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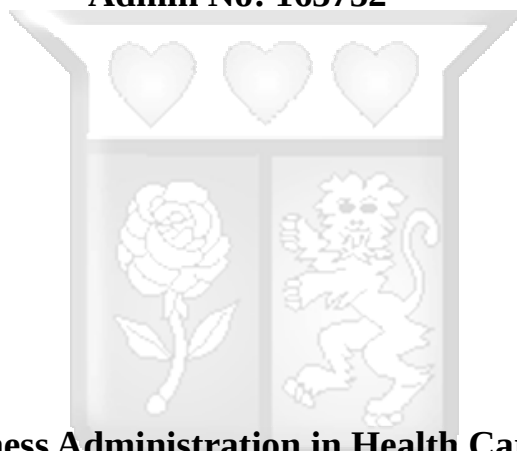
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# **Health Technology Assessment of Artificial Intelligence in Radiology Within Kenya; Multicriteria Decision Analysis**

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**Admin No: 165752**



**Master of Business Administration in Health Care Management**

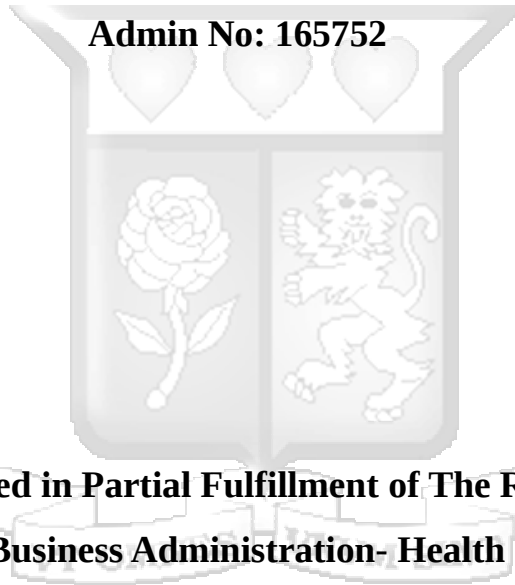


**2025**

**Health Technology Assessment of Artificial Intelligence in Radiology Within  
Kenya; Multicriteria Decision Analysis**

**Miriam Miima**

**Admin No: 165752**



**Dissertation Submitted in Partial Fulfillment of The Requirements for The  
Degree of Master of Business Administration- Health Care Management at  
Strathmore University**

**March, 2025**

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## ABSTRACT

Enhanced technology in healthcare improves patient outcomes, stream lines operations and enhances diagnostic capacity. Enhanced diagnostic capacity is fueled by advanced development and adoption of artificial intelligence (AI) solutions. Europe and North America have made bigger strides in the regulation and implementation of AI in radiology compared to Africa and Asia. AI technology can be developed locally or imported for implementation. Assessment of software as a medical device locally remains unclear which affects comprehensive standardization and articulation of its value proposition. This informs the need for a health technology assessment (HTA) tool for systemic appraisal of economic, social, ethical and clinical health care priorities in Kenya. Radiologists in America and Europe demonstrate that embedding user centered artificial intelligence in radiology improves efficiency and effectiveness in the radiology workflow. Few radiologists use AI in radiology within Kenya and more are willing to train artificial intelligence models despite multi factorial barriers. A normative assessment framework remains unclear in the design, development and clinical implementation of AI in radiology within Kenya. This study developed a health technology assessment (HTA) tool for AI in radiology using a hypothetical AI lesion detection software for pulmonary embolism (PE) on computed tomography pulmonary embolism (CTPA) images. The study evaluated AI in radiology using radiology multi-society practical considerations (MSC), the radiology AI deployment and assessment rubric (RADAR), and developed a local HTA tool for AI in radiology. Relevant institutional ethical permission was granted, data privacy and confidentiality was observed. The tool was piloted among 3 domain experts for construct and face validity, data was collected from 54 decision makers through online surveys and extracted into spreadsheets for analysis. This was an action research methodology on deductive themes analyzed using a multicriteria decision analysis (MCDA). Descriptive proportions were presented using categorical data where majority of the participants favored the third iteration of the tool. Inferential statistics analyzed using SPSSv25 confirmed intra class correlation coefficient using Cronbach  $\alpha > 0.7$  with significant reliability ( $p = 0.001$ ) for each deductive theme. Each item on the final HTA tool demonstrated statistical significance ( $p > 0.05$ ). Despite hypothetical application of the AI software, HTA tool provides a foundation for comprehensive evaluation of AI in radiology with good reliability. The HTA tool iteratively supports multicriteria decision making among strategic decision makers on AI in radiology against global standards.

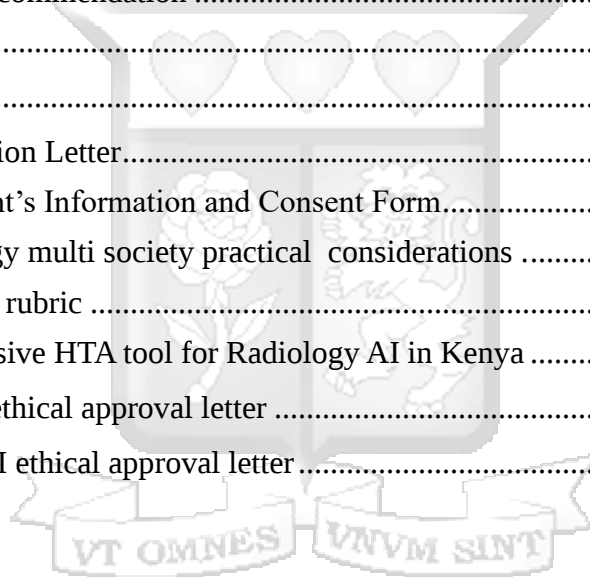
**Key words:** *Health technology assessment, Artificial Intelligence, Radiology, Multicriteria Decision Analysis*

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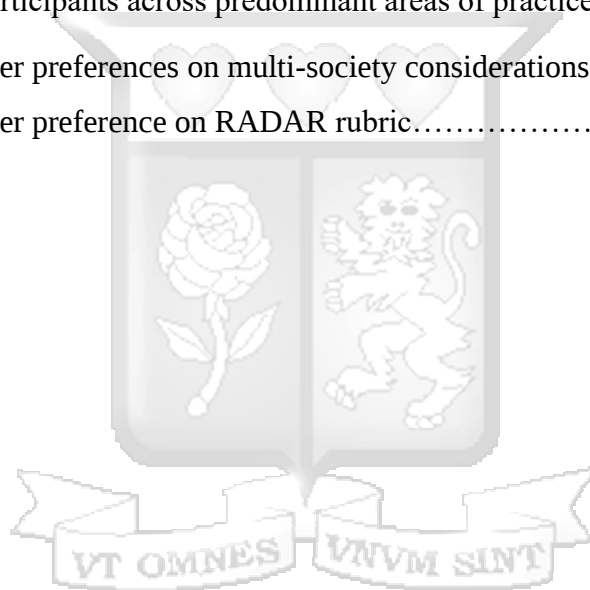
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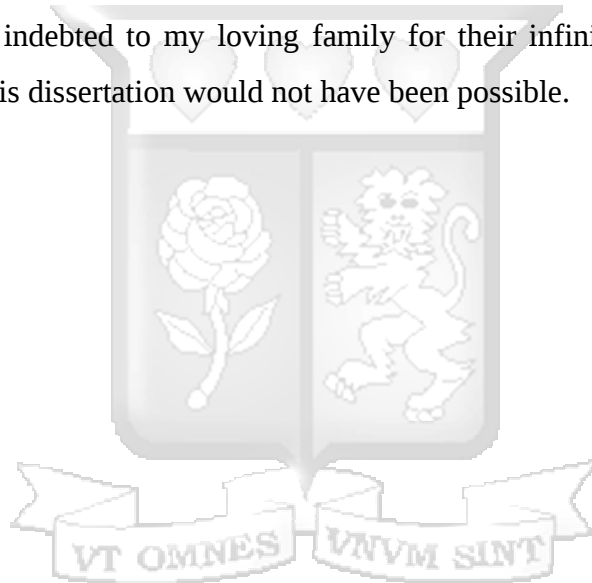


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## ABBREVIATIONS AND ACRONYMS

**AFCT:** Analysis Function Core Team-UK

**AI:** Artificial Intelligence

**BcT:** Block Chain Technology

**CTPA:** Computed Tomography Angiogram

**DICOM:** Digital Imaging and Communication in Medicine

**DL:** Deep Learning

**DLS:** Distributed Ledger System

**EHR:** Electronic Health Records

**Gen AI:** Generative Artificial Intelligence

**GoK:** Government of Kenya

**HTA:** Health Technology Assessment

**ICC:** Intra class Correlation Coefficient

**IoMT:** Internet of Medical Things

**ML:** Machine Learning

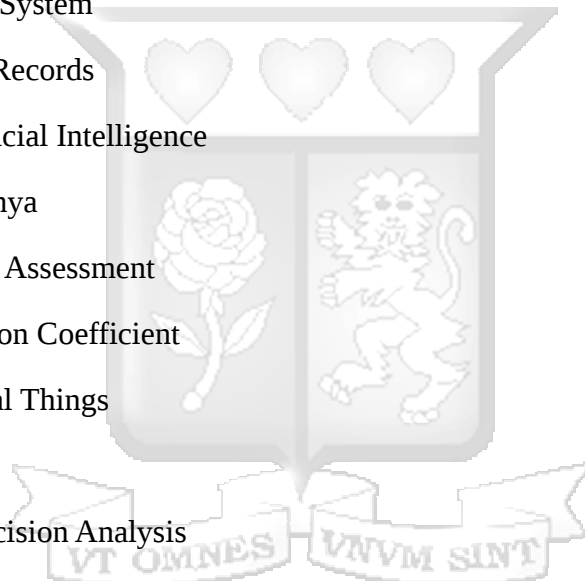
**MCDA:** Multicriteria Decision Analysis

**PACS:** Picture Archiving Communications System

**PAR:** Participatory Action Research

**PE:** Pulmonary Embolism

**WHO:** World Health Organization



## DEFINITION OF TERMS

**Artificial Intelligence:** Computational technology mimicking human intelligence. (Dwivedi, 2023).

**Computed Tomography Pulmonary Angiography:** A radiological imaging modality specifically used in the detection of Pulmonary Embolism (Nabrawi, 2023).

**Efficacy:** Ability to produce desired or intended effect (Boverhof, 2024).

**Health technology assessment:** systematic, evidence informed decision-making tool in the assessment of value proposition from health technologies (WHO W. H., 2023).

**Pulmonary Embolism:** A blood clot within the lung vascular bed (Kahn, 2022).

**Radiology workflow:** Used interchangeably with medical imaging workflow in highlighting the pre imaging, imaging and post imaging processes during medical imaging (Pierre, 2023).

**Radiologist:** Used interchangeably with medical radiologist in identifying medical doctors with specialization in diagnostic and/ or interventional medical imaging procedures (Najjar, 2023).

**Radiographer:** A trained healthcare professional typically certified or licensed to produce medical imaging (such as X-rays or CT scans) for diagnosis or screening (SORK, 2024).

**CT scan technician:** A medical radiographer who produces CT scans and manage CT scan machines (SORK, 2024)

# **CHAPTER 1**

## **INTRODUCTION TO THE STUDY**

### **1.1 Introduction of the chapter**

The chapter provides the background of the study, the problem statement, research objectives, significance of the study, scope of the study, limitations of the study and a summary of the chapter.

### **1.2 Background of the study**

Healthcare system building blocks coherently guide non-relational healthcare investments (WHO, 2010). Strategic investments in healthcare respond to complex, dynamic and uncertain health care systems (Huebner, 2022). These building blocks include leadership and governance, service delivery, information, health work force, healthcare financing, medical products/ vaccines and technologies. Healthcare systems have evolved across at least four civilizations over the past few decades (Ahsan, 2022). Healthcare 1.0 was largely limited to providing physical health services such as delivering babies naturally. Modern medicine in healthcare 2.0 added mechanical services like surgery and medical equipment to its repertoire and healthcare 3.0 elevated patient-centric health and healthcare system designs.

Currently, healthcare 4.0 is a data-driven ecosystem enabled by increased connectivity, device miniaturization, data and technological portability. This ecosystem is enacted through Internet of Medical Things (IoMT), cloud computing, big data analytics, cyber physical systems robotics, augmented reality, horizontal-vertical system integration, digital twinning, artificial intelligence (AI) and block chain technology (BcT) (Mwanza, 2023). Mwanza et al systemic review of healthcare 4.0 in Africa highlights its utility in healthcare system, while acknowledging that barriers to optimization are multifactorial. (Mwanza, 2023). They include meagre infrastructure, constrained funding and limited skills (Musa, 2023). This study will assess governance, service delivery, information and technology in understanding the landscape of the fourth industrial revolution in the Kenyan healthcare system.

### **1.2.1 Artificial intelligence technology**

Digitization in healthcare supports multiple and cross functional work flows. Automation and data generation alone does not increase efficiency in service delivery, unless data is mined, cleaned, processed, analyzed and visualized. Healthcare data analytics is a systemic statistical discovery of new information, knowledge management and acquisition of wisdom that drives critical decisions for effective management and improved healthcare delivery (Wan, 2020). Big data utilization therefore infuses a dynamic value proposition which sustains resilient agility when founded on a concrete data strategy (Lugerta, 2018; Muehlbauer, 2022).

Incipient strategic data management by Robert S. Ledley and Lee Browning established theoretical foundations on computerized clinical decision making, diagnosis and therapy after the Turing test in the 1950s (Masic I. , 2014; Najjar, 2023). Seven decades later, technological devolution is supported by, wireless communication, physiological sensor miniaturization, electronic medical records (EHR), connected data repositories and advanced big data analytics. Nascent conception of AI in the 1950s was designed to mimic human problem-solving skills through the logic theorist computer program (Anyoha, 2017; Dwivedi, 2023). In the 1980s, AI algorithmic scope evolved into expert systems modelled on Bayesian statistics and decision theory (Dwivedi, 2023).

AI simulates human intelligence using computational technologies (Dwivedi, 2023). Machine learning (ML) is a subclass of AI where decision making and predictions are automated by human trained AI models while deep learning (DL) is an enhanced subclass of ML that analyzes neural networks without human involvement (Dwivedi, 2023). AI in healthcare spans across at least three epochs (Howell, 2024). AI 1.0 symbolically encodes human knowledge into computational rules and probabilistic models, task specific AI 2.0 develops deep learning models for predictive AI, and transformative generative AI 3.0 multi tasks intrinsically with reinforced learning from old data sets. AI epochs frame the decision pivots for healthcare stakeholders and actors across the healthcare system.

### 1.2.2 Artificial intelligence in healthcare

The healthcare system burst of activities supporting a delicate omnichannel of medical and administrative operations. Omar et al in a systemic review of more than 1988 articles posits that AI is superior to humans in terms of accuracy, efficiency and timely execution of medical and related administrative processes (Ali O, 2023). AI technologies in healthcare parallel the definition of health in supporting promotive, preventive, diagnostic and rehabilitative health services; physically, socially and mentally (WHO, 2010; Ali O, 2023). Value-added AI in healthcare re engineers' creative IT service delivery models, supply chain management, clinical research, governance, finance, audit & quality management (Mwanza, 2023).

Practical and theoretical aspects of AI remain obscure when clinical translational and the contours of technological autonomy seem undefined in its application (Ali O, 2023). The AI strategy provides a roadmap on how AI initiatives deliver measurable value. Africa's AI strategy generically scopes the potential socio-economic transformation and cultural renaissance of the technology in Africa (AU, 2024). Kenya is in the process of drafting its own AI strategy which will comprehensively guide how the country harnesses the transformative power of AI ethically (MICDE, 2025). This anchors the policies, tools and framework that will support governance, practice, ethics and the quality of AI technologies in healthcare. The anticipated value of AI in Kenya will be to enhance quality and accessibility of healthcare across the country.

Ali et al proffers an analytical framework for AI in healthcare through four dimensions: Firstly, benefit to the people, the organization and the health care sector; secondly, challenges in data infrastructure, patient attributes and the legal framework; thirdly, methodologies in data and image processing; lastly, functionalities in the clinical ecosystem, patient ecosystem and the sectoral ecosystem (Ali O, 2023). The sectoral ecosystem cream skims AI in medical radiology as the most advance and promising application compared to other medical specialties such as clinical service delivery, biomedical engineering, surgical and interventional procedures. High quality data availability and visual pattern recognition confer standardized technical strengths to radiology compared to its peer medical specialties (Pierre, 2023; Yordanova, 2024).

### 1.2.3 Artificial intelligence in medical radiology

AI in radiology mimics human intelligence in task automation, rapid learning cycle and big data analytics. Radiology is the fastest growing healthcare specialty in AI innovation and adoption over the past decade (Yardanova, 2024). Literature review of AI in radiology estimates over 200 commercially available AI tools utilized in radiology. Interpretive AI in radiology is applied in lesion detection within the head-neck, heart-blood vessels, lungs, abdomen and musculoskeletal systems in the body (Yardanova, 2024). AI technology can be applied across various radiological imaging modalities including Ultrasound (US) scans, Computed Tomography (CT) scans, Xray scans, Magnetic Resonance Imaging (MRI) scans, nuclear imaging and hybrid scanners (Nabrawi, 2023; Yardanova, 2024).

Non interpretative AI tools do not detect body lesions instead they improve work flows, automate structured reports, assist in image protocoling and scheduling (Yardanova, 2024). Radiology Information System (RIS) is a computer-based system which manages the administrative and clinical workflow (Najjar, 2023). RIS supports the Picture Archiving and Communication System (PACS) as a computer based medical imaging technology which electronically stores, retrieves and displays medical image report from various modalities. Digital Imaging and Communication in Medicine (DICOM) is an international standard for storing, transmitting and communicating radiology related data (Fernandesa, 2022; Pierre, 2023).

Integration of RIS in the diagnostic workflow is more advanced in Europe and North America compared to Africa (Najjar, 2023; Pierre, 2023). Workflow integration is an enabler to AI utilization, as proxy indicator of robust data architecture, radiology infrastructure, advanced technology and skills (Mwanza, 2023). Africa is riddled with healthcare data poverty, meagre infrastructure and limited skills which undermine diffusion of AI in radiology (Kawooya, 2022; Musa, 2023). Kawooya et al contends that this can be circumvented through AI, research and collaboration (Kawooya, 2022). AI application in radiology within Kenya is observed at 12.6% in routine practice with 67.8% willingness to train AI models among radiologists (Mwaniki, 2023).

#### **1.2.4 Health Technology Assessment**

Health Technology Assessment (HTA) is a systematic, evidence informed decision-making tool in the adoption of affordable, relevant and cost-effective technologies (WHO W. H., 2023). HTA appraises healthcare priority setting on diagnostic tests, medical devices, medical procedures, medicines and population health interventions against clinical, ethical, economic or social factors. Embedding AI in radiology involves changes in the diagnostic workflow which directly affects business, clinical and operational pathways related to health care delivery. Integration of digital technologies in the healthcare system warrants structured appraisal of its value proposition and sustainability by strategic decision makers (Brady, 2024; Farah\*, 2024).

The strategic decision-making apex of AI implementation in radiology is made up of radiographers, radiologist, clinicians and health care managers, with governance support from policy makers and regulators, and knowledge management supported by academicians and researchers (Brady, 2024; Faric, 2024). Co creation of AI enabled radiology with strategic decision makers optimizes task technology fit framed on user centered design (Hua, 2024). Farah et al posits that valuable insights on responsible implementation and maximum benefits of AI technology can be defined using HTA frameworks (Farah\*, 2024).

HTA framework guides result comparability across different jurisdictions in policy, decision making and clinical practice (WHO W. H., 2023). A scoping review on the existing HTA frameworks by Farah et al highlights heterogeneity in AI evolution, data requirements, complexity, clinical validation, safety requirements, economic evaluation, regulatory and ethical considerations (Farah\*, 2024). Local adaptation is therefore encouraged in defining HTA expertise and contextualizing HTA iterations (Brady, 2024; Farah\*, 2024). There is paucity of local frameworks and tools for AI assessment in healthcare within Kenya (KEBS, 2024). The study proposes HTA of AI in radiology within Kenya informed by global standards and considerations (Brady, 2024; Boverhof, 2024; Farah\*, 2024).

### **1.2.5: Decision making in healthcare management**

The modern healthcare milieu is intricately intertwined with decision making processes in shaping the contours of excellence and value in healthcare delivery. Healthcare management increasingly operates in a volatile, uncertain, complex and ambiguous (VUCA) environment fueled by advanced technology, shifting labor dynamics, increase in healthcare options, sustainability actuation and a ballooning population (Ahsan, 2022). Transformative healthcare accelerates innovation and information overload which creates demand for cross functional competencies in decision making (Huebner, 2022). Strategic decision-making forms the bedrock of leadership and management in the governance of healthcare systems.

Decision making process in healthcare selects the best alternative based on the available information (Masic I. , 2022). Operational and tactical decision are typically structured while tactical and strategic decisions are typically unstructured (Huebner, 2022). Systems thinking addresses interconnectedness within the healthcare system and the need for multiple perspectives in strategic decision making (WHO, 2010; Huebner, 2022). Multicriteria decision analysis (MCDA) comprehensively guides a structured approach to decision making by systematically evaluating alternatives simultaneously (Gongora-Salazar, 2023). MCDA complements traditional HTA approaches which are limited in comprehensive analysis of multiple attributes and multiple stakeholders.

MCDA combines qualitative elements in exploring stakeholder perspectives and quantitative elements in articulating stakeholder preference and options (AFCT, 2024; Boverhof, 2024). This involves defining the decision problem, selecting the evaluation criteria, assessing the performance scores of each alternative on each criterion, determining the criteria weights, aggregating performance scores and criteria weights in the overall value, dealing with uncertainty, and deliberating over the findings. (Gongora-Salazar, 2023). Rationality in decision making and group decision making is facilitated by MCDA however psychological traps and intuition cannot be fully eliminated in the decision-making process (AFCT, 2024).

### 1.3 Problem statement

AI innovation in healthcare fuels disruptive tools and technologies at an exponential rate. The attributes of the technology vary from technological/ technical aspects, clinical effectiveness aspects, organizational/institutional aspects, user centered aspects, ethical/ safety aspects, economic and legal aspects (Kristensen, 2017). These multiple attributes favor innovative designs that jointly optimize social, technical and environmental subsystems for responsible and sustainable AI tools and technologies in health care (Kaplan, 2024; Hua, 2024).

Radiology augments clinical care and health system performance in medicine (Alowais, 2023; Hua, 2024; Yordanova, 2024). This is occasionally undermined by human errors, fragmented workflows and user training gaps (Nabrawi, 2023). Literature review on more than 200 AI tools in radiology demonstrate benefits in lesion detection on all imaging modalities while supporting diagnostic workflow and operational excellence. (Yordanova, 2024). Kenya navigates the benefits of AI in radiology through independent and collaborative initiatives. The process is however dysregulated, opaque and fragmented due to a dearth in clarity of its value proposition, since technology commonly outpaces regulation in healthcare (MICDE, 2025).

HTA supports generic evaluation and standardizations of software as a medical device (Farah\*, 2024). Positional statement from Asian Oceanian society of radiology on adoption and implementation of AI in radiology is limited to bioethical consideration. Multi society considerations (MSC) from radiologists in USA, Canada, Europe, Australia, and New Zealand propose practical considerations in the development, purchase, implementation and monitoring of AI tools in radiology (Brady, 2024). Boverhof et al propose the radiology AI deployment and assessment rubric (RADAR) for the valuation of radiology AI from conception to local implementation (Boverhof, 2024). Kenya needs its own framework aligned to the local AI strategy so as to impute its value attributes drawn from global considerations.

There is literature gap on comprehensive HTA considerations from Africa and Kenya on AI in radiology (Kawooya, 2022; Mwaniki, 2023). HTA is not a linear knowledge product, its heterogenicity draws perspectives from different stakeholders, technologies, people, processes and information. Rationale and group decision making summons multi criteria decision analysis in accommodating diverse stakeholder perspectives despite nuanced influences from psychological traps and intuition-based decision making (Martelli, 2016; AFCT, 2024). HTA standardization supports credibility, acceptance and comprehensive value assessment of AI in radiology among multiple decision makers, across multiple attributes, against global evidence (AFCT, 2024; Farah\*, 2024).



## **1.4 Research Objectives**

### **1.4.1 General Objective**

The general objective of the study was to develop a health technology assessment tool for artificial intelligence in radiology within Kenya.

### **1.4.2 Specific Objectives**

1. To assess artificial intelligence in radiology using radiology multi-society practical considerations.
2. To assess artificial intelligence in radiology using the radiology AI deployment and assessment rubric.
3. To evaluate health technology assessment of artificial intelligence in radiology through multicriteria decision analysis.

## **1.5 Research questions**

### **1.5.1 General research question**

Can a health technology assessment tool for artificial intelligence in radiology be developed in Kenya?

### **1.5.2. Specific research questions**

1. Can radiology multi society practical consideration assess artificial intelligence in radiology?
2. Can radiology AI deployment and assessment rubric assess artificial intelligence in radiology?
3. Can health technology assessment in artificial intelligence in radiology be evaluated using multicriteria decision analysis?

## **1.6 Significance of the Study**

Digital inclusion and knowledge management of AI in healthcare continues to lag behind in Sub Saharan Africa limiting its innovative potential. Technology commonly outpaces regulation hence the need for a structured appraisal on value proposition. Findings from this study will inform the adoption of AI as a medical device, co-created by strategic decision makers in the development and deployment of AI in radiology. This provides a foundation for responsible, ethical, equitable and sustainable AI investments in radiology within Kenya.

## **1.7 Scope of the study**

This study principally proposes a health technology assessment tool for AI in radiology within Kenya. The tool was primed by radiology multi society practical consideration and the radiology AI deployment and assessment rubric. The hypothetical application case was an AI enabled lesion detection software of pulmonary embolism on computed tomography pulmonary angiogram images. Geographically, the assessment was performed among Kenyan experts. Theoretically, this research was nested within the socio technical system theory supported by the Health Technology Assessment model 3.0. Methodologically, this was an action research designed to propose the development and implementation of a health technology assessment tool for AI in radiology among strategic decision makers through multicriteria decision analysis.

## **1.8 Limitations of the study**

The AI software was a hypothetical illustration of lesion detection software on radiology images. This widens the AI chasm in the adoption cycle when translating hypothetical illustrations to real illustrations. However, baseline research provides incipient market intelligence in the development and deployment of AI in radiology while de risking the capital requirements for full integration of AI in a standard radiology workflow.

## **1.9 Summary**

Healthcare data analytics supports data driven decisions. Complex and inefficient diagnostic workflows can be improved through AI in radiology. This is however complicated by information overload and rapid technological advancement of AI in radiology. Multi criteria decision analysis of health technology assessment by strategic decision makers improves rationality in group decision making process. This study proposes a standardized and credible HTA tool for AI in radiology within Kenya.

## CHAPTER 2

### LITERATURE REVIEW OF THE STUDY

#### 2.1 Introduction of the chapter

This chapter posits an anchor theory and the supportive model, it interrogates relevant literature and research gaps, operationalizes the research variables and the conceptual framework.

#### 2.2 Theoretical Review

This section fronts the socio technical systems theory supported by health technology assessment model 3.0 in HTA assessment of AI in radiology.

##### 2.2.1 Socio technical theory

Socio technical theory (STS) was developed in 1951 by Eric Trist and Fred Emery at the Tavistock Institute in London (Ropohl, 1999). STS highlights reciprocity in designing hybrid socio-technical systems (Feng, 2022). It operates in three sub-systems. Social; related to human factors, Technical; related to tools and skills, and Environmental; related to internal and external organizational context (Abbas, 2023). Socio technical design underscores the people and the technology in joint optimization, equifinality and multi-dimensionality in curating agile and innovative open system (Abbas, 2023).

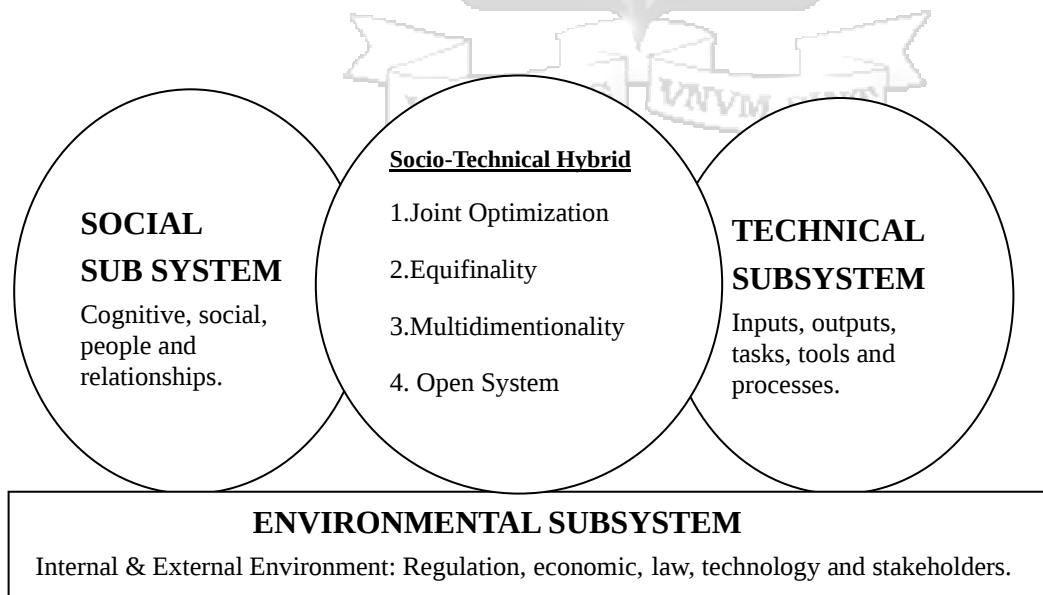


Figure 2.1 Social Technical Subsystems illustration (Source; Author, 2024)

STS focuses on the interactions between the people, the technology and the environment in expressing the socio-technical fit within the three subsystems. This study looks at the generic appraisal of AI attributes in radiology which favors STS as a generic theoretical anchor (Abbas, 2023). The diffusion of innovation theory interrogates how technology spreads informing user acceptance while STS actuates how innovation interacts with the system informing systemic design for successful implementation. (El Malouf, 2023; Abbas, 2023). Ethics, equity, cost and evaluation theories are also limited in scope based on the technological attributes the study is evaluating (Farah, 2023).

Despite its broad application, STS has been criticized on slow adaptation to technological change due to over emphasis on human centric design (Abbas, 2023). This flaw is more prominent in non-clinical AI technologies however, clinical AI favors AI-human augmentation as a safety valve to safe and ethical medical AI (Hua, 2024). Lack of clear implementation guidelines and difficulties in measuring clear outcomes stifles commitment to the Kenyan AI strategy and value translation in design, implementation and deployment of AI in radiology (Abbas, 2023; MICDE, 2025). This informs the need of a supportive model that clarifies implementation guidelines as well as measurable outcomes for AI in radiology i.e. HTA core model 3.0.

### **2.2.2: HTA Core Model 3.0**

HTA model was developed between 2006-2008 as an international framework for multi-dimensional value assessment of healthcare technologies (Kristensen, 2017). The model was developed by more than 70 institutions and can be applied globally within the international, national and local contexts. The model has undergone several iterations with the latest revision; HTA core model 3.0 supported by the European union. It commissions multidisciplinary, comprehensive or limited HTA, done either early or late in the lifespan of the technology. Value frameworks vary across healthcare pathways and decision makers, therefore standardization of structures and interventions across a shared repository communicates credible and contextualized global evidence while reducing duplicity.

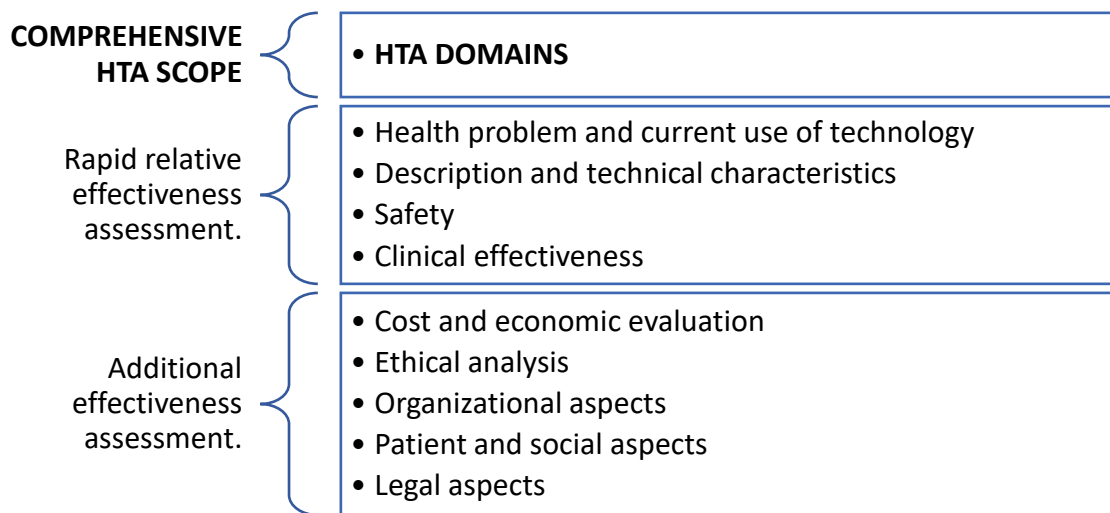


Figure 2.2: HTA core model domains and scope, Source: (Farah, 2023)

The generic model undergoes continuous revision which allows for flexibility responsive to user needs in domain scope, application and decision support systems. The model provides HTA domains for AI technologies which lack explicit reference (Ferizovik, 2022). Farah et al in a systemic review further posits lack of comparability in HTA evaluations for AI medical devices across jurisdictions calling for research on novel suitable approaches (Farah\*, 2024).

### 2.2.3 Application of the theory and the model

STS is founded on the concepts of; joint optimization based on the degree of fit in the social technical system, equifinality alluding to multiple successful design options of the system producing the same outcome, open system view alluding to reciprocity in the interaction between the environment and the organization/ institution and multi dimensionality predicating multiple perspectives in assessing the system which has multiple attribute as seen in the HTA core model domains 3.0 (Abbas, 2023; Farah, 2023).

HTA core models 3.0 provides a decision-making framework against patient attributes, organizational attributes, ethical/safety attributes, technical attributes, cost/economic attributes and healthcare rationale attributes. (Farah, 2023). Decision making analytical models provide a formal approach to the process for optimal decision making despite uncertainty (Martelli, 2016; AFCT, 2024). Multicriteria decision analysis (MCDA) reflects progression in decision and management science from the foundational principles of mathematical decision making in the 1940s to computational decision-making models in the 2000s (Masic I. , 2014; Gongora-Salazar, 2023). Four main blocks of activity in the MCDA processes are; to structure the problem, establish options and performance, elicit preferences of the decision stakeholders and review the input (AFCT, 2024).

This study explores multidimensionality as a concept within the social technical theory in the health technology assessment of AI in radiology. The assessment was statistically validated using multicriteria decision analysis of perspectives from strategic decision makers. Environmental subsystem factors were deduced from legal, cost and economic attributes. Technical subsystems were deduced from current use of the technological and technical characteristics. Social subsystems were deduced form patient and social attributes.

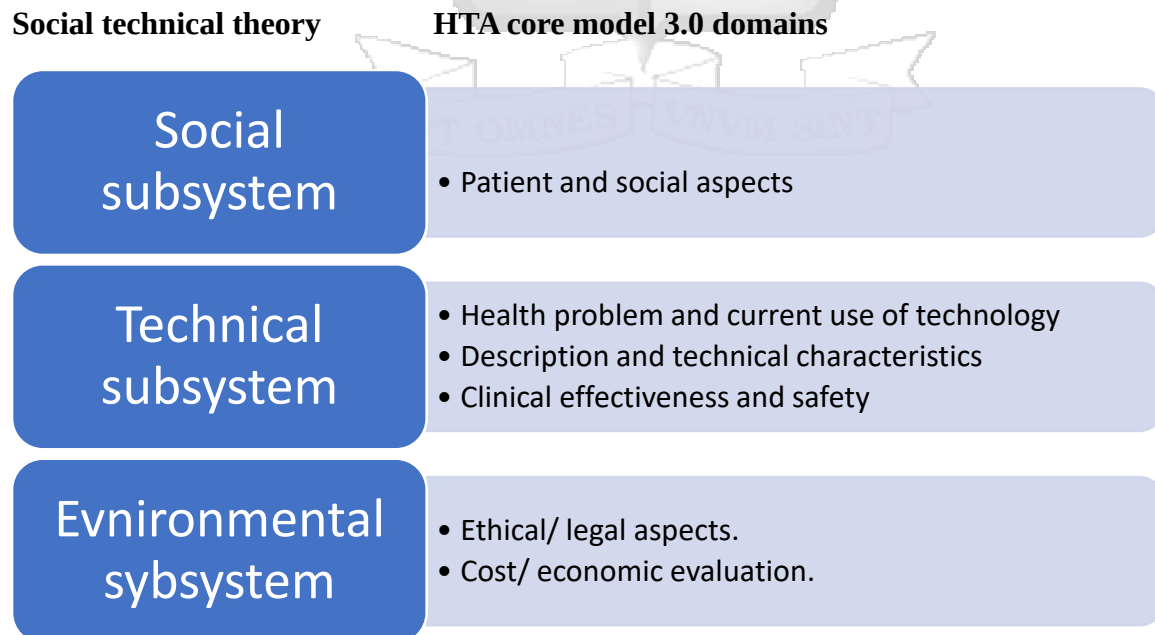


Figure 2.3: Interaction between STS subsystems and HTA domains (Source, Author 2024)

## 2.3 Empirical review

Evidentiary value of the objectives was assessed on radiology and AI in Kenya.

### 2.3.1 Radiology and AI in Kenya

Radiologists are consultative partners whose insights directly influence patient care. Multi society statement from radiologists globally put forward value-based radiology as a concept defining their value in healthcare (European Society of radiology, 2021). Radiology practice is transitioning from value defined in clinical, academic and financial productivity to patient outcome and societal benefit (European Society of radiology, 2021). This global position does not feature Africa and Asia. However, Wee et al focused on bioethical principles in value delivery within Asia (Wee, 2024) while Kawooya et al focused-on quality and safety in value delivery within Africa (Kawooya, 2022). They argue that patient centered value delivery remains a distant milestone unless stakeholder collaboration and ethical AI technologies are marshalled in closing the gap.

AI enabled radiology has been rigorously evaluated on diagnostic performance with little attention to comprehensive assessment before clinical translation (Cheikh, 2022; Kahraman, 2023; Ul Islam, 2024). Incipient studies in assessment of AI in healthcare are quite heterogenous advocating for local adaptation given contextual variations (Boverhof, 2024; Brady, 2024; Farah\*, 2024). Maturity of AI in radiology is at best in the exploratory phase in development, regulation, assessment and clinical application within Kenya (Mwaniki, 2023; Castonguay, 2024). Decision makers in the implementation of patient centered radiology within Kenya are commonly radiologist, radiographers, clinical care providers and healthcare managers.

Kenya is finalizing on its AI strategy (MICDE, 2025), the strategy is supported by the Health Act 2017 (GoK\*, 2022) Data Protection Act of 2019 (GoK`, 2019) and the Digital Health Act of 2023 (GoK', 2023) in regulating health technologies and digital health services in Kenya. Software as a Medical Device (SaMD) is registered and licensed by the Kenya Pharmacy and Poisons Board provisioned by the Pharmacy and Poisons Act 244 (GoK., 2012) with governance on AI code of practice by the Kenya Bureau of Standards (KEBS, 2024). Despite significant exploration on SaMD in radiology locally, there is a gap in published reports regarding comprehensive HTA frameworks on AI and AI radiology within Kenya.

### **2.3. Radiology multi society practical considerations on AI (MSC)**

Organizational readiness and impact of AI can be measured in terms of stakeholder acceptance, organization alignment and financial business plan (Farah\*, 2024). Brady et al give a multisociety account on practical considerations during development, purchase, implementation and monitoring of AI tools in Radiology (Brady, 2024). The multi-society representatives drawn from the American College of Radiology (ACR), Canadian Association of Radiologists (CAR), European Society of Radiology (ESR), Royal Australian and New Zealand College of Radiologists (RANZCR), and Radiological Society of North America (RSNA) define user considerations when appraising AI value in clinical practise and regulation.

Regulator conformity does not guarantee successful implementation of AI into the workflow. The intended use, benefit , risk and cost of AI form baseline considerations in justifying AI adoption in radiology (Farah, 2023). These considerations form strategic objectives aligned to the expected institutional performance. Performance can be linked to cost reduction, innovation, quality & safety, or competitive advantage (Brady, 2024). Specific objectives reduce ambiguity in measurement while safeguarding explainability and deployment (Abbasian, 2024). These objectives inform software costs, vendor compatibility and digital adaptation kits. Software performance and bias are the biggest direct risk to clinical effectiveness. This can be cured by radiologist led AI augmentation, provided that deskilling is prophylactically addressed (Brady, 2024).

Domain experts in radiology practise are the bioethical gatekeepers, AI model validation yardsticks and detectors of model drift in the software development cycle (Brady, 2024). Medical ethics based on non maleficence, beneficence, justice and autonomy sign post universal bioethical principles in healthcare (Brady, 2024). User behavior, attitude and intention should therefore be incooperated in the design and development on AI as enablers and barriers to diffusion of AI in radiology (Hua, 2024; Kaplan, 2024). Adoption apathy, increased error rates and lack of trust are un intended consequences of user dissatisfaction with AI design (Farah, 2023).

### **2.3.4 Radiology AI deployment and assessment (RADAR) rubric**

Radiology AI deployment Assessment Rubric (RADAR) is an adaptation of Fryback and Thornbury's imaging efficacy framework designed to evaluate contribution of diagnostic imaging to a patient management process (Fryback, 1991). RADAR progresses through seven hierarchical levels of efficacy, each step forming a rate limiting step to the next (Boverhof, 2024). The rubric attributes include; RADAR-1 technical efficacy, RADAR-2 diagnostic accuracy efficacy, RADAR -3 diagnostic thinking, RADAR-4 therapeutic process, RADAR-5 actual patient outcomes, RADAR-6 cost effectiveness efficacy and RADAR -7 local efficacy. RADAR 1& 2 are foundational measures which predominantly assess clinical implementation. Radar 3,4 & 5 zone in on actual patient outcomes and RADAR 6 &7 assess technological socio-economic factors.

RADAR1-5 measures clinical value without temporal specification i.e. prospective clinical solutions vis retrospective proof of concept. Valuation methodology can be cohort, cross sectional, randomized control trial or virtual trials, based on the priority in the valuation and tradeoffs in appraisal of the software (Boverhof, 2024). This was a prospective evaluation of a hypothetical AI lesion detection software. It taps into the rubrics dynamic design to meet diverse needs throughout the model's lifecycle.

RADAR 6 &7 evaluates AI model beyond clinical value. Health economic evaluations inform the financial feasibility of AI in medical imaging which is generally scarce. Cost analysis measures the cost of AI against clinical outcomes (Boverhof, 2024). Budget impact analysis contextualizes local budgetary constraints and population composition in discerning affordability and sustainability of AI in radiology (Boverhof, 2024; Farah\*, 2024). Multi criteria decision analysis weighted against contextual priorities provides rationality in optimizing socio technical fit informed by propositions from strategic decision makers.

## 2.4 Research gaps

The following section outlines the knowledge, contextual and methodological gaps filled by the research objectives. The gaps were derived from three main studies in health technology assessment of AI in radiology

Table 2.1: Research gaps (Source: Author, 2024)

| Authors                                                                                          | Title                                                                                                                                          | Findings                                                                                                                                                        | Research gap                                                                                           |
|--------------------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------|
| Brady, A.P., Allen B., Chong J., Kotter E., Kottler N., Mongan J et al (2024)                    | Developing, Purchasing, Implementing and Monitoring AI tools in radiology                                                                      | Radiologists' multi-society practical considerations during development, purchase, implementation and monitoring of AI tools in Radiology<br><br>Expert opinion | Contextual, knowledge and methodological gap on considerations for HTA of AI in radiology              |
| Boverhof, B-J., Redekop W.K., Bos D., Starman M.P.A., Birch J., Rockall A and Visser J.J. (2024) | Radiology AI Deployment and Assessment Rubric (RADAR) to bring value-based AI into radiology practice                                          | Valuation of AI in radiology from conception to local implementation                                                                                            | Contextual, knowledge methodological gap on HTA on AI in radiology                                     |
| Farah, L., Bourgete I., Martelli A and Vallee N (2024)                                           | Suitability of the Current Health Technology Assessment of Innovative Artificial Intelligence-Based Medical Devices: Scoping Literature Review | A comprehensive adapted HTA framework for AI-based medical devices can guides on responsible of AI                                                              | Contextual, knowledge, methodological gap on HTA assessment of AI in radiology using HTA core domains. |

## 2.5 Conceptual Framework

The conceptual framework is a conjecture model for assessment of AI in radiology before implementation.

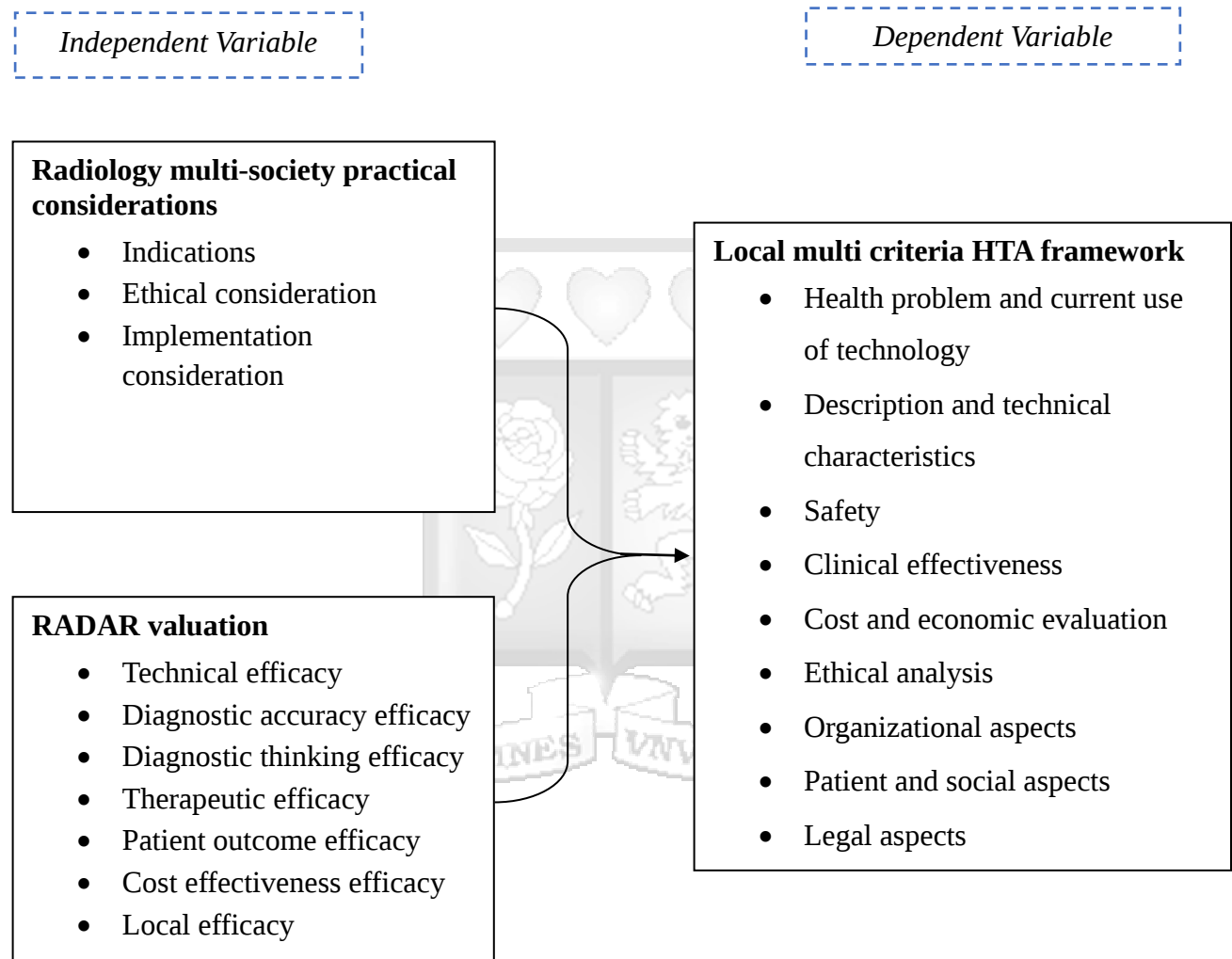


Figure 2.3: Conceptual framework (Source: Author, 2024)

## 2.6 Operationalization of variables

Variables under study were measured as indicated in table 2.2 against the specific objectives.

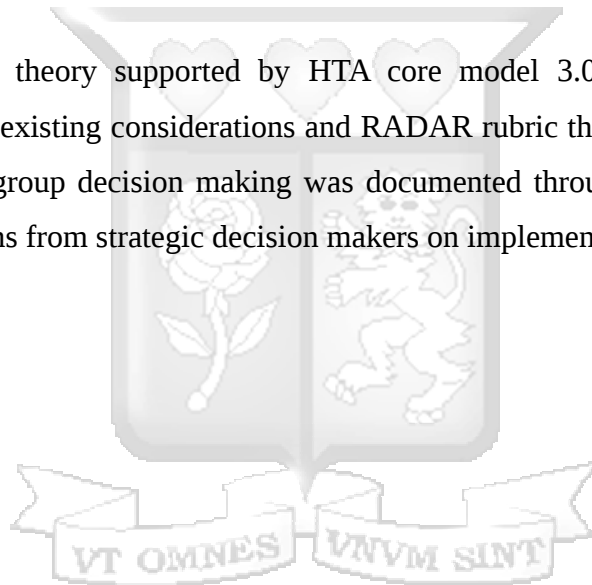
Table 2.2: Operationalization of variables (Source: Author,2024)

| Measurement                                                               | Variables                                                                                                                                                                                                                                                  | Data Collection Instrument | Citation                           |
|---------------------------------------------------------------------------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|----------------------------|------------------------------------|
| <b>Objective 1:</b><br>Radiology multi-society practical considerations   | Indications<br>Ethical consideration<br>Implementation consideration                                                                                                                                                                                       | Check list                 | (Brady, 2024)                      |
| <b>Objective 2: RADAR rubric</b>                                          | Technical efficacy<br>Diagnostic accuracy efficacy<br>Diagnostic thinking efficacy<br>Therapeutic efficacy<br>Patient outcome efficacy<br>Cost effectiveness efficacy<br>Local efficacy                                                                    | Check list                 | (Boverhof, 2024)                   |
| <b>Objective 3: HTA core domains 3.0 multi criteria decision analysis</b> | Health problem and current use of technology<br>Description and technical characteristics<br>Safety<br>Clinical effectiveness<br>Cost and economic evaluation<br>Ethical analysis<br>Organizational aspects<br>Patient and social aspects<br>Legal aspects | Work book sheets           | (Martelli, 2016; Kristensen, 2017) |

Independent variables were derived from the multi society considerations and the RADAR rubric while dependent variables were derived from the HTA core domains 3.0 (Boverhof, 2024; Brady, 2024; Farah\*, 2024). Deductive thematic measurements were calibrated against a 3 Likert ordinal scale. Participants were asked to score perceived indications, bioethical consideration and implementation considerations (Appendix III). The RADAR valuation tool was evaluated against technical efficacy, diagnostic accuracy efficacy, diagnostic thinking efficacy, therapeutic efficacy, patient outcome efficacy, cost effectiveness efficacy, local efficacy (Appendix IV).

## 2.7 Summary

Socio technical systems theory supported by HTA core model 3.0 proposed a local HTA framework derived from existing considerations and RADAR rubric through contributory action research. Rationality in group decision making was documented through multicriteria decision analysis of expert opinions from strategic decision makers on implementation of AI in radiology.



## **CHAPTER 3**

### **RESEARCH METHODOLOGY**

#### **3.1 Introduction to the chapter**

This chapter describes the research philosophy, research paradigm, research design, sample size, sampling, data collection methods, data analysis and ethical considerations of the study.

#### **3.2 Research Philosophy**

The research philosophy fronted a set of basic beliefs which guided the design and execution of the study in addressing knowledge creation. It grounded the research strategy since the research process was based on assumptions. The study applied both the positivism philosophical approach and the social constructivism philosophy. The positivism philosophical approach assumed objectivity in dissociating personal values from the research process using deductive themes for the study. The social constructivism philosophy assumed that reality constructs were influenced by social interactions through decision making based on expert opinions (Dawadi, 2021; Saunders, 2023). Both philosophies allowed for joint optimization in proposing a HTA tool for AI in radiology within Kenya.

#### **3.3 Research paradigm**

The research paradigm fronts the authors assumption's in conducting research. Three pillars of the research paradigms were explored (Dawadi, 2021; Saunders, 2023). Ontologically the research explored multiple realities where co creation of the tool had inputs from decision makers as well as established frameworks of reference. Epistemologically knowledge and reality validation were underpinned on deductive themes, rationale decision analysis and inferential statistical validation. The axiology pillar was defined by ethical principles and guidelines as stipulated by ethical research committee and practiced by the researcher/research team. Validity, reliability, and ethical principles were employed in safeguarding research quality, objectivity and ethics.

### **3.4 Research design**

The research design outlined a framework through which the researcher gathered & presented research findings. This was action research which transformed abstract thoughts from rhetoric into practical application through knowledge co creation iteratively (Shani, 2019). Action research suitably provides a research strategy in designing agile and sustainable systems for rapidly changing and emerging technologies in strategic healthcare management (Saunders, 2023).

Major activities in the action research cycle included; planning the action, taking action, evaluating the action and adopting or rejecting the action (Saunders, 2023). This study proposes a HTA tool for AI in radiology, using deductive themes from the radiology professional multi society considerations and the RADAR rubric (Boverhof, 2024; Brady, 2024). Domain experts and decision makers iteratively proposed an assessment tool anchored on the HTA core model 3.0 which provides a global reference framework (Farah\*, 2024).

### **3.5 Target population**

The target population focused on medical doctors and radiographers with one or more roles in the healthcare system. They inform strategic decision on AI in radiology as radiologist/radiographers, healthcare managers/clinical providers. The study invited expert opinions from digital health experts, healthcare policy makers and participants in healthcare academia and research. HTA in radiology and implementation of AI in radiology is a relatively new and evolving concept hence the target population is expected to be small. A proxy indicator study by Mwaniki et al among radiologists indicated that almost 40% are not willing to integrate AI in Radiology with concerns on job security (Mwaniki, 2023).

### **3.6 Sample size and sampling procedure**

Action research explores interorganizational dynamics expressed through appreciative inquiry and collaborative management research. Quality of the relationships depicting richness and impact informed a purposive multi stage sampling of approach guided by stakeholder representation and thematic saturation (Shani, 2019). Three domain experts recruited from the Kenya Association of Radiologist (KAR), the Society of Radiographers in Kenya (SORK), the Kenya Medical Practitioners and Dentist Council (KMPDC) and the Non-Clinical Doctors (NCD) group were invited to validate the tool.

The tool iterations were shared with strategic decision makers through professional on-line platforms. Data was collected from 54 respondents which fulfilled the proposed statistical validation of the respondents qualitatively. (Rahimi, 2024). Quantitative validation of the data through parametric tests was also feasible since the central limit theorem of 30 respondents was exceeded (White, 2023).

### **3.7 Eligibility criteria**

#### **3.7.1 Inclusion criteria**

- Medical doctors in clinical practice e.g. radiologists, generalists and specialists
- Medical doctors in non-clinical practice e.g. digital health practitioners, policy makers, healthcare managers and academic/ research practitioners
- Radiographers in clinical and non-clinical practice.
- CT scan technicians

#### **3.7.2 Exclusion criteria**

- Non-English-speaking participants
- Participants not familiar with the CT scan radiology diagnostic workflow.

### 3.7 Data Collection

Permission was sought from both the Strathmore University Ethical Research Committee (SU-SERC) and the National Commission for Science Technology and Innovation (NACOSTI). Written informed consent was also sought from all the respondents (Appendix I &II). Data was collected electronically between July, 24 and September, 24. The original tool developed by the researcher was validated by three domain experts (DE); a radiographer, a radiologist and a health care manager who is also a medical doctor with more than five years of experience in clinical practice.

The DE were practicing actively in tertiary facilities with infrastructure and capacity to detect pulmonary embolism on CT scan images. They filled a check list derived from the Multi society practical considerations and RADAR rubric (Appendix III). The 1<sup>st</sup> iteration was done within one week in July, 24 by the three DE. 2<sup>nd</sup> iteration was done within 1 week in July, 24 by the three DE and final questionnaire was filled between August and September, 24 by the fifty-four decision makers (DM). The link was closed on 3<sup>rd</sup> Oct, 24. Data completion, validity and iterations were confirmed by the researcher and mined on to spreadsheet for analysis.

### 3.8 Data Analysis

Descriptive analytics were presented as proportions and visualized as bar graphs, radar charts and pie charts. The first three iterations were done through sequential elimination and multicriteria decision analysis (MCDA). MCDA complements HTA in making structured and transparent decisions (Martelli, 2016) through a series of steps in figure 3.1 (Gongora-Salazar, 2023).



Figure 3.1: Steps in multicriteria decision analysis (Source: Researcher, 2024)

The problem was to decide on the HTA items. The evaluation criteria were provided by the multi society considerations and the RADAR rubric. Criteria weights were assigned based on expert opinion from decision makers with direct rating of the scores against a 3 Likert ordinal scale.

Parameter uncertainty was addressed through statistical validation of final tool on SPSS v25 and deliberations presented as the final HTA tool.

### **3.8 Research quality**

Reliability and validity of research cleped as the scientific canons of inquiry by Saunders, are central to credibility in research (Saunders, 2023). The quality and integrity of the study will be safeguarded through measures of validity and reliability in developing objective metrics of the study as follows.

#### **3.8.1 Measures of reliability**

Reliability appraises consistency (Saunders, 2023). Stakeholder validation may not allow for result generalization however the tool allows for contextual validation in low resource set up where AI in radiology is at the exploratory phase and HTA tools are not explicit. Psychological traps and intuition were partly addressed using deductive themes which are objective. Deductive themes were statistically validated using the Cronbach alpha intraclass correlation co efficient which ranges between 0-1, where acceptable reliability is represented by  $\alpha > 0.7$  (Ranganathan, 2024).

#### **3.8.2 Measures of Validity**

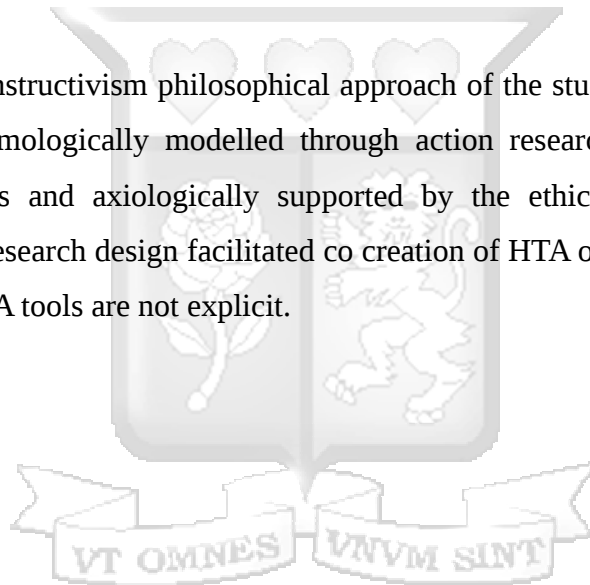
Validity appropriates measures of generalizability; it appraises data relevance and accuracy. Internal validity checks on reproducibility/credibility of the study while external validity checks on generalizability of the study (Saunders, 2023). The tool was initially validated among the three domain experts for face, content, construct and criterion validity. Threats to internal validity of the tool were addressed through iterations of the tool using action research. Construct and criterion validity were reinforced in further iterations and statistical validation of the local HTA tool (Ranganathan, 2024).

### 3.9 Ethical Considerations

The main ethical issues in the study revolved around data handling, transfer, privacy and data protection. Ethical principles were applied by ensuring academic and scientific soundness of the research. The study was approved by the Strathmore Scientific Ethical Review Committee (SU-ISERC) ref no. SU-ISERC2327/24 and NACOSTI license no: NACOSTI/P/24/38065. Written informed consent from participants was sought and participants freely opted out without any consequence. (Appendix I&II) Data was de - identified after mining and confidentiality was enforced through rights control and password protected spread sheets.

### 3.10 Summary

Positivism and social constructivism philosophical approach of the study ontologically explored multiple realities, epistemologically modelled through action research, analyzed using multi decision criteria analysis and axiologically supported by the ethical review and statistical validation process. The research design facilitated co creation of HTA of AI in radiology in a low resource setup where HTA tools are not explicit.



## CHAPTER 4

### PRESENTATION OF RESEARCH FINDINGS

#### 4.1 Introduction to the chapter

This chapter describes participants in the study, iterations on the tools and proposes the final tool.

##### Participants profile

Fifty-four medical doctors and radiographers participated in the study representing decision makers on the implementation of AI in radiology. Most participants had practiced for more than 10 years however most radiologists and radiographers had been practitioners for less than 10 years as demonstrated in Figure 4.1 below.

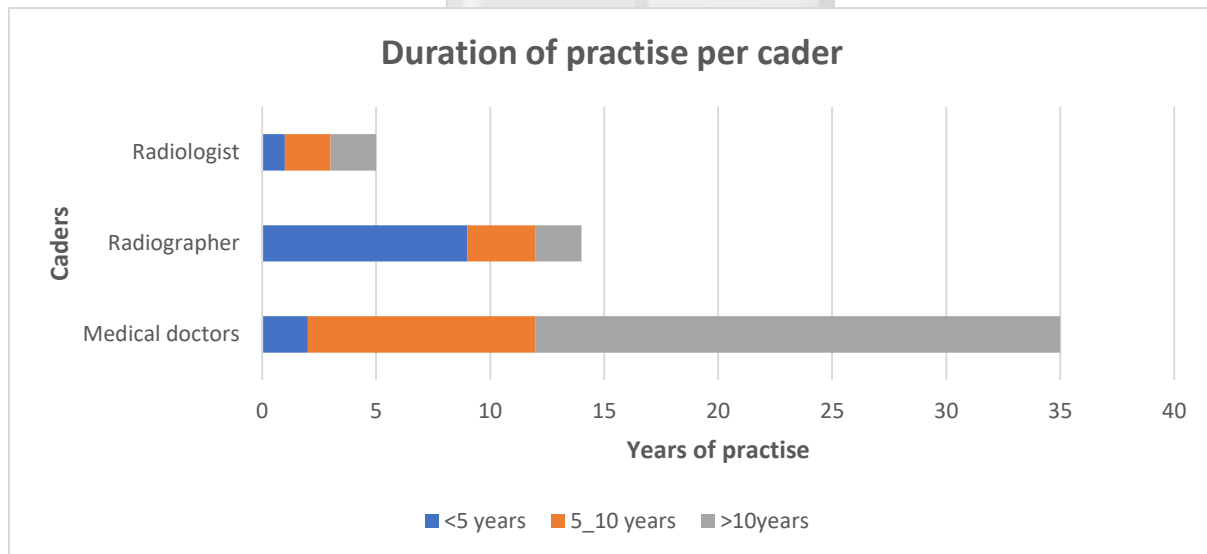


Figure 4.1: Frequency of practice duration among medical doctors and radiographers.

(Source: Researcher, 2024)

Radiographers use AI in radiology more frequently than radiologist as shown in figure 4.2. There was no inquiry on the use of AI in radiology among the other cadres since the hypothetical use case was an explicit radiological competence reserved for radiologists and radiographers.

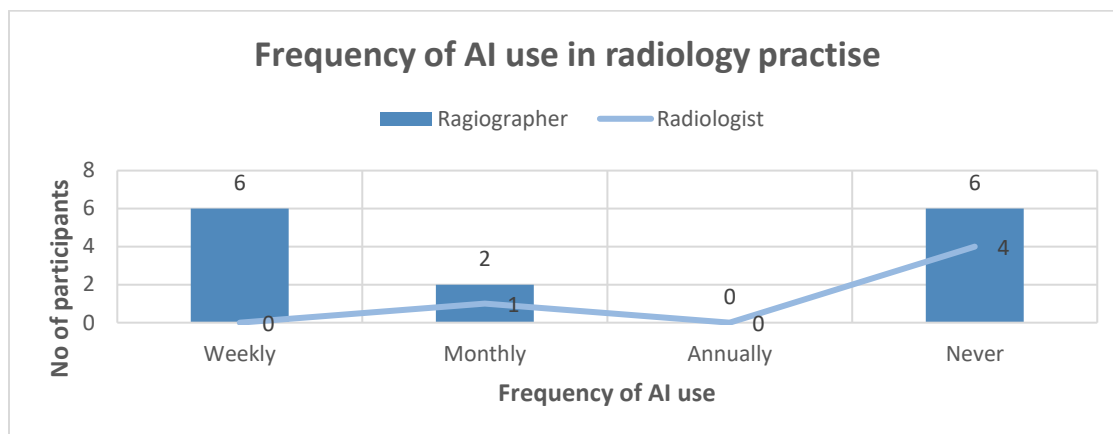


Figure 4.2 Frequency of AI use in radiology (Source: Researcher, 2024)

All participants were either medical doctors or radiographers with additional predominant practice in policy/regulation, digital health, academics/research or administration/management. Digital health, policy/regulation practitioners were least represented compared to the other cadres as shown in figure 4.3

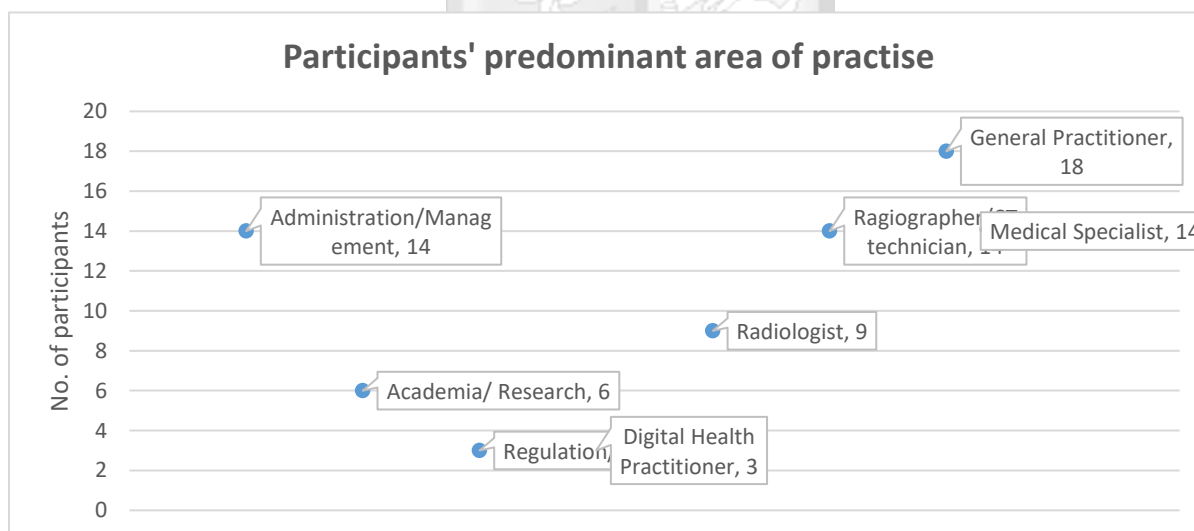


Figure 4.3: Number of participants across predominant areas of practice (Source: Author, 2024)

### **4.3 Stakeholder preference iterations**

Stakeholder preference was defined by three domain experts (DE). DE were requested to rank 66 items on the original tool as high (to retain the item in the next iteration), moderate (items can be retained or removed in the next iteration) or low (item should be removed in the next iteration). (Appendix III & IV). Agreement to retain any item in the subsequent iteration was defined by DE consensus in the ranking across each item. DE expressed that the hypothetical AI application is of moderate to high complexity and recommended a 3 Likert scale for ease of use as opposed to 5 or 7 Likert scales.

The first iteration demonstrated an interrater agreement of 0.94 where 26 items were removed and three items with similar constructs were merged by DE. Considerations on long term stability of the model and human AI interaction had the highest dissent. DE felt AI is rapidly evolving and long-term plans will be obsolete. The amended tool was shared once more with the DE for the second iteration and an inter-rater agreement of 0.98 was demonstrated where 1 item was removed (Appendix V).

### **4.4 Multicriteria decision analysis**

Multicriteria decision analysis (MCDA) was applied on the third iteration of stakeholder preference among 54 decision makers (DM). The decision problem was to validate multi society considerations and the RADAR rubric which forms the evaluation criteria. Performance was scored against a 3 Likert scale where decision maker preference was scored as high, moderate or low for each item.

Multi society considerations as an evaluation criterion was ranked by decision makers against an ordinal scale. Majority of the DM preferred items from the third iteration. The highest indication for AI was clinical benefit (47;87%) and clinical risk management (46;85%). Fairness (33;61%) had the least consideration as a bioethical principle and DM considered peer recommendation moderately (22;41%) in the implementation of AI I radiology.

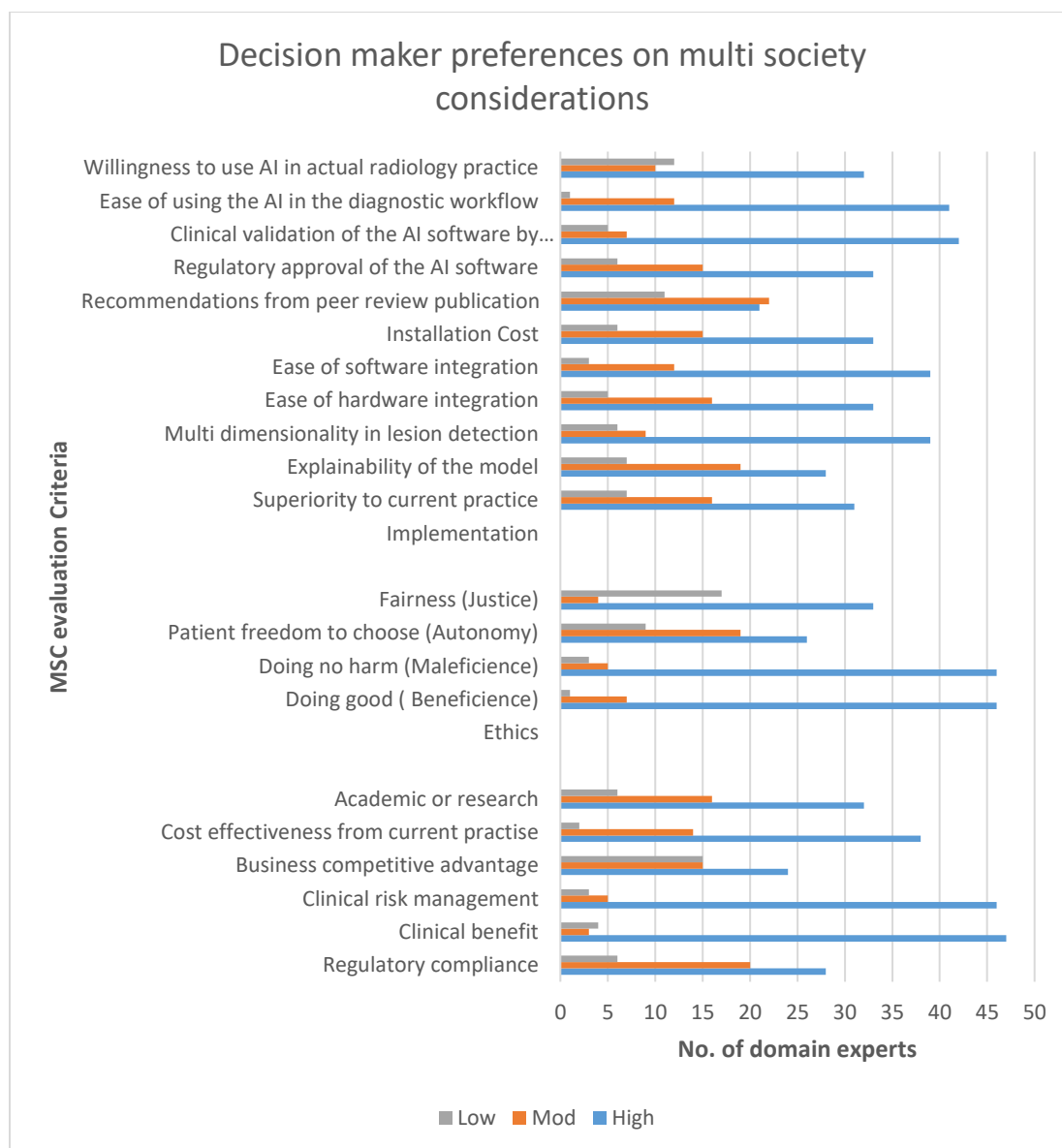


Figure 4.4: Decision maker preferences on multi-society considerations (Source: Author, 24)

Evaluation criteria proposed by the RADAR rubric was also ranked by decision makers against an ordinal scale and majority of the decision makers ranked the items as high (Figure 4.5). The highest DM preference was on explainability of the results as a technical capacity (45;83%), ability to detect lesion as a diagnostic capacity (43;80%), and impact on patient outcomes as a contribution to patient management (41;76%). Most DEs assigned moderate scores to usefulness of AI results (21;39%) and actionable insights from AI results (22;41%). Affordability of AI implementation was least ranked on cost effectiveness of AI implementation (14;26%).

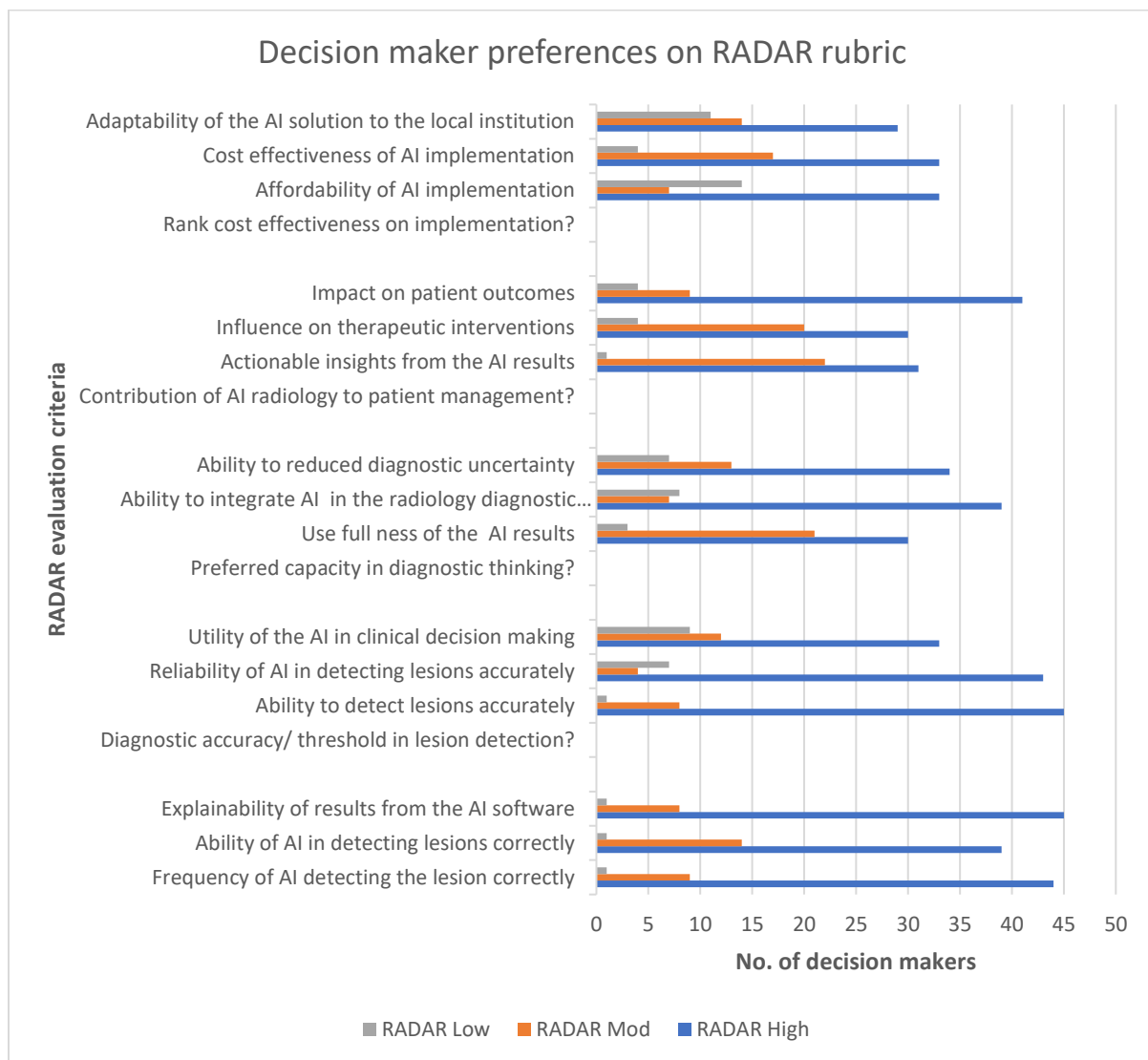


Figure 4.5: Decision maker preference on RADAR rubric (Source: Author, 2024)

The performance of each alternative criterion was weighted on a 3 Likert scale tool with overall performance shown in figure 4.4 and figure 4.5. Deductive themes/ items on the tools were not aggregated to preserve the construct of the items so that no item is lost in translation.

## 4.5 Reliability of the tool

Intra-class correlation coefficient (ICC) was calculated on SPSS v25 using Cronbach alpha for MSC and RADAR rubric showing a significant ( $p < 0.001$ ) acceptable reliability  $> 0.7$  with good agreement for most deductive themes/ domains. “Indication” in MSC had the lowest ICC (.64; 95%CI=.46-.77) with questionable reliability. F test comparing two variances was also lowest on indication  $F(53, 212) = 2.76$ ,  $p = 0.0000$  rejecting the null hypothesis which assumed no difference between the three MSC domains as shown in table 4.1.

Table 4.1: ICC for MSC deductive themes (Source: Author, 2024)

| MSC domains    | Intraclass Correlation | 95% Confidence interval |             | F Test with True Value 0 |     |     |          |
|----------------|------------------------|-------------------------|-------------|--------------------------|-----|-----|----------|
|                |                        | Lower Limit             | Upper Limit | Value                    | df1 | df2 | P<0.0001 |
| Indication     | .638                   | 0.4594                  | 0.7709      | 2.7637                   | 53  | 212 | 0.0000   |
| Ethics         | .710                   | 0.5582                  | 0.8196      | 3.4535                   | 52  | 156 | 0.0000   |
| Implementation | .784                   | 0.6870                  | 0.8601      | 4.6223                   | 53  | 530 | 0.0000   |

Excellent ICC  $> 0.75$  was observed for diagnostic accuracy, preferred capacity in diagnostic thinking and cost-effective implementation of AI in radiology with F values  $> 4$ . Significant p value  $< 0.0001$  on all the domains rejected the null hypothesis which assumed no difference between the five RADAR rubric domains as shown in table 4.2.

Table 4.2: ICC for the RADAR rubric deductive themes (Source: Author, 2024)

| RADAR rubric domains                                | Intraclass Correlation | 95% Confidence Interval |             | F Test with True Value 0 |     |     |          |
|-----------------------------------------------------|------------------------|-------------------------|-------------|--------------------------|-----|-----|----------|
|                                                     |                        | Lower Limit             | Upper Limit | Value                    | df1 | df2 | P<0.0001 |
| Technical properties?                               | .745                   | 0.5982                  | 0.8446      | 3.9267                   | 52  | 104 | 0.0000   |
| Diagnostic accuracy/ threshold in lesion detection? | .777                   | 0.6501                  | 0.8634      | 4.4900                   | 53  | 106 | 0.0000   |
| Preferred capacity in diagnostic thinking?          | .794                   | 0.6756                  | 0.8734      | 4.8429                   | 53  | 106 | 0.0000   |
| Contribution of AI radiology to patient management? | .738                   | 0.5882                  | 0.8393      | 3.8149                   | 53  | 106 | 0.0000   |
| Rank cost effectiveness on implementation?          | .780                   | 0.6543                  | 0.8651      | 4.5452                   | 53  | 106 | 0.0000   |

## 4.6 HTA tool for AI in radiology

Statistical significance was referenced to median as a measure of central tendency since data was right skewed and reduced outlier effect was desired. Non parametric Wilcoxon signed rank test indicated statistical significance  $p < 0.05$  against a median of 3 for all items as shown in table 4.3.

Table 4.3: Rapid assessment HTA tool for AI in radiology (Source: Author, 2024)

| HTA core domains                                      | HTA tool for AI in radiology                             | High<br>n (%) | Moderate<br>n % | Low<br>n (%) | p<0.05 |
|-------------------------------------------------------|----------------------------------------------------------|---------------|-----------------|--------------|--------|
| <b>Health problem &amp; current use of technology</b> | Clinical benefit                                         | 47 (87)       | 3 (6)           | 4 (7)        | 0.0090 |
|                                                       | Clinical risk management                                 | 46 (85)       | 5 (9)           | 3 (6)        | 0.0090 |
|                                                       | Superiority to current practice                          | 31 (57)       | 16(30)          | 7 (13)       | 0.0000 |
|                                                       | Adaptability of the AI solution to the local institution | 29 (54)       | 14(26)          | 11 (20)      | 0.0000 |
| <b>Description &amp; technical characteristics</b>    | Frequency of AI detecting the lesion correctly           | 44 (81)       | 9 (17)          | 1 (2)        | 0.0020 |
|                                                       | Ability of AI in detecting lesions correctly             | 39(72)        | 14(26)          | 1 (2)        | 0.0050 |
|                                                       | Explainability of results from the AI software           | 45 (83)       | 8(15)           | 1 (2)        | 0.0000 |
|                                                       | Multi dimensionality in lesion detection                 | 39 (72)       | 9(17)           | 6 (11)       | 0.0000 |
|                                                       | Ease of using the AI in the diagnostic workflow          | 41 (76)       | 12(22)          | 1 (2)        | 0.0000 |
|                                                       | Willingness to use AI in actual radiology practice       | 32 (60)       | 10 (19)         | 12 (22)      | 0.0000 |
|                                                       | Recommendations from peer review publication             | 21 (39)       | 22 (41)         | 11 (20)      | 0.0000 |
| <b>Safety</b>                                         | Ability to reduced diagnostic uncertainty                | 34 (63)       | 13 (24)         | 7 (13)       | 0.0000 |
|                                                       | Clinical validation of the AI software by radiologists   | 42 (78)       | 7 (13)          | 5 (9)        | 0.0010 |
| <b>Clinical effectiveness</b>                         | Ability to detect lesions accurately                     | 45 (83)       | 8 (15)          | 1 (2)        | 0.0040 |
|                                                       | Reliability of AI in detecting lesions accurately        | 43 (80)       | 4 (7)           | 7 (13)       | 0.0020 |
|                                                       | Utility of the AI in clinical decision making            | 33 (61)       | 12 (22)         | 9 (17)       | 0.0000 |

Academic and research was added as a statistically significant new item as shown in table 4.4.

Table 4.4: Add on to complete full HTA tool for AI in radiology (Source: Author, 2024)

|                                     |                                                              | High    | Moderate | Low     |        |
|-------------------------------------|--------------------------------------------------------------|---------|----------|---------|--------|
| HTA core domains                    | HTA items for AI in radiology                                | n (%)   | n (%)    | n (%)   | p<0.05 |
| <b>Cost &amp; economic analysis</b> | Affordability of AI implementation                           | 33(61)  | 7 (13)   | 14 (26) | 0.0000 |
|                                     | Cost effectiveness of AI implementation                      | 33 (61) | 17 (31)  | 4 (7)   | 0.0000 |
|                                     | Adaptability of the AI solution to the local institution     | 29 (54) | 14 (26)  | 11 (20) | 0.0000 |
|                                     | Installation Cost                                            | 33 (61) | 15 (28)  | 6 (11)  | 0.0000 |
| <b>Ethical analysis</b>             | Doing good (Beneficence)                                     | 46 (85) | 7 (13)   | 1 (2)   | 0.0070 |
|                                     | Doing no harm (Maleficence)                                  | 46 (85) | 5 (9)    | 3 (6)   | 0.0080 |
|                                     | Patient freedom to choose (Autonomy)                         | 26 (48) | 19 (35)  | 9 (17)  | 0.0000 |
|                                     | Fairness (Justice)                                           | 33 (61) | 4 (7)    | 17 (31) | 0.0000 |
| <b>Organizational aspects</b>       | Ease of hardware integration                                 | 33(61)  | 16 (30)  | 5 (9)   | 0.0000 |
|                                     | Ease of software integration                                 | 39 (72) | 12 (22)  | 3 (6)   | 0.0000 |
|                                     | Ease of using the AI in the diagnostic workflow              | 41 (76) | 12 (22)  | 1 (2)   | 0.0000 |
|                                     | Willingness to use AI in actual radiology practice           | 32(59)  | 10 (19)  | 12 (22) | 0.0000 |
|                                     | Use full ness of the AI results                              | 30 (56) | 21 (39)  | 3 (6)   | 0.0000 |
|                                     | Ability to integrate AI in the radiology diagnostic workflow | 39 (72) | 7 (13)   | 8 (15)  | 0.0000 |
|                                     |                                                              |         |          |         |        |
| <b>Patient &amp; social aspects</b> | Actionable insights from the AI results                      | 31 (57) | 22 (41)  | 1 (2)   | 0.0000 |
|                                     | Influence on therapeutic interventions                       | 30 (56) | 20 (37)  | 4 (7)   | 0.0000 |
|                                     | Impact on patient outcomes                                   | 41 (76) | 9 (17)   | 4 (7)   | 0.0010 |
| <b>Legal aspects</b>                | Regulatory approval of the AI software                       | 33 (61) | 15 (28)  | 6 (11)  | 0.0000 |
| <b>New aspect</b>                   | Academic and research                                        | 32 (59) | 16 (30)  | 6 (11)  | 0.0000 |

## CHAPTER 5

### DISCUSSION

#### 5.1 Introduction to the chapter

This section summarizes key finding with relevant existing academic argument on AI in radiology globally.

#### 5.2 Discussion

Radiology is a highly tech enabled and data rich medical field which fans AI innovation in healthcare. Most domain experts lack AI education which explains significant dissent on long term plans, knowledge gap on frequency of use of AI (Figure 4.1) and the number of participants in the radiology and radiography field (Figure 4.2). Mwaniki et al highlighted that almost 40% of radiologists are not willing to train AI/ML models in radiology which confirms the low participation among radiologist and radiographers (Mwaniki, 2023). Kawooya et al zones in on the meagre technological infrastructure for training and deployment of AI technologies (Kawooya, 2022). Despite these challenges, Hua et al posit that user acceptability and AI literacy among domain experts drives technological revolution which is value laden (Hua, 2024). This study provides a social technical assessment tool which promotes knowledge management as a driver of AI acceptability in radiology within Kenya and similar low resource set up.

Brady et al invite decision makers in value appropriation of AI in radiology through collaborative action research with software developers (Brady, 2024). Boverhof et in in the value assessment of AI in radiology proffers clinical assessment through cross-sectional, longitudinal, randomized clinical trials and insilico trials (Boverhof, 2024). Boverhof`s approach however muffles user centeredness in the social technical design (Brady, 2024; Hua, 2024). Rapid technological evolution is sustainably understood using the action research framework (Shani, 2019). Action research strategically favors co creation (Saunders, 2023). Multiple perspectives from stakeholders enrich standards, credibility and comprehensive inputs facilitated by multi criteria decision analysis (Martelli, 2016). Gongora Salazar et al in a scoping review of HTA in healthcare cites priority setting in decision making as a common application of MCDA (Gongora-Salazar, 2023) with statistical parameter validation (Ranganathan, 2024).

Ferizovik et al highlighted the lack of explicit tools in the HTA assessment of AI in radiology (Ferizovik, 2022). Farah et al affirms this when interrogating suitability of existing tools in radiology (Farah\*, 2024). Deductive themes and items in this study were drawn from European and American standards (Kristensen, 2017; Boverhof, 2024; Brady, 2024) which limit contextual considerations. Africa and Asia lack explicit HTA tools (Kawooya, 2022; Mwaniki, 2023; Wee, 2024). The deductive themes and the individual items in the final tool were validated by strategic decision makers using dynamic tools that can be applied in various stages across AI lifecycle development; including design development and implementation of AI technologies in radiology (Farah, 2023; Boverhof, 2024; Brady, 2024).

Decision makers and domain experts prioritized all the deductive themes in the final tool; Comprehensive HTA tool for Radiology AI in Kenya (Appendix V). RADAR rubric (Boverhof, 2024) and MSC considerations (Brady, 2024) are heterogeneous which further informs Farah et al interrogation on the suitability of the existing HTA consideration (Farah\*, 2024). The comprehensive HTA tool for radiology AI in Kenya proposes versatile valuation of AI in radiology within proposed global standards (Farah, 2023). This tool can further be deployed when translating the hypothetical case into an actual case, or as a generic value appraisal tool when deploying AI in radiology with relevant contextual modifications (Farah, 2023; Farah\*, 2024). This explains a higher p value for line items as compared to the domain items (Figure 4.1- Figure 4.4)

Mwaniki highlights adoption inertia of AI in radiology within Kenya with lack of AI knowledge on related concepts (Mwaniki, 2023). Academics and research as a new aspect in the comprehensive HTA tool for radiology AI in Kenya underscores the relevance on knowledge management on AI in radiology which remains meager at best in Kenya and in Africa (Kawooya, 2022; Mwaniki, 2023). Bounded awareness and bounded rationality between software developers, healthcare managers and radiologists corrupt value delivery of AI in healthcare when they operate in silos (Brady, 2024; Hua, 2024). This research frames relevant domains that can inform the AI strategy in radiology addressing labor dynamics, technological sustainability and responsible AI.

Kawooya et al propose collaboration and AI technology in improving safety in radiology within Africa (Kawooya, 2022; Musa, 2023). Safety as a deductive theme within the comprehensive HTA tool for Radiology AI in Kenya draws line items from both the multi society consideration and the RADAR rubric (Appendix V, Figure 4.4). Positional statement from Asia fosters Kawooya's proposition on adoption of safe AI as guided by bioethical principles (Wee, 2024). Comprehensive HTA tool for Radiology AI in Kenya, provisions for the four common bioethical principles in medical practice (Appendix V). This tool standardizes communication in favor of a collaborative framework responsive to Kawooya et al, Mwaniki et and Wee et al in domesticating and valuation of AI in radiology against global standards.

Europe and America conduct HTA through agencies and frameworks iterated in their own context. Leveraging on existing research reduces research waste however, where HTA approach is not explicit, novelty is warranted (Ferizovik, 2022; Farah\*, 2024). AI in healthcare posits a new intricacy in HTA as transformative levers beyond software as medical devices (Alami, 2020). Value delivery is anchored on strong foundational principles such as HTA core model 3.0 in the holistic assessment of AI in radiology (Alami, 2020; Farah, 2023) The Comprehensive HTA tool for Radiology AI in Kenya proposes utility value points in low resource set up.

Value appropriation of the utility value points was delegated to strategic stakeholders and articulated using MCDA. MCDA provides analytical versatility on complexity, skill, technology, modelling and iterations (AFCT, 2024). Boverhof et al proposes MCDA in the alignment of local requirements using local stakeholders (Boverhof, 2024). Systemic literature review in 2020 on MCDA dominance in healthcare complements our study on its application in priority setting during decision making (Gongora-Salazar, 2023). It confirms high priority on user/ patient facing attributes with low priority on cost and peer recommendation attributes. Potential bounded awareness on AI related concepts confirmed by Mwaniki et al explains this divergence (Mwaniki, 2023). Moreover, divergence on scoring and weighting in the systematic literature review was predominantly through modelling and linear regression techniques as opposed to expert opinions and Likert scales in this study. Modelling and linear regression techniques were not warranted due to a small decision-making apex; 54 respondents.

## **CHAPTER 6**

### **CONCLUSIONS AND RECOMMENDATION**

#### **6.1: Introduction to the chapter**

This chapter draws conclusions from key findings in the study and provides tiered recommendation on the way forward.

#### **6.2 Conclusions and recommendation**

Generically, AI in radiology is a rapidly developing value laden technology supporting patient safety, operational efficiency and professional innovation. This warrants user acceptability by decision makers through articulation of value proposition on multiple attributes against local and global standards. This study recommends a decision-making tool in a low resource set up for decision makers who influence deployment of AI in radiology in health care management/clinical practice, digital health, policy/ regulation, academics/ research and radiology medical practitioners.

Technically, attributes of the tool support AI literacy, shared communication and credibility in rationale and group decision making. This sets the base for training institutions and regulatory bodies on health technology assessment that build into the AI strategy in radiology and healthcare at large. Healthcare system is highly interconnected therefore inter-disciplinary collaboration enriches AI literacy widening the window of opportunity and voice aggregates informing sound policy recommendations with evidence-based iterations, monitoring and evaluation.

Globally, AI favors business re-engineering which confers competitive advantage in radiology as a discipline as well as Kenya as a medical tourist destination. Coordinated development and deployment of AI in radiology nested within relevant policies and strategies hosts digital commodities which can be exported regionally and developed locally beyond the traditional competencies and technologies in radiology. This favorable innovative milieu within and beyond healthcare attracts resources for learning, growth and development in the country and the healthcare industry.

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## APPENDICES

### Appendix 1: Introduction Letter

/2024

Strathmore Business School  
Nairobi

Dear Respondent,

Re: Introduction letter seeking informed consent.

I am Miriam Miima a graduate student of Master of Business Administration- Healthcare Management degree at the Strathmore University Business School. I am carrying out a research study in partial fulfillment of my degree award of the degree and enhancing my knowledge on AI in healthcare. The study is titled the “**Health technology assessment of artificial intelligence in radiology**”

I wish to request for your participation with guaranteed confidentiality of the data collected. The outcome of this study will be local framework for health technology assessment of an artificial intelligence enabled pulmonary embolism detection software. The findings of the study will be availed to you at your request. Any assistance offered in the collection of data will be deeply appreciated.

Yours faithfully,

Miriam Miima  
Investigator

## Appendix II: Participant's Information and Consent Form

My name is Miriam Miima a student of Healthcare Management at the Strathmore University. I am carrying out a research study titled **Health technology assessment of artificial intelligence in radiology**. The study has been approved by the institutional scientific ethical review committee. Ref no. SU-ISERC2327/24. and NACOSTI license no: NACOSTI/P/24/38065

The objective of this survey is to improve construct and content validity an assessment tool which will inform an appraisal framework of AI in radiology. In this study think of an AI enabled software that can detect pulmonary embolism on CT scan images as an example.

Eligible participants are clinical/ non clinical medical doctors and radiographers familiar with the radiology diagnostic workflow. The questionnaire can be filled in approximately 5-10 minutes.

The findings of the study will be availed to you on request. Any assistance offered in the collection of data will be highly appreciated.

**Participant's Signature: ..... Date .....**

**Do you agree to participate in the study**

- ☐ **Yes**
- ☐ **No**

**Do you wish to receive the findings of this study?**

**If YES, please indicate your email address below OR**

Kindly reach out to me on: Email: miriam.miima@strathmore.edu OR

Phone number: 0721917972

**THANK YOU**

### Appendix III: Radiology multi society practical considerations .

| <b>IMPLEMENTATION PRIORITY LEVEL</b>   |      |          |     |
|----------------------------------------|------|----------|-----|
| <b>INDICATION</b>                      | High | Moderate | Low |
| Regulatory                             |      |          |     |
| Clinical benefit                       |      |          |     |
| Clinical risk management               |      |          |     |
| Competitive advantage                  |      |          |     |
| Cost effectiveness                     |      |          |     |
| Academic and research                  |      |          |     |
| <b>ETHICS</b>                          |      |          |     |
| Doing good (Beneficence)               |      |          |     |
| Doing no harm (Non maleficence)        |      |          |     |
| Patient freedom to choose (Autonomy)   |      |          |     |
| Fairness (Justice)                     |      |          |     |
| <b>MODEL CONSIDERATIONS</b>            |      |          |     |
| Superiority to current practice        |      |          |     |
| Explainability                         |      |          |     |
| Multi dimensionality                   |      |          |     |
| Hardware integration                   |      |          |     |
| Software integration                   |      |          |     |
| Installation cost                      |      |          |     |
| Maintenance cost                       |      |          |     |
| <b>MODEL CONSIDERATIONS</b>            | High | Moderate | Low |
| Peer review publication                |      |          |     |
| Regulatory approval                    |      |          |     |
| Model accuracy                         |      |          |     |
| Clinical validation                    |      |          |     |
| Monitoring/ update schedule            |      |          |     |
| <b>HUMAN – AI CONSIDERATIONS</b>       |      |          |     |
| Self-efficacy                          |      |          |     |
| Ease of use                            |      |          |     |
| Willing ness to use in daily practice  |      |          |     |
| Trust in the model                     |      |          |     |
| Accuracy of the model                  |      |          |     |
| Validation of the model                |      |          |     |
| <b>LONG TERM STABILITY</b>             |      |          |     |
| Strategic                              |      |          |     |
| What` s the problem, risk and benefit? |      |          |     |
| Regulatory compliance                  |      |          |     |
| Legal and ethical                      |      |          |     |
| Performance                            |      |          |     |
| Efficacy, monitoring, fairness         |      |          |     |

|                                       |  |  |  |
|---------------------------------------|--|--|--|
| Workflow integration                  |  |  |  |
| Ease of use                           |  |  |  |
| Technical                             |  |  |  |
| Infrastructure and skill              |  |  |  |
| Economic costs                        |  |  |  |
| Can return on investment be monitored |  |  |  |



## Appendix IV: RADAR rubric

| IMPLEMENTATION PRIORITY LEVEL                                |      |     |     |
|--------------------------------------------------------------|------|-----|-----|
| Technical properties?                                        | High | Mod | Low |
| Frequency of AI detecting the lesion correctly               |      |     |     |
| Ability of AI in detecting lesions correctly                 |      |     |     |
| Explainability of results from the AI software               |      |     |     |
| Diagnostic accuracy/ threshold in lesion detection?          |      |     |     |
| Ability to detect lesions accurately                         |      |     |     |
| Reliability of AI in detecting lesions accurately            |      |     |     |
| Utility of the AI in clinical decision making                |      |     |     |
| Preferred capacity in diagnostic thinking?                   |      |     |     |
| Use full ness of the AI results                              |      |     |     |
| Ability to integrate AI in the radiology diagnostic workflow |      |     |     |
| Ability to reduced diagnostic uncertainty                    |      |     |     |
| Contribution of AI radiology to patient management?          |      |     |     |
| Actionable insights from the AI results                      |      |     |     |
| Influence on therapeutic interventions                       |      |     |     |
| Impact on patient outcomes                                   |      |     |     |
| Rank cost effectiveness on implementation?                   |      |     |     |
| Affordability of AI implementation                           |      |     |     |
| Cost effectiveness of AI implementation                      |      |     |     |
| Adaptability of the AI solution to the local institution     |      |     |     |

## Appendix V: Comprehensive HTA tool for Radiology AI in Kenya

| HTA core domains                                      | HTA tool for AI in radiology                                                                                                                                                                                                                                                                   | High | Moderate | Low |
|-------------------------------------------------------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|------|----------|-----|
| <b>Health problem &amp; current use of technology</b> | Clinical benefit<br>Clinical risk management<br>Superiority to current practice<br>Adaptability of the AI to the local institution                                                                                                                                                             |      |          |     |
| <b>Description &amp; technical characteristics</b>    | Frequency of AI detecting the lesion correctly<br>Ability of AI in detecting lesions correctly<br>Explainability of results from the AI software<br>Multi dimensionality in lesion detection<br>Ease of using the AI in the diagnostic workflow<br>Willingness to use AI in radiology practice |      |          |     |
| <b>Safety</b>                                         | Recommendations from peer review publication<br>Ability to reduced diagnostic uncertainty                                                                                                                                                                                                      |      |          |     |
| <b>Clinical effectiveness</b>                         | Clinical validation of the AI software by radiologists<br>Ability to detect lesions accurately<br>Reliability of AI in detecting lesions accurately<br>Utility of the AI in clinical decision making                                                                                           |      |          |     |
| <b>Cost &amp; economic analysis</b>                   | Affordability of AI implementation<br>Cost effectiveness of AI implementation<br>Adaptability of the AI solution to the local institution<br>Installation Cost                                                                                                                                 |      |          |     |
| <b>Ethical analysis</b>                               | Doing good (Beneficence)<br>Doing no harm (Maleficence)<br>Patient freedom to choose (Autonomy)<br>Fairness (Justice)                                                                                                                                                                          |      |          |     |
| <b>Organizational aspects</b>                         | Ease of hardware integration<br>Ease of software integration<br>Ease of using the AI in the diagnostic workflow<br>Use full ness of the AI results<br>Integration of AI in the radiology workflow                                                                                              |      |          |     |
| <b>Patient &amp; social aspects</b>                   | Actionable insights from the AI results<br>Influence on therapeutic interventions<br>Impact on patient outcomes                                                                                                                                                                                |      |          |     |
| <b>Legal aspects</b>                                  | Regulatory approval of the AI software                                                                                                                                                                                                                                                         |      |          |     |
| <b>New aspects</b>                                    | Academic and research                                                                                                                                                                                                                                                                          |      |          |     |

## Appendix VI: SU IREC ethical approval letter

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4<sup>th</sup> July 2024

Dr Miima Miriam,  
miriam.miima@strathmore.edu

Dear Dr Miima,

**RE: Health Technology Assessment of Artificial Intelligence in Radiology:  
Pulmonary Embolism Detection Software**

This is to inform you that SU-ISERC has reviewed and **approved** your above **SU-masters** proposal. Your application reference number is **SU-ISERC2327/24**. The approval period is from **4<sup>th</sup> July 2024** to **3<sup>rd</sup> July 2025**.

This approval is subject to compliance with the following requirements:

- i. Only approved documents including (informed consents, study instruments, MTA) will be used.
- ii. All changes including (amendments, deviations, and violations) are submitted for review and approval by SU-ISERC.
- iii. Death and life-threatening problems and serious adverse events or unexpected adverse events whether related or unrelated to the study must be reported to SU-ISERC within 72 hours of notification.
- iv. Any changes anticipated or otherwise that may increase the risks or affected safety or welfare of study participants and others or affect the integrity of the research must be reported to SU-ISERC within 72 hours.
- v. Clearance for the export of biological specimens must be obtained from relevant institutions.
- vi. Submission of a request for renewal of approval at least 60 days prior to the expiry of the approval period. Attach a comprehensive progress report to support the renewal.
- vii. Submission of an executive summary report within 90 days of completion of the study to SU-ISERC.

Before commencing your study, you will be expected to obtain a research license from National Commission for Science, Technology, and Innovation (NACOSTI) <https://research-portal.nacosti.go.ke/> and obtain other clearances needed.

Yours sincerely,

**Mr Ambrose Rachier,**  
**Chairperson; SU-ISERC**

## Appendix VII: NACOSTI ethical approval letter

|                                                                                                                                                                                                                                                                                                                                                                                              |                                                                                                                                                               |
|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------|
| <br><b>REPUBLIC OF KENYA</b>                                                                                                                                                                                                                                                                                | <br><b>NATIONAL COMMISSION FOR<br/>SCIENCE, TECHNOLOGY &amp; INNOVATION</b> |
| Ref No: <b>387872</b>                                                                                                                                                                                                                                                                                                                                                                        | Date of Issue: <b>24/July/2024</b>                                                                                                                            |
| <b>RESEARCH LICENSE</b>                                                                                                                                                                                                                                                                                                                                                                      |                                                                                                                                                               |
|                                                                                                                                                                                                                                                                                                             |                                                                                                                                                               |
| <b>This is to Certify that Dr. Miriam Miima of Strathmore University, has been licensed to conduct research as per the provision of the Science, Technology and Innovation Act, 2013 (Rev.2014) in Nairobi on the topic: <u>HEALTH TECHNOLOGY ASSESSMENT OF ARTIFICIAL INTELLIGENCE IN RADIOLOGY: PULMONARY EMBOLISM DETECTION SOFTWARE</u> for the period ending : <b>24/July/2025</b>.</b> |                                                                                                                                                               |
| License No: <b>NACOSTI/P/24/38065</b>                                                                                                                                                                                                                                                                                                                                                        |                                                                                                                                                               |
| Applicant Identification Number                                                                                                                                                                                                                                                                                                                                                              |                                                                          |
|                                                                                                                                                                                                                                                                                                                                                                                              | Director General                                                                                                                                              |
|                                                                                                                                                                                                                                                                                                                                                                                              | <b>NATIONAL COMMISSION FOR<br/>SCIENCE, TECHNOLOGY &amp;<br/>INNOVATION</b>                                                                                   |
|                                                                                                                                                                                                                                                                                                                                                                                              | Verification QR Code                                                                                                                                          |
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| <b>NOTE: This is a computer generated License. To verify the authenticity of this document,<br/>Scan the QR Code using QR scanner application.</b>                                                                                                                                                                                                                                           |                                                                                                                                                               |
| <b>See overleaf for conditions</b>                                                                                                                                                                                                                                                                                                                                                           |                                                                                                                                                               |