radiographers were registered with the Health Professions Council of South Africa as independent practitioners. This section discusses the gender, age, as well as province and qualifications of the respondents.

6.3.1 Gender

The gender distribution reveals that most respondents were female Radiographers, making up a total percentage of 61.1% (n=162) as compared to males, which constituted 38.9 % (n=103). The higher proportion of female to male Radiographers noted in the current study correlates with national figures, as indicated by the Health Systems Trust (2017: 306), which reported that in 2016, there were 573 female and 93 male Radiographers registered by the HPCSA in the province of KwaZulu-Natal. This represents an approximate percentage of 84% female and 16% male registered Radiographers. In the UK, the National Health Service Scotland's Education and Workforce Report (2015: 14) published data on the demographics of undergraduate radiography students. The report found a similar imbalance in the number of female and male Radiographers, stating that from 2005 to 2013, around 85% of all enrolled students were female, and the remaining 15% were male. Radiography in South Africa is known to be dominated by females (Davy, 2019: 10). According to the literature, women form the backbone of radiography (Anim-Sampong *et al.* 2018: 337). A study by Gam (2015: 64) acknowledged that the radiographic profession has a higher number of females as compared to males (88.4%), and a study by Erasmus (2018: 46) highlighted this similar phenomenon of female domination with a ratio of 9:1.

6.3.2 Age

The age groups of the respondents varied across several age categories. However, most respondents at 30% (n=80) were between the age group of 35-44 years old. This aligned with a similar study conducted in Ghana by Botwe *et al.* (2021: 260) which had a mean age ($\pm$ standard deviation) of 33.6 ± 7.3 years. Furthermore, another similar study conducted on an African scale by Botwe *et al.* (2021: 861) had most of the respondents falling between the age group of 30-39 years old. Most of respondents in this age group are known as the millennials. According to Delgado *et al.* (2020: 35),

millennials currently represent the largest generation in the workforce. This segment will continue to rise as previous generations slowly retire. Millennials, recurrently referred to as “digital natives”, have a different understanding of technology when compared with, for example, baby boomers (Obal and Kunz, 2013: 13). Myers and Sadaghiani (2010: 234) elaborate that rather than viewing technology as a tool, for millennials, the practical use of technology is entwined into their daily routines. This is supported by Dannar (2013: 786), who described technology as a crucial part of the identity of millennials. Similarly, millennials are considered to be better at learning new technologies than any previous generation and are more comfortable with internet-based technology than previous generations.

6.3.3 Province and Qualification

Most respondents were Radiographers practicing in the province of KwaZulu-Natal (n=56). This could have been attributed to the fact that the researcher works within the KZN province, hence she encouraged her colleagues and friends to participate in the study. Approximately 43% (n=114) of the respondents had a B-tech qualification. This is similar to the respondents of the African study by Botwe *et al.* (2021: 861), as 47.3% of the respondents had a B-tech as their highest level of qualification. However, similar studies conducted globally had the majority of the respondents having a bachelor's degree as their highest educational level (Aldhafeeri, 2022: 13; Pedersen, 2024: 776). Fewer Radiographers had attained master's or doctoral-level qualifications, this was similar across the majority of similar studies (Botwe, 2021: 861; Botwe, 2021: 260; Pedersen, 2024: 776; Aldhafeeri, 2022: 13).

6.4 DISCUSSION IN LINE WITH THE RESEARCH OBJECTIVES

This section discusses the findings of the study in line with the outlined research objectives. Analysing the collected data provides insights that address each objective, offering a comprehensive analysis. The findings of the study are then compared to the broader context of existing literature, which paves the way for developing informed conclusions and recommendations.

6.4.1 To assess the basic understanding of Radiographers regarding AI

Section B of the questionnaire asked respondents if they were aware of certain AI concepts and applications in radiography. This section was used to analyse the basic understanding of Radiographers of AI based on their knowledge of the concepts and application of AI. Concerning AI concepts such as AI itself, machine learning, computer-aided detection, deep learning, and automatic exposure control. The finding that 93.9% of South African Radiographers demonstrated awareness of AI concepts contrasts sharply with Zuma *et al.*'s (2022: 58) KZN-based study, where most respondents had never encountered the term 'AI'. This discrepancy may be explained by temporal factors; Zuma *et al.*'s data were collected in 2020-2021, when AI discourse in South African radiography was less pervasive. The intervening years have seen increased professional discussion, vendor marketing, and academic publications on AI, likely raising awareness levels. Alternatively, the difference may reflect sampling: the present study's nationwide sample (n=265) captured Radiographers from all nine provinces, while Zuma *et al.*'s smaller KZN sample (n=87) may have been less representative. This finding suggests that AI literacy among South African Radiographers has increased rapidly, but also highlights the importance of considering when and where studies are conducted when comparing results

Differences were observed in terms of technical understanding and awareness of AI concepts amongst Radiographers. Regarding other concepts such as machine learning, computer-aided detection, and deep learning, a significant percentage knew of the concept but did not have much knowledge about it. There was a drop in the respondents' understanding of the more technical components of AI, as only 18% knew a lot about machine learning; 37.4% knew much about computer-aided detection; and 18% knew much about deep learning. This indicated that Radiographers recognize general AI concepts and are aware of some of AI's functional roles within the field, but are unfamiliar with the more technical components of the technology. A study in the UAE by Abuzaid *et al.* (2022: 87) found that 31% of their respondents had a working knowledge of AI, yet only 4% understood AI basics. Similar results were noted in a European study conducted by Coakley *et al.* (2022: 943), as there was a 20% notable drop in respondents' understanding of the more technical components of AI when they were later questioned more specifically about machine learning and algorithms. Respondents were asked about their level of awareness

regarding four AI applications in various imaging modalities of radiography, and the majority of the respondents had little to no knowledge about these applications.

In another study in the UK, a large proportion of the respondents indicated that they understood AI in general. However, there was a lack of understanding of specific terminologies used in modern AI, such as “deep learning” and “algorithms”. Other studies also report that there is a general lack of understanding of AI amongst Radiologists (Tejani 2020: 4, SIIM 2017). Lindqwister *et al.* (2020: 1076) point out that the knowledge and understanding of AI at this level of detail are essential when engaging with literature around modern AI. It was noted that those with more years of experience had a higher level of awareness of radiography applications. Lindqwister *et al.* (2020: 1076) elucidate that many applications of AI in medicine are currently in the development stage; therefore, all clinicians must understand the literature to have a critical appreciation of the potential, pitfalls, and risks of proposed technology as they move into the inevitable implementation phase.

The results from the study demonstrated that respondents with higher qualifications had more knowledge of the concepts and applications of AI, turkey post hoc analysis showed that those with a master's qualification have significantly more awareness than those with a diploma ($P < .0001$), B-Tech ($P = .004$), or degree ($P = .003$). This aligns with a study by Kandholfer (2023), which demonstrated that those with higher levels of education show greater awareness of AI. Moreover, independent sample tests showed that there is significantly more awareness and knowledge amongst those employed in private than in government sectors, $t(263) = 4.850$, $p < .001$. This could be because the adoption of AI in the public sector has been slower than in the private sector, as mentioned by Desouza *et al.* (2020). Additionally, the private sector uses more technologically advanced equipment such as advanced CT scanners, like a Siemens Pro Pulse Scanner, which has reconstruction features that use smart algorithms to automatically align the image stacks for optimal cardiac imaging (Siemens 2020), and GE portable x-ray units that are equipped with on-device AI that provides on-screen quality checks (GE Healthcare, 2021). This may contribute to the higher level of awareness amongst Radiographers in the private sector as compared to the government sector.

6.4.2 To assess the willingness of Radiographers to accept the integration of AI into their profession

Section D of the questionnaire was used to assess the attitudes and perceptions of Radiographers to determine their willingness to accept the integration of AI into their profession. From the results, it is clear that Radiographers in South Africa have positive attitudes towards the integration of AI into medical imaging. There is significant agreement amongst Radiographers: 98.5% are excited about the integration of AI, and 99.3% are willing to accept the changes that come with it. The finding that 98.5% of South African Radiographers expressed excitement about AI integration corroborates both Pedersen *et al.*'s (2024: 776) Nordic study and Botwe *et al.*'s (2021: 861) pan-African research, which similarly documented similarly high levels of enthusiasm. This cross-continental consistency is striking given the substantial differences in healthcare infrastructure, AI adoption rates, and professional scope between these regions. It suggests that Radiographers' positive orientation toward AI may be driven less by local experience with the technology and more by a shared professional discourse that frames AI as inevitable and beneficial. The uniform willingness to undergo further training (99.3% in this study) across diverse contexts reinforces this interpretation, indicating that Radiographers globally recognise the need to prepare for AI-integrated practice, regardless of whether AI is currently present in their workplaces.

A study conducted in Ghana by Botwe *et al.* (2021: 260) highlighted a positive attitude towards integrating AI into medical imaging. However, there were concerns about AI-related errors, job displacement, and salary reduction. In contrast to these findings, the respondents in this study exhibited limited concern regarding such factors. Over 90% of the respondents in this study disagreed that AI would harm the radiography profession. A recent meta-analysis study by Lui *et al.* (2019: 271) highlighted that AI tools are trustworthy. A lack of understanding of the features and functions of AI tools may cause the discrepancy between this viewpoint and the literature. To mitigate some of these concerns, further assurance and training on the safe utilization of AI are necessary.

A one-sample statistics test was conducted to determine if the average agreement or disagreement score differs significantly from the neutral or central score. The central

score of this statistical test was 3.5. Values less than 3.5 indicate significant disagreement, and values above 3.5 indicate significant agreement. Respondents disagreed that AI could compromise patient privacy and the security of data; that AI lacks transparency [$t(265) = 3.33$]; that AI is untrustworthy [$t(265) = 2.82$]; and that AI models are at high risk of data bias [$t(265) = 3.11$]. However, respondents from another study expressed worries that the unethical exploitation of patient data for unnecessary commercial objectives could result from the usage of AI systems. This idea may originate from the fact that deep learning algorithms used by modern AI-powered devices to automate duties need patient data for training (Ranschaert *et al.*, 2019: 329), and patient data may be endangered if ethical guidelines and data "truthfulness" are not followed.

Consistent with other studies, most of the respondents were interested in undergoing further educational training to learn about AI (Wong *et al.*, 2021: 44; Liang, 2019: 1961). However, it is accepted that the respondents are likely those who have some appreciation of AI, resulting in potential bias. It is imperative to investigate the non-respondents who may not have an understanding and are perhaps more in need. Jungmann *et al.* (2020: 1076) state that there are upcoming challenges for educators to integrate AI learning into programs for the wider medical community. It is an acquired skill to learn collaborative working with AI-driven semi-automated processes. The European Society of Radiology (ESR) emphasizes the importance of AI education, especially implementation into practice in future training curricula. The Society of Radiographers in South Africa (SORSA) does not seem to have an opinion regarding the implementation of AI education into practice. The employment impact of AI as a compatible new technology is expected to be broad, more powerful, and longer-lasting than previous technological revolutions (Ford, 2015). Frey and Osborne (2017) argue that artificial intelligence will directly replace 13% of jobs, including those that are more brain-intensive and more financially rewarding. Many scholars regard the intervention of new technology as an external factor of the organization, which will threaten the stability of the employee's working state. If the organization does not take the corresponding adjustment measures in time, the employee's anxiety will have a negative impact on the organization (Hoboff, 1989: 13). Greenhalgh and Rosenblatt (1984) originally defined this emotion as job insecurity, and the inability of employees to maintain the status quo when threatened at work.

A one-sample statistics test was conducted to determine whether the average agreement or disagreement score differs significantly from the neutral or central score. The central score of this statistical test was 3.5, and values less than 3.5 indicate significant disagreement, and values above 3.5 indicate significant agreement. Findings from this test suggested that the majority of respondents disagreed that AI would displace them from their Jobs [$t(265) = 2.60$] and that their salary might be reduced [$t(265) = 2.28$]. Contrary to this, respondents in a study in Zimbabwe believed that the acceptance of AI would result in job losses and would render the radiography education programs obsolete (Chivandire *et al.*, 2022: 263). This was unsurprising, given that there has been much discussion about how AI will lead to the mechanization of professions and the widespread replacement of the human workforce. However, this could be because of what happened to darkroom assistants with the advent of digital radiography. In South Africa, darkroom assistants who were employed by public hospitals to process radiographic films were rendered obsolete by the introduction of digital radiography equipment. This perception of job insecurity has also been reported in another study (Botwe *et al.*, 2021: 861). Some Radiographers were very concerned about job losses as a result of AI implementation. Murphy (2019: 50) argues that the assertion on job insecurity and salary reduction is difficult to accept as AI has not yet demonstrated how it could, for example, replace the human face of patient positioning by Radiographers for various imaging studies and the necessary instructions that they have to provide to patients. Hardy (2019: 92) emphasizes that Radiographers should be assured that AI is a potential support to the practice of their profession. Evidence suggests that, in spite of these concerns, there have been no reported instances of individuals losing their employment in the healthcare industry due to AI implementation. Instead, AI is supporting the advancement and development of nearly every professional sector.

6.4.3 To evaluate the impact of AI on the job performance of Radiographers

Section C of the questionnaire, which was associated with the benefits of AI and its applications, was used to evaluate the impact of AI on the Job performance of Radiographers. A one-sample statistics test was conducted to determine if the average agreement or disagreement score differs significantly from the neutral or central score. The central score of this statistical test was 3.5, and values less than 3.5 indicate

significant disagreement, whilst values above 3.5 indicate significant agreement. Findings from this statistical test indicate a significant agreement amongst the respondents that AI will have many benefits for the job performance of Radiographers. Respondents agreed that AI would make their job easier [$t(265) = 4.94$], improve the quality of their work [$t(265) = 5.14$], workflow within the department [$t(265) = 5.05$], and reduce radiation dose levels [$t(265) = 5.07$]. This is comparable to research by Botwe *et al.* (2021: 861) that discovered Radiographers concurred that AI would "ease" their work. Arguments in the literature that AI is supposed to speed up tasks may have an impact on this perspective. Nonetheless, there is still disagreement regarding whether AI might result in more or less work in radiology departments.

Whilst it is predicted that AI may allow for individual patient time efficiencies with AI speeding up or taking over tasks, this may be counterbalanced by increased patient throughput, as found in a study conducted in the Netherlands in 2017 (Aarts *et al.*, 2017: 64). Although there is widespread concern that AI will replace human jobs as per Felten *et al.* (2019), there seems to be no evidence to support this hypothesis (Liu *et al.*, 2019: 271). A study by Abuzaid *et al.* (2022: 87) elaborates that AI can be misinterpreted, which could account for this notion. The majority of respondents expressed that they believe AI will help them facilitate their jobs as Radiographers, and most respondents expressed positive views regarding AI's role in dose optimization and image quality. These findings align with a study by Aldhaeeri (2022: 13) in which 65.4% of the respondents had the same sentiments. In another study by Antwi *et al.* (2021: 9) a large number of the respondents also stated that AI may be a useful tool to help them in their roles as Radiographers (82.2%), optimize radiation dose (68.8%), and improve medical imaging in general (87.4%) (Hardy and Harvey, 2020: 93, Chaix *et al.*, 2019: 5; Lewis *et al.*, 2019: 292; Lai *et al.*, 2020: 14). The majority of the respondents concurred that AI would lead to the role extension of Radiographers. Hardy and Harvey (2020: 1108) discuss that AI provides the opportunity for a role expansion of Radiographer's responsibility into AI-supported image reporting and auditing roles. The reporting of diagnostic images by appropriately qualified Radiographers has been an established role development in the UK for over 20 years. In Africa, and South Africa to be specific, image reporting is left solely to the Radiologist. Radiographers are mainly responsible for acquiring the requested

images. This backwardness can be seen as a hindrance to providing efficient radiology services, especially in the public sector, where all general X-rays are unreported.

Introducing AI systems that can assist Radiographers in reporting basic general X-rays can lift the load off Radiologists. According to Budhu *et al.* (2023: 457), the health sector of South Africa is burdened by the shortage of Radiologists, which leads to the underreporting of radiographic images and ultimate mismanagement of patients. Radiographers reporting on general X-rays with the assistance of AI would be extremely beneficial to the health sector of South Africa. While this activity predominantly relates to projection radiography and mammography, evidence suggests that appropriately trained and supported Radiographers can supplement radiology reporting across a wide range of imaging modalities (Spencer, 2003: 902; Culpan *et al.*, 2019: 155). The value of reporting Radiographers was acknowledged within the CQC Radiology Review (2018) and Cancer Workforce Plan (2017), which specifically identified the expansion of the reporting Radiographer workforce as being key to enabling earlier cancer diagnosis, greater cancer screening turnaround times, and addressing reporting backlogs. Hardy and Harvey (2020: 1108) elucidate that developing systems for AI and Radiographers' double reading of imaging examinations may go some way towards alleviating persisting concerns, and may prove more cost-effective than a single Radiologist or Radiographer interpretation for certain high-volume modalities such as chest radiography, CT lung screening, and screening mammography. According to Hardy and Harvey (2020: 1108), there is an opportunity to explore areas where there are reporting backlogs or workforce issues and perform research to measure the potential for Radiographer-led AI-supported reporting services, and develop implementation plans for easy and consistent adoption.

All automated systems must have quality control checks, according to European Medical Device Regulations (MDR 2017/745), and there will be a growing role for reporting Radiographers to undertake regular audits and reviews of the outputs and decisions of an AI image evaluation system. A proportion of all AI automated cases will likely require some form of post-decision check or "peer review" to establish system sensitivity, specificity and accuracy, and it is Radiographers who must seize this opportunity to own the process and perhaps, in the future, establish systems for AI

review and the audit of human image interpretation to establish parity or the lack thereof (Hardy and Harvey, 2020; 1108). However, to lead and create such opportunities, Radiographers must have a high-level technical understanding of AI systems' operation and functionality. The need for education programs and CPD to support the evolution of the Radiographer workforce and their adaptation to new AI-enabled services is imperative and should not be overlooked (Hardy and Harvey, 2020; 1108).

6.4.4 To assess the barriers to adopting AI in Radiography

A one-sample statistics test was conducted to determine whether the average agreement or disagreement score differs significantly from the neutral or central score. The central score of this statistical test was 3.5, and values less than 3.5 indicate significant disagreement and values above 3.5 indicate significant agreement. Findings from the study identified 14 factors that pose a barrier to the implementation of AI in Radiography from the one-sample statistics test, namely:

- i. Lack of dedicated courses or learning materials, $t(265) = 5.41$
- ii. Lack of financial resources to implement, $t(265) = 5.20$
- iii. Lack of motivation for change or interest to learn, $t(265) = 4.66$
- iv. Lack of knowledge/awareness amongst Radiographers, $t(265) = 4.54$
- v. Presence of data bias, $t(265) = 3.84$
- vi. Lack of time to learn new technologies, $t(265) = 4.19$
- vii. Fear of the unknown, $t(265) = 4.98$
- viii. Lack of trust with AI, $t(265) = 4.67$
- ix. High equipment costs, $t(265) = 5.42$
- x. Fear of losing a job, $t(265) = 4.86$
- xi. Fear of cyber threats, $t(265) = 4.65$
- xii. Possibility of losing core professional radiographic skills, $t(265) = 5.36$
- xiii. Lack of necessary skills to perform equipment maintenance, $t(265) = 5.15$
- xiv. High cost of maintaining AI equipment, $t(265) = 5.35$

These findings were echoed in a similar study conducted in Ghana by Antwi *et al.* (2021: 9), where most respondents agreed that a major obstacle to Ghana's adoption of AI is the country's lack of awareness and expertise of the technology, as well as

cyber dangers. Similarly, Sit *et al.* (2020: 11) stated that respondents felt more prepared to use these technologies after completing some kind of AI education. This implies that hospitals and companies that manufacture medical imaging equipment should start holding regular conferences and training sessions to educate practitioners about cybersecurity concerns and the real-world clinical uses of AI tools (Ongena *et al.*, 2020: 1033). Furthermore, according to 78.1% of respondents, Ghana's adoption of AI technologies may be constrained by their high cost. Similar conclusions were drawn from this study, which showed that healthcare technology developments are currently difficult in developing countries, as the equipment is costly. Therefore, the assertion of respondents from both studies may be true.

According to Chivandire *et al.* (2022: 263), economic challenges frequently result in broken equipment as a result of poor maintenance, which is likely to be the case with AI. The cost of the implementation and maintenance of AI may be prohibitively expensive for developing countries, further lagging them behind in terms of healthcare improvement. Similar to this study, the majority of respondents were concerned about the high cost of maintaining AI equipment, $t(265) = 5.35$. Poor equipment preservation, poor-quality management systems, and outmoded medical equipment are amongst the infrastructural concerns noted by studies on medical equipment infrastructure in the West African sub-region (Honsy, 2018: 500). A lack of trust by clinicians has been cited as a potential barrier to the implementation of AI in the clinical setting (Quinn *et al.*, 2021: 28; Kitamura *et al.*, 2021; Jungmann *et al.*, 2023: 834). Goddard (2014: 368) argues that excessive trust in AI systems by clinicians may also lead to an increased likelihood of the clinician changing their mind from their initial decision. Adequate trust levels are needed to ensure the beneficial use and management of expectations of end-users. The majority of respondents in this study alluded that a lack of trust in AI systems poses a barrier to its implementation, $t(265) = 4.67$. Similarly, a study by Jungmann *et al.* (2023: 834) examining the attitudes of Radiologists, IT specialists, and industry to AI demonstrated that only a quarter of respondents felt that they could trust results from an AI system.

The lack of dedicated courses or learning materials was considered to be a significant barrier to the implementation of AI by the respondents in this study, $t(265) = 5.41$. Ahmed *et al.* (2023: 10) elaborated that the adoption of AI is significantly hindered by

the education and training of the healthcare workers, as indicated by 27 papers in a systematic analysis of the obstacles to AI adoption in healthcare. Significant AI education and training will be required, as an in-depth understanding of the possibilities and operations of AI in the medical field is still basic (Pranjape *et al.*, 2021: 823). Panch *et al.* (2019: 77) elucidate that before the workforce that will need to use the technology is at ease or proficient in clinical practice, the disparities in technical literacy, satisfaction with, and comprehension of the current technology must be addressed. Healthcare providers will need to create a training curriculum that is tailored to physicians who use AI systems, and that handles the various issues brought on by new technologies (Singh, 2020: 45).

There was significant agreement amongst respondents that the fear of losing jobs amongst Radiographers poses a threat to the implementation of AI, $t(265) = 4.86$. According to Ahmed *et al.* (2023: 10), the concern about potential job insecurity or significant changes to career plans resulting from the advancement of increasingly sophisticated and capable AI is a common topic. This concern could theoretically lead to behaviours and practices in the future being designed to guarantee the responsibilities and continued relevance of human practitioners in healthcare (Brady, 2020: 231). The lack of financial resources to implement AI ($t(265) = 5.41$) as well as the high cost of maintaining AI equipment ($t(265) = 5.35$) were noted as significant barriers to the implementation of AI by respondents. Similar findings were found in a study in Ghana and Africa (Botwe *et al.*, 2021: 861; Botwe, 2021: 260). Even when the anticipated efficiencies from the deployment of AI technologies are considered, workforce financing constraints remain a glaring obstacle. It is exceedingly costly to get expert input for AI algorithm training data, and maintaining AI will need a large amount of continuous funding (Ahmed *et al.*, 2023: 10; Baxter *et al.*, 2019: 30; Sendal *et al.*, 2020: 151). The uneven distribution of costs and benefits associated with AI implementation across departments and providers may pose challenges in evaluating the impact of these changes and in effectively allocating healthcare resources (Ahmed *et al.*, 2023: 10).

6.5 DISCUSSION IN RELATION TO THE THEORETICAL FRAMEWORK

The study aimed to assess the knowledge and perspectives of Radiographers in South Africa regarding the integration of AI in diagnostic imaging in order to provide unique

recommendations to support the training of Radiographers in their readiness to provide quality patient care using AI. To do so, it is imperative to explore Radiographers' attitudes, beliefs, and intentions concerning the adoption and use of artificial intelligence (AI) in the field of medical imaging. The Technology Acceptance Model 2 (TAM 2) provides a relevant theoretical framework for understanding the factors influencing the acceptance of AI technology amongst Radiographers in this context. The components of TAM 2 relate to the study in the following ways:

Perceived ease of use (PEOU): This refers to the user's perception of the effort required to use a particular technology (Davis 1986). According to Holden and Karsh (2010: 159), if a user believes that a technology is easy to use, they are more likely to adopt it. This was the case in the current study, as the majority of the respondents believed that AI tools are easy to use. Hence, they had a positive attitude towards the integration of AI and were accepting of the technology and the technological changes that come with it. Some respondents were willing to undergo further educational training to ensure that they could efficiently use AI systems. There was significant agreement amongst Radiographers that they are excited about the integration of AI into radiography (98.5%), and they think that it is important that radiology departments start planning for the integration of AI into medical imaging.

Perceived usefulness (PU): This represents the user's perception of the degree to which technology enhances their job performance or facilitates achieving specific goals (Davis, 1989). According to Holden and Kash (2010: 159), if a user believes that a technology is useful, they are more likely to accept it. There was a positive correlation between the PU and the findings of this study. A one-sample statistics test was conducted to determine if the average agreement or disagreement score differs significantly from the neutral or central score. The central score of this statistical test was 3.5, and values less than 3.5 indicate significant disagreement, whilst values above 3.5 indicate significant agreement. Findings from the one-sample statistical test indicated that respondents significantly agreed that AI will be beneficial to the Radiography practice in 15 ways, namely:

- i. AI will make the job easier, $t(265) = 4.94$
- ii. AI will improve the workflow with the radiology department, $t(265) = 5.05$

- iii. AI will improve the quality of Radiographer's work, $t(265) = 5.14$
- iv. AI will allow Radiographers to fulfill their job roles and responsibilities, $t(265) = 5.03$
- v. AI will lead to the role extension of Radiographers, $t(265) = 4.99$
- vi. AI will have a positive impact on Radiography, $t(265) = 4.97$
- vii. AI will improve quality assurance because of its efficiency in diagnosis, $t(265) = 5.16$
- viii. The integration of AI will reduce occupational stress amongst Radiographers in SA, $t(265) = 4.87$
- ix. The integration of AI will reduce burnout amongst Radiographers in SA, $t(265) = 4.92$
- x. The integration of AI will reduce scan times, $t(265) = 5.1$
- xi. The integration of AI will improve image post-processing, $t(265) = 5.25$
- xii. The integration of AI will ensure diagnoses are accurate, $t(265) = 4.90$
- xiii. The integration of AI will reduce radiation dose to patients, $t(265) = 5.07$
- xiv. The integration of AI will improve general Radiography practice, $t(265) = 5.02$
- xv. The integration of AI will improve the clinical care of patients, $t(265) = 4.83$

Radiographers in South Africa significantly agree that AI comes with many benefits, hence they are accepting of the technology advancements and have positive attitudes.

6.6 SUMMARY OF THE CHAPTER

This chapter discussed the findings from the study and compared them with findings from other similar studies. There is consensus amongst most of the studies that Radiographers have positive attitudes toward AI. This chapter discussed in depth the results of the study, the objectives of the study, and the theoretical framework. There is a positive correlation between the 2 factors of the theoretical framework and the findings from the study. The following chapter focuses on discussing unique recommendations that support the integration of AI into radiography, as well as the conclusion of the study.

CHAPTER 7: CONCLUSION, LIMITATIONS AND RECOMMENDATIONS

7.1 INTRODUCTION

This study aimed to ascertain the knowledge and perspectives of Radiographers in South Africa regarding the integration of AI in diagnostic imaging to provide unique recommendations that support the training of Radiographers. The results of the study led to conclusions and recommendations discussed in this chapter. The conclusions made were derived from this research study and are aimed at answering the objectives of this study. The recommendations outlined are for the benefit of Radiographers, education institutions, radiography boards/associations, and radiology departments. The researcher also acknowledges and discusses the limitations of this study in the chapter.

7.2 EVALUATION OF THE AIMS AND OBJECTIVES OF THE STUDY

This section provides an evaluation of the current study by assessing whether the aims and objectives set for the study have been achieved.

7.2.1 Aim

The current study aimed to determine the knowledge and perspectives of Radiographers in South Africa regarding the integration of AI in diagnostic imaging to provide unique recommendations that support the training of Radiographers. Radiographers in South Africa are knowledgeable about the general terms of artificial intelligence, such as the term 'Artificial Intelligence' itself, machine learning, computer-aided detection, deep learning, and automatic exposure control. A significant 93.9 % of the respondents recognize general AI concepts but are unfamiliar with the technical components of this technology. Radiographers in South Africa had a positive perspective on the integration of AI, and 98.5% of the Radiographers were excited. Furthermore, most respondents had a strong belief that AI would make their jobs easier and that AI systems are easy to use ($t(265) = 4.94$). Some respondents were willing to undergo further educational training to ensure that they could efficiently use AI systems. These findings were in line with the theoretical framework for the study, as Radiographers in South Africa believed that AI is easy to use and beneficial to the radiology field, hence they had positive sentiments. The recommendations to support Radiographers are discussed later in this chapter.

7.2.2 Objectives

Objective One: to assess the basic understanding of Radiographers regarding AI

Most of the Radiographers in South Africa understand the term 'Artificial Intelligence' as 93.9% of the respondents had heard of the term and knew much about it. Differences were noted in terms of the technical understanding and awareness of AI concepts amongst Radiographers in SA. There was a drop in the respondents' understanding of more technical components of AI, as only 18% knew of the terms 'machine learning' and 'deep learning' respectively, and only 37.4% knew of the term 'computer-aided detection'. Furthermore, most respondents had little knowledge about the four AI application systems that are currently being used in the medical imaging field. It can be concluded that Radiographers in South Africa understand the basic terms of AI, but they are unfamiliar with more technical components related to AI, as well as AI-equipped application systems.

Objective Two: to assess the willingness of Radiographers to accept the integration of AI into medical imaging

There is significant agreement amongst Radiographers in South Africa (98.5%) that they are excited about the integration of AI in medical imaging. Furthermore, 99.3% of the respondents indicated that they are willing to accept the changes that come with AI. Over 90% of the respondents disagreed that AI would have any negative effects on the radiography profession. Unlike other similar studies conducted by Ranscahert *et al.* (2019: 329), Chivandire *et al.* (2022: 263), and Botwe *et al.* (2021: 861), Radiographers in South Africa had no concerns regarding job security, salary reduction, and the compromising of patient privacy and security of data by AI systems. From the results of this study, it can be concluded that Radiographers in South Africa are willing to accept the integration of AI into their profession.

Objective Three: to evaluate the impact of AI on the job performance of Radiographers

There was significant agreement amongst Radiographers in SA that AI would have many benefits that would enhance their job performance, which include making their job easier, improving the quality of their work and workflow within the department, and

reducing radiation dose levels. Radiographers in South Africa expressed that they believe that AI will help them facilitate their jobs as Radiographers and expressed positive views regarding AI's role in dose optimization and image quality. Furthermore, there was significant agreement that AI would open doors of opportunity in the role extension of Radiographers in South Africa. This could be AI-supported roles, such as image reporting and the auditing of AI systems. Similar to other studies, it can be concluded that Radiographers in South Africa perceive AI as a benefit rather than a threat to their job performance (Aldhaeeri, 2022: 13; Antwi *et al.*, 2021: 9; Harvey and Hardy, 2020: 93; Lewis *et al.*, 2019: 292).

Objective Four: to assess the barriers to adopting AI in radiography

Findings from the study identified 14 factors that pose a barrier to the implementation of AI in radiography. High equipment costs, a lack of dedicated courses or learning materials, the possibility of losing core professional radiographic skills, a lack of financial resources to implement, and high costs of maintaining AI equipment were ranked as the top five barriers to implementing AI by Radiographers in South Africa. The cost of implementing and maintaining AI systems may be prohibitively expensive for developing countries. The lack of dedicated courses was predominant in several studies. Detailed knowledge regarding AI basics, as noted in this study, and considerable AI training are needed for Radiographers in South Africa.

7.3 RESEARCH LIMITATIONS

According to Van Der Walt and Van Rensburg (2008: 324), limitations are regarded as inherent deficiencies within a study. Ioannidis (2007: 324), elucidates that limitations are vital to understanding because they place research findings into context, deduce the rigor of the scientific work, and assign a credibility level to the conclusions of the study.

The limitations experienced in this study are as follows:

- **Focus on South Africa:** The findings cannot be generalized to Radiographers in other countries or regions with different healthcare systems, resources, and levels of AI integration.
- **Theoretical vs. Practical Knowledge:** Some Radiographers did not have first-hand experience with AI in their daily work, which could have led to opinions

that are based on theoretical understanding rather than practical interaction with AI.

- **Healthcare System Factors:** South Africa has a dual healthcare system (public and private sectors), and this resulted in differing perspectives based on where the Radiographers work, potentially limiting broader applicability due to the different views.
- **Participant Recruitment:** The study was conducted online using a survey research design, which proved to be a limitation as it was difficult to reach and convince Radiographers across the country to participate in the research.

7.4 RECOMMENDATIONS

The following recommendations are based on the findings of the current study. To facilitate a smooth integration of AI into medical imaging, the following actions and measures can be recommended to various stakeholders:

7.4.1 Recommendations for Radiographers

- Radiographers should prepare themselves and learn more about AI through educational programs such as CPD activities, AI-related courses, certifications, and training programs to build confidence in understanding and using AI tools.
- Radiographers should stay informed and updated with advancements in AI technologies, their applications, and implications for medical imaging through journals, webinars and workshops.
- Radiographers should embrace change and recognize AI as an opportunity for professional growth rather than a threat to job security.

7.4.2. Recommendation for Educational Institutions

- Educational institutions should update the radiography curriculum training programs to include AI-related modules to familiarise students with the basics of AI, its applications in radiography, and its limitations, as well as focus on how AI tools are used in diagnostic imaging, workflow optimization, and quality assurance.
- Educational institutions should create continuous professional development (CPD) opportunities by developing specialized short courses or certifications on

AI for Radiographers and host regular events to discuss the latest developments in AI and its impact on radiography.

- Educational institutions should encourage research and innovation by supporting student initiatives and research projects focused on AI in radiography.

7.4.3 Recommendations for South African Radiography Boards/Associations

- South African radiography associations/boards should clearly define the AI scope of Radiography by establishing guidelines on the acceptable use of AI in image acquisition, analysis, and quality assurance, thereby ensuring that Radiographers remain the final decision-makers.
- South African Radiography associations/boards should ensure regulatory oversight by advocating for AI systems to be certified by regulatory bodies to ensure safety, accuracy, and ethical compliance in clinical settings.
- South African Radiography associations/boards should consider developing new career pathways that specialize in areas like AI quality assurance, system management, and data interpretation, creating advanced roles for Radiographers.
- South African Radiography associations/boards should clearly define the interaction between Radiographers and AI by clarifying that AI is a tool to augment Radiographers' work, not replace it, thus emphasizing their critical role in clinical decision-making and patient care.

7.4.4 Recommendations for Radiology/X-ray departments

- Radiology departments should have feedback mechanisms by creating channels for Radiographers to provide continuous feedback on AI systems to improve usability and effectiveness.
- Radiology departments should maintain human oversight by ensuring that Radiographers retain a key decision-making role in the interpretation and validation of AI-generated results.

7.4.5 Summary of Implementation Strategies

To translate these recommendations into practice, a coordinated, multi-level approach is required. For individual Radiographers, implementation begins with personal

accountability: each practitioner should enrol in an accredited foundational AI course, dedicating at least 10 hours per quarter to AI learning and documenting this for CPD portfolios. Educational institutions must act as curriculum innovators, integrating AI content progressively across all years of study from introductory concepts in the first year to hands-on clinical application in the final year, while training educators through vendor partnerships and appointing departmental AI champions. Professional bodies (HPCSA and SORSA) need to establish a multidisciplinary task force to develop comprehensive AI practice guidelines, mandate a minimum of 5 AI-focused CPD points per registration cycle, and create formal recognition for Radiographers specialising in AI quality assurance. Individual radiology departments should appoint an AI lead Radiographer to coordinate implementation, develop structured training programs, and establish daily, weekly, and monthly quality assurance checklists before AI systems go live. Vendors must support these efforts by providing on-site, role-specific training, designing intuitive interfaces that integrate with existing workflows, and providing transparent documentation of algorithm functionality and limitations. Crucially, all stakeholders should establish feedback mechanisms, such as weekly huddles, anonymous reporting tools, and quarterly review meetings, to ensure continuous improvement. This phased, collaborative approach ensures that AI integration in South African radiography is not merely aspirational but systematically achieved through concrete, measurable actions.

7.5 CONCLUSION

From the findings of this study, it can be concluded that Radiographers in South Africa recognise general AI concepts and are aware of some of AI's functional roles within the field, but remain unfamiliar with the more technical components of the technology. Therefore, the introduction of AI into the radiography curriculum is pivotal to ensuring that Radiographers have a strong foundation for understanding AI. It was noted that Radiographers in South Africa believe that AI will have multiple benefits for their job performance, including improved workflow, reduced scan times, and enhanced image quality. A particularly significant finding is that South African Radiographers do not perceive AI as a threat to their job security, contrary to findings from several other African studies. This addresses a common misconception that AI will replace Radiographers and reinforces the study's contribution to clarifying this important issue.

Instead, Radiographers view AI as a supportive tool that will enhance rather than replace their professional roles.

Since AI is equipped with benefits for Radiographers, several perceived barriers that hinder the implementation of AI in radiography were also noted. The top five perceived barriers identified were: high equipment costs; lack of dedicated courses or learning materials; the possibility of losing core professional radiographic skills; lack of financial resources to implement; and the high cost of maintaining AI equipment. The findings of this study demonstrate an overall positive attitude towards AI and an urgent requirement for appropriate education. The AI industry evolves rapidly, and this study highlights that the radiography profession in South Africa must prepare and adapt at the same speed. This research offers new perspectives and evidence-based insights to help train the radiography workforce, ensuring that South African Radiographers are knowledgeable, confident, and prepared to embrace AI as a tool that enhances patient care and professional practice.

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APPENDICES

Appendix A: Letter of Information



LETTER OF INFORMATION

Title of the Research Study: Artificial Intelligence in Medical Imaging: Knowledge and perspectives of South African Radiographers

Principal Investigator/s/researcher: Precious Mutambara (BHSc Diagnostic Radiography)

Co-Investigator/s/supervisor/s: Thandokuhle Emmanuel Khoza (Phd: Diagnostic Radiography)

Brief Introduction and Purpose of the Study:

Greetings, hope you are well. I am a qualified diagnostic Radiographer, and I am currently conducting research for my master's study. I would like to invite you to participate in this research study, as your voice as a Radiographer is a crucial element of the study. Research is termed as a systematic Investigation for generalized new knowledge. This study will be researching artificial intelligence in Radiography. Artificial intelligence is gradually being introduced into the diagnostic imaging system of South Africa. However, the introduction of AI has an impact on the role of Radiographers as it minimizes the role of a Radiographer by efficiently taking over certain tasks. This study serves to assess the knowledge and perspectives of Radiographers in South Africa on the emerging integration of AI into diagnostic imaging. This is to provide unique recommendations that will support the training of Radiographers to ensure a smooth integration of AI technologies into Radiography practices.

Outline of the Procedures:

This study is aimed to assess the knowledge and perspectives of South African Radiographers regarding the integration of AI in diagnostic imaging in order to provide unique recommendations to support the training of Radiographers in their readiness to provide quality patient care using AI. The objectives of the study are as follows:

- Evaluate the level of awareness among South African Radiographers about the concepts and potential applications of AI in the field of Radiography.
- Assess the current knowledge of Radiographers regarding the benefits and limitations of integrating AI technologies in radiographic practices.
- Identify the attitudes and perceptions of Radiographers towards the incorporation of AI tools in their daily workflow.
- Explore the potential barriers and challenges Radiographers might anticipate when adopting AI in their workplace.
- Propose recommendations and strategies for South African Radiographers, educational institutions, and policymakers to facilitate a smooth integration of AI technologies into Radiography practices.

Once permission has been granted and IREC had granted full approval the researcher will Inform Radiographers across south africa about the study. This will be done via social media platforms mainly Radiography WhatsApp Groups, Facebook and LinkedIn. The link to the survey will be distributed via the social media platforms mentioned.

Before answering the questionnaire (Appendix C), a brief Introduction and purpose of the study will be shared with you on the first page. Furthermore, consent will be obtained before you commence with the questionnaire, and you must confirm having read the purpose of the study and give consent to proceed. The questionnaire will take approximately 8-10 minutes to complete, and it is split into 5 sections. The eligibility to participate in the study includes diagnostic Radiographers registered with the Health Professional Council (HPCSA) as an independent practitioner or completing community service. Student Radiographers, Radiographers not registered with

HPCSA, Sonographers, Nuclear medicine therapists, and Radiation therapists are not eligible to participate in the study. Nonprobability purposive sampling was used, and the sample size for the study is 267 Radiographers across South Africa. You are entitled to discuss the study with your family and friends and are under no obligation to commit at this stage. For this purpose, I will give you a copy of the Letter of Information document.

Risks or Discomforts to the Participant: There are no risks or discomforts associated with participating in this study.

Explain to the participant the reasons he/she may withdraw from the Study: Participation is voluntary, and you may withdraw at any time, If you so wish to without any penalty. If you withdraw from the study kindly, please inform the researcher. There is no obligation to complete the study.

Benefits: The study's findings will help by providing unique recommendations that support the training of Radiographers by ensuring they are knowledgeable and their concerns are addressed. This is key to the optimal Integration of AI into medical Imaging.

Remuneration: There Is no remuneration for participating in this research study.

Costs of the Study: You do not need to pay anything to participate in this study.

Confidentiality: All information and data will be kept strictly confidential. All questionnaire responses will be kept under pseudonyms. The questionnaire responses' data will be kept on a computer that only the researcher has access to. The data will be kept for 5 years and deleted thereafter.

Results: the findings will be published in a DHET-accredited journal and or presented at a conference.

Research-related Injury: There will not be any in related to the study.

Storage of all electronic and hard copies including tape recordings: the questionnaire data will be stored in a password-protected computer which Is only accessible to the researcher. This will be stored for 5 years, thereafter It will be deleted from the computers hard drive.

Persons to contact in the Event of Any Problems or Queries: Please contact me, Miss Precious Mutambara, on 061 0672084, the researcher or my supervisor, Dr Thandokuhle Emmanuel Khoza, on 031 373 2509 or the Institutional Research Ethics Administrator on 031 373 2375. Complaints can be reported to the Acting Director: Research and Postgraduate Support on 031 373 2577 or researchdirector@dut.ac.za.

Appendix B: Consent



Full Title of the Study: Artificial Intelligence in Medical Imaging: Knowledge and Perspectives of South African Radiographers

Names of Researcher/s: Precious Mutambara

Statement of Agreement to Participate in the Research Study:

- ☐ I hereby confirm that I have been informed by the researcher, Precious Mutambara, about the nature, conduct, benefits, and risks of this study - Research Ethics Clearance Number: IREC 184/23
- ☐ I have also received, read, and understood the above written information (Participant Letter of Information) regarding the study.
- ☐ I am aware that the results of the study, including personal details regarding my sex, age, date of birth, initials, and diagnosis, will be anonymously processed into a study report.
- ☐ In view of the requirements of research, I agree that the data collected during this study can be processed in a computerized system by the researcher.
- ☐ I may, at any stage, without prejudice, withdraw my consent and participation in the study.
- ☐ I have had sufficient opportunity to ask questions and (of my own free will) declare myself prepared to participate in the study.
- ☐ I understand that significant new findings developed during the course of this research which may relate to my participation, will be made available to me.

Full Name of Participant **Date** **Time** **Signature** / **Right**

Thumbprint

I, _____ (name of researcher) Herewith confirm that the above participant has been fully informed about the nature, conduct and risks of the above study.

Full Name of Researcher Date Signature

Full Name of Witness (If applicable) Date Signature

Full Name of Legal Guardian (If applicable) Date Signature

Appendix C: Questionnaire

Please answer the following questions by selecting one option that best applies to you. You may only select one answer for each question, unless stated otherwise.

SECTION A: DEMOGRAPHICS

1. What gender were you assigned at birth?

Male	Female

2. Your age (years)

18- 24	25-34	35-44	45-54	55-64	65+

3. Are you registered with the HPCSA as a diagnostic Radiographer?

Yes	No

4. Are you practicing as a Radiographer in South Africa?

Yes	No

5. Which Province are you practicing as a Radiographer in South Africa?

Gauteng	KwaZulu-Natal	Free State	Northern Cape	Eastern Cape
Limpopo	Mpumalanga	North West	Western Cape	

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6. Which of the following imaging modalities do you use in your work? (Select all that apply)

6.1	General X-ray	
6.2	Computed Tomography	
6.3	Magnetic Resonance imaging	
6.4	Fluoroscopy	
6.5	Mammography	
6.6	Other	

7. What is your highest Radiography qualification?

Diploma	B-tech	Degree	Masters	PhD	Other (Please specify)

8. How many years of clinical experience do you have as a diagnostic Radiographer (including your community service year)?

Less than 5 years	5-< 10 years	10 -<20 years	20 -30 years	More than 30 years

9. In which sector are you employed?

Private	Government

10. What is the geographical setting of your workplace?

Urban	Rural

SECTION B: AWARENESS OF AI CONCEPTS AND APPLICATIONS

Determine your level of awareness and knowledge of the following concepts and applications:

	I have never heard of it	I have heard of it but know nothing about it	I have heard of it and know a bit about it	I have heard of it and know a lot about it
B1 Artificial intelligence (concept)				
B2 Machine learning (concept)				
B3 Computer aided detection (concept)				
B4 Deep learning (concept)				
B5 Automatic exposure control (concept)				
B6 Radiology smart assistance (application)				
B7 CT ceiling mounted 3D camera (Application)				
B8 Deep Resolve TM (Application)				
B9 True Fidelity TM (application)				

SECTION C: BENEFITS OF AI APPLICATION IN RADIOGRAPHY

1 Indicate your level of agreement that the following are benefits of integrating AI (computer systems which are capable of performing complex tasks commonly associated with human intelligence) into radiographic practices

	Strongly	Disagree	Slightly	Slightly agree	Agree	Strongly
C1.1 AI will make my job easier						
C1.2 AI will improve the workflow within the radiology department						
C1.3 AI will improve the quality of my work.						
C1.4 AI will allow me to fulfill my job-roles and responsibilities.						
C1.5 AI will lead to further opportunities related to the role extension of Radiographers						
C1.6 AI will have an overall positive impact on the Radiography profession						
C1.7 AI will improve quality assurance because of its efficiency in diagnosis						
C1.8 The integration of AI will reduce occupational stress amongst Radiographers in SA.						
C1.9 The integration of AI will reduce burn out amongst Radiographers in SA.						
C1.10 The integration of AI will reduce scan times						
C1.11 The integration of AI will improve image post-processing						
C1.12 The integration of AI will ensure diagnoses are accurate						
C1.13 The integration of AI will reduce radiation dose to patients						
C1.14 The integration of AI will improve general Radiography practice						

C1.15 The integration of AI will improve the clinical care of patients						
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2 Indicate your level of agreement that AI (computer systems which are capable of performing complex tasks commonly associated with human intelligence) would be beneficial when applied to the following clinical areas

	Strongly	Disagree	Slightly	Slightly agree	Agree	Strongly
C2.1 General x ray						
C2.2 Computed Tomography						
C2.3 Fluoroscopy						
C2.4 Magnetic Resonance imaging						
C2.5 Theatre Radiography						
C2.6 Interventional radiology						
C2.7 Mammography						
C2.8 Picture archiving system						
C2.9 Radiology information system						

SECTION D: Attitudes and perceptions of Radiographers towards AI

Attitudes

Indicate your level of agreement with the following statements:

	Strongly	Disagree	Slightly	Slightly agree	Agree	Strongly
D1.1 I am excited about the integration of AI within diagnostic Radiography.						

D1.2 I am willing to accept the changes that come with Artificial Intelligence.						
D1.3 I am well-prepared to work with imaging equipment that has Artificial intelligence (AI).						
D1.4 I believe imaging equipment that has Artificial Intelligence systems is easy to use.						
D1.5 I embrace AI as the future of medical imaging						
D1.6 I am willing to undergo further education and/or training to be able to embrace these emerging AI trends in medical imaging						
D1.7 I think it's important that radiology departments start planning for the integration of AI into medical imaging.						

Perceptions

Indicate your level of agreement with the following statements:

	Strongly	Disagree	Slightly	Slightly agree	Agree	Strongly
D2.1 Artificial intelligence will displace me from my job.						
D2.2 My salary could be reduced because of Artificial Intelligence						
D2.3 AI Systems are complicated to use.						
D2.4 AI models are at a high risk of data bias.						

D2.5 AI assisted decision making in untrustworthy and unreliable.						
D2.6 Qualified Radiographers are intelligent enough to make accurate decisions without the use of AI						
D2.7 AI Lacks transparency						
D2.8 AI will compromise patient privacy and security of data						
D2.9 AI will negatively affect the Radiography profession						

SECTION E Barriers to adopting AI in Radiography

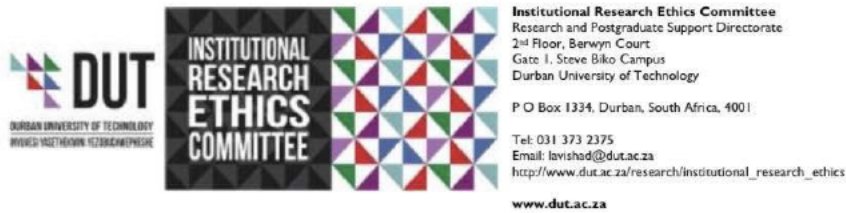
Indicate your level of agreement that the following are barriers or challenges in the application and implementation of AI in Radiography:

	Strongly	Disagree	Slightly	Slightly agree	Agree	Strongly
E1 Lack of dedicated courses or learning materials						
E2 Lack of financial resources to implement						
E3 Lack of Knowledge/awareness amongst Radiographers						
E4 Lack of motivation for change or interest to learn						
E5 Presence of data bias						
E6 Lack of time to learn new technologies						
E7 Fear of the unknown						
E8 Lack of trust with AI						
E9 High equipment cost						

E10 Fear of cyber threats						
E11 Fear of losing job						
E12 Possibility of losing core professional radiographic skills						
E13 Lack of necessary skills to perform equipment maintenance						
E14 High cost of maintaining AI equipment						

THANK YOU FOR YOUR TIME

Appendix D: Ethics Certificate



17 April 2024

Ms P Mutambara
51 Cherry
129 Loon Road
Sherwood
Durban

Dear Ms Mutambara

Artificial Intelligence in medical imaging: Knowledge and Perspectives of South African Radiographers

Ethics Clearance Number: IREC 184/23

The DUT-Institutional Research Ethics Committee acknowledges receipt of your notification regarding the piloting of your data collection tools.

Kindly ensure that participants used for the pilot study are not part of the main study.

Please note that **FULL APPROVAL** is granted to your research proposal. You may proceed with data collection.

Any adverse events [serious or minor] which occur in connection with this study and/or which may alter its ethical consideration must be reported to the DUT-IREC according to the DUT-IREC SOP's.

Please note that any deviations from the approved proposal require the approval of the DUT-IREC as outlined in the DUT-IREC SOP's.

It is compulsory for a student or researcher to apply for recertification on an annual basis. The failure to do so will result in withdrawal of ethics clearance. It is the responsibility of the researcher and the supervisor to apply for recertification.

Please note that you are required to submit a Notification of Completion of Study form together with an abstract to the DUT-IREC office on completion of your study.

Yours Sincerely

Prof J K Adam
Chairperson: DUT-IREC

Appendix E: Editor's Report

EDITING LETTER

696 Clare Road
Clare Estate
Durban
4091
6 April 2025

To: Whom it may concern

Editing of Dissertation: P Mutambara

ARTIFICIAL INTELLIGENCE IN MEDICAL IMAGING: KNOWLEDGE AND PERSPECTIVES OF SOUTH AFRICAN RADIOGRAPHERS

This letter serves as confirmation that the aforementioned dissertation has been language edited. The requisite grammatical conventions have been met/recommended. Suggestions have been made to the candidate where necessary.

Any queries may be directed to the author of this letter.

Regards

MP MATHEWS
Lecturer and Language Editor
Mercimathews4@gmail.com
083 676 4778

Appendix F: Statistics Confirmation Letter

Gill Hendry B.Sc. (Hons), M.Sc. (Wits), PhD (UKZN)
Mathematical and Statistical Services

Cell: 083 300 9896
Email: gillhendrystats@gmail.com

4 March 2026

Re: Statistical assistance

Please be advised that I assisted Precious Mutambara (Student number 21824465), who is currently studying for an MHSc: Diagnostic Radiography at the Durban University of Technology, with the questionnaire alignment and analysis of her data.

Yours sincerely

Dr Gill Hendry
Private Consulting Statistician

