

MEDICAL IMAGING EQUIPMENT DEVELOPMENT, MANUFACTURING
METHODOLOGIES FOR LOW-COST COUNTRIES

by

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METHODOLOGIES FOR LOW-COST COUNTRIES

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Dedication

“This thesis is lovingly dedicated to my family, whose unwavering support has been my strength, and to my beloved parents, for their endless sacrifices.”

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ABSTRACT

MEDICAL IMAGING EQUIPMENT DEVELOPMENT, MANUFACTURING METHODOLOGIES FOR LOW-COST COUNTRIES

Accessible and affordable medical imaging products are becoming more and more important in low- and middle-income countries (LMICs) in which healthcare systems are grappling with limited resources, poor infrastructure, and lack of highly qualified personnel. The study is done on development and adoption of cost-effective medical imaging systems, including portable ultrasound systems, hand-held X-rays, and small-sized digital radiography systems that helped fulfill these challenges. The paper also investigates how artificial intelligence (AI) can improve the accuracy and efficiency of diagnoses in a place where there are few medical professionals. By assessing factors such as cost-effectiveness, scalability, and integration into existing healthcare systems, the study provides valuable insights into the feasibility of these technologies in LMICs.

The study has a multi-dimensional nature that considers both technological and systemic issues. It brings out the necessity of low-cost medical imaging equipment that can be used within the resource limits, including unreliable power supplies and technical support. The paper also examines the possibilities of these technologies to be implemented into the current healthcare systems without interfering with the current healthcare service provision. It also highlights the need to establish a very strong policy framework, such as proper training of healthcare providers and support mechanisms of sustaining these technologies in the long-term.

Although the low costs of imaging technologies are promising, the study indicates that there are a number of challenges to their use, including inadequate infrastructures, technical support and absence of a common set of regulations. The literature gaps that the study finds are especially the need to combine affordability, technological development, AI, and the readiness of the healthcare system. The results imply that the solution to these

barriers should be a holistic and systems-based approach that incorporates technological innovation, infrastructure development and policy reform. The study is concluded by a series of recommendations to the manufacturers, healthcare providers and policymakers to develop sustainable, scalable, and context-specific imaging solutions that could enhance healthcare access and outcomes in LMICs.

Keywords: Healthcare system, medical imaging products, resource limits, diagnoses, policy framework, regression analysis, Structural Equation Model

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2026

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CHAPTER 1:

INTRODUCTION

1.1 Introduction

The requirement to possess affordable and available solutions to medical imaging has been growing by a tremendous margin in the low- and middle-income countries (LMICs) where disease burden continues to rise with scarce healthcare resources. The rapidly growing population, urbanization, and alterations in the lifestyle of people and the rise in both communicable and non-communicable diseases have put an extra strain on already limited health care facilities. In most LMICs, the healthcare infrastructure is still underdeveloped, and access to modern diagnostic equipment is still uneven in terms of the distribution between urban and rural regions. This has led a significant percentage of the population to still use simple or primitive forms of diagnosis that, in many cases, do not detect a disease early enough. This shortcoming causes late diagnosis, development of diseases into their severe stages, increased costs of treatment, and, eventually, worse patient outcomes (Frija et al., 2021).

X-ray, computed tomography (CT), magnetic resonance imaging (MRI), and ultrasound are examples of medical imaging technologies that have been of great significance to the current healthcare systems. These technologies allow healthcare professionals to visualize internal structures of the human body without any invasive procedures, hence assisting in the correct diagnosis, proper planning of treatment, and constant monitoring of a disease. As an example, imaging is needed in cancer early diagnosis, cardiovascular defects, neurology, and chronic illnesses. In developed nations, the technologies are highly adopted in the normal healthcare delivery systems and have greatly enhanced clinical practices and patient survival. But not all people in LMICs have the privileges to benefit from these technologies because of various structural and economic barriers.

The conventional imaging systems are cost-intensive, need a fixed infrastructure and competent personnel, which restricts their availability in LMICs. The acquisition of

equipment like MRI and CT scanners is very expensive, and other costs associated with their installation, maintenance, and running costs add even more burden on health care systems. Such systems also need an electricity supply, a temperature-controlled and steady electricity supply, and other advanced digital infrastructure to store and transmit images. These requirements are not easily achieved in most LMICs, particularly in rural and remote locations. Moreover, the lack of qualified radiologists and technicians poses extra impediments to the effective use of the imaging technologies.

Healthcare facilities in most low-resource settings are characterized by poor and unstable power supply, absence of maintenance services, and trained radiologists. The Blackouts may interfere with the imaging processes and destroy delicate equipment, and the lack of availability to spares and technical services often results in the unavailability of equipment. Moreover, the absence of training activities and experienced staff makes it hard to access the imaging results in a proper way. All these problems result in the inability to introduce and maintain high-level imaging technologies in these settings. Consequently, the patients can be left undiagnosed or misdiagnosed, hence leading to high mortality rates, prolonged illness, and low-quality healthcare services.

The recent developments in the low-cost and portable imaging technologies have opened new possibilities to enhance the diagnostic access in LMICs. Portable ultrasound gadgets, handheld X-ray machines, battery-powered imaging systems, and compact digital radiography units are other innovations that have been specifically tailored to solve the cost, infrastructure, and access problems. The devices are small-sized, user-friendly, and only a small infrastructure is needed, and hence they can be used in remote clinics, mobile health units, and emergencies. They enable healthcare professionals to carry out diagnostic processes at the point of care, eliminating the need for patients to cover long distances in an effort to access imaging services. This not only enhances access but also makes the diagnosis and treatment timely, which is vital in enhancing health outcomes.

Along with the innovations in hardware, artificial intelligence (AI) is also a significant aspect of medical imaging. Artificial intelligence technologies can help identify abnormalities, increase the level of diagnostic accuracy, and minimize the workload of

medical workers. Medical images can be analyzed using machine learning and deep learning algorithms, and provide decision support to the clinicians. In fields where there are no talented specialists, these technologies can also be applied to a particular purpose since they can be used to ensure the gap between demand and expert availability is bridged. A standard interpretation of images and minimization of human error and enhancement of efficiency in high-volume health care institutions can also be achieved using AI.

Nevertheless, even with such developments, there are still a number of issues. Such problems as cost, durability, maintenance, and compatibility with the existing healthcare systems still prevent the widespread implementation of the affordable imaging technology. A number of cheap products can be confronted with issues of long-term functionality, with regard to durability in severe environmental factors, and technical service accessibility. Also, the implementation of such technologies in the current healthcare processes should be well-planned, well-trained, and supported by policies. Data quality, infrastructure, and contextual adaptation are also important to the effectiveness of AI-based systems and might not be universally applicable.

Thus, there is a high necessity to investigate the way affordable medical imaging solutions can be developed and implemented successfully in LMICs. This involves the knowledge of the technological, economic, and operational considerations that affect their use and sustainability. To solve these issues is imperative in improving access to diagnostics, minimizing healthcare disparities, and improving health outcomes generally in resource-constrained environments (Hoagland and Kipping, 2024).

1.2 Research Problem

In many low- and middle-income countries (LMICs), affordable, scalable and integrated medical imaging solutions are not yet available, and health care systems are not able to offer timely and effective medical imaging services. In spite of significant developments in medical imaging technologies worldwide, the majority of innovations have been developed mainly for high income health care system environments with a high level of technical competence, financial resources and infrastructure. As a result, there are numerous advanced imaging technologies that are challenging to effectively use in a

resource-limited healthcare environment, because they can be expensive to operate, complex to use, and require infrastructure and equipment. (Murali et al., 2024).

Most current studies in medical imaging technologies have been on single aspects like imaging performance, cost savings or AI systems. These studies offer valuable technological and clinical lessons, but few studies have investigated the concepts of affordability, scalability, artificial intelligence (AI) capability, and healthcare system compatibility in one analytical model. Consequently, there is little knowledge about how low-cost imaging technologies can be implemented, scaled, and integrated into real-world LMIC healthcare system sustainably. This divide makes it difficult for healthcare providers, policymakers and manufacturers to support decisions on adoption and sustainability of cost-effective imaging solutions. Furthermore, the use of AI in low-cost imaging devices or technologies has not been explored in the context of health care systems in LMICs. Most AI models are built with data from high-income countries, despite the fact that AI-enabled diagnostic systems have proven to be very effective for improving diagnostic accuracy and efficiency. Such datasets may not be representative of the disease epidemiology, imaging conditions, and population in LMICs. Therefore, there are concerns about the reliability, applicability and clinical validity of AI-enabled imaging systems in LMIC healthcare environments.

The current literature also offers scarce information about the implementation of low-cost imaging technologies in the current healthcare practice and institutional processes. Existing studies do not address important implementation factors, such as the compatibility of workflow, digital interoperability, workforce readiness, technical supports, and regulatory approval processes. An integrated systems-based approach remains a challenge for effective implementation and scaling up of affordable medical imaging technologies in LMIC healthcare settings.

The study hypotheses derived from these research gaps are those concerning the affordability, scalability, integration with the healthcare system and AI assistance in diagnostic performance. The current study, therefore, is tasked with proposing a comprehensive framework to address the need for a framework that incorporates

affordability, scalability, healthcare system integration, and AI-enabled diagnostic ability in the context of medical imaging technologies in LMICs. The study aims at shedding light on sustainable and context-specific imaging solutions for enhancing the healthcare accessibility, diagnostic efficiency, and healthcare outcomes in a resource constrained environment (Shem et al., 2022).

1.3 Purpose of Research

The aim of this study is to investigate the development and implementation of low-cost medical imaging technologies in the low- and middle-income countries (LMICs). The study is focused on the accessibility of diagnostics, the efficiency of healthcare, and the effectiveness of the clinical practice in resource-limited healthcare systems, enabled by low-cost imaging solutions (Marey et al., 2025).

The study in particular focuses on the application of affordability, scalability, integration of the healthcare system and artificial intelligence to the adoption and performance of medical imaging technologies in LMIC healthcare systems. The study investigates the feasibility of the use of low cost, portable imaging devices such as handheld ultrasound and compact radiography technologies to improve diagnostic capacity in rural clinics, community health centers and district hospitals. The study also explores whether AI-enabled imaging systems can enhance the accuracy, efficiency, and clinical decision making in settings with limited access to specialized radiologists.

The study also seeks to define the operational and institutional challenges and elements affecting the successful implementation of low-cost imaging technologies, such as workflow integration, readiness of infrastructure, staff capability, maintenance support, and compatibility of the healthcare system. The study aims to create a more holistic view of implementing and scaling affordable imaging solutions in LMIC healthcare environments both technologically and from a health system perspective.

The overall research adds to the existing literature by offering a comprehensive system that integrates affordability, portability, healthcare integration, and AI-supported diagnostic capability within medical imaging systems. The findings will also provide guidance for healthcare providers, policy makers, researchers and medical device

manufacturers to enhance healthcare access and delivery in resource-limited settings (Altaf et al., 2025).

1.4 Significance of the Study

This study is important because it adds to the ever-increasing body of literature related to affordable medical imaging technologies and what they can be used for in low- and middle-income countries (LMICs). The research offers a holistic understanding of the possibilities of affordability, scalability, integration within the healthcare system, and the use of artificial intelligence to make diagnostics more accessible and improve healthcare delivery in resource-limited health care settings (Akah et al., 2025).

The study offers healthcare practitioners real-world insights into how low-cost, portable imaging technologies can enhance diagnostic performance and patient results. The findings could help health care practitioners grasp the potential of affordable imaging systems to help them diagnose faster, make better clinical decisions and increase diagnostic capabilities in rural and underserved health care settings. Additionally, the study emphasizes the importance of using portable and AI-assisted imaging tools to assist frontline healthcare professionals when access to specialized radiologists and advanced diagnostic equipment is not feasible.

The study provides evidence-based policy and healthcare system implementation and integration insights for affordable imaging technologies for policymakers and healthcare administrators. The study highlights the need for enabling regulatory frameworks, sustainable procurement practices, readiness of infrastructure, workforce training, and policy support, which are crucial for the successful implementation of low-cost medical imaging solutions. These findings can inform healthcare policy-makers to enhance healthcare accessibility and healthcare service delivery in LMIC healthcare systems.

The study also advances academic research with the creation of a more comprehensive analytical framework, which integrates affordability, scalability, artificial intelligence capability, and integration with healthcare systems into the medical imaging technologies field. The present study differs from many past studies that have focused on

one or two of these dimensions by integrating them to gain a more comprehensive insight into their mutual interactions in actual healthcare context. The study also highlights critical research gaps regarding long-term sustainability, scalability, and contextualization of low-cost imaging technologies for LMICs to guide future research on the topic.

The study offers valuable insights for medical device companies and technology developers seeking to design and develop low-cost, long-lasting, and context-appropriate imaging solutions that can be used in resource-limited healthcare environments. The results highlight the need for low maintenance, ease of operating, energy efficiency and suitability to demanding healthcare settings. This knowledge can help pave the way for more scalable imaging solutions, which can enhance the reach of healthcare services and contribute to the international advancement of healthcare.

In general, the study will help achieve the overall goal of decreasing health inequities by facilitating access to diagnostic imaging services. The study highlights the need to identify sustainable and scalable imaging solutions in resource-limited settings, contributing to the continued goal of enhancing healthcare equity, diagnostic effectiveness, and healthcare outcomes in LMIC healthcare systems (Makhmirzaeva et al., 2025).

1.5 Scope and Limitations

Scope of the Study

This paper aims to address cost-effective medical imaging solutions in the low- and middle-income countries (LMICs), where the healthcare systems have severe financial, infrastructural, and operational limitations. The first one is to assess the ability of low-cost imaging technologies to enhance the availability of diagnostic services and promote effective healthcare delivery in resource-constrained settings. The paper gives specific attention to three major dimensions, such as cost-effectiveness, scalability, and inclusion in healthcare systems (Ben Charif et al., 2022).

Cost-effectiveness is analyzed concerning the ability of imaging technologies to be affordable to save the capital investment, the cost of operation, and long-term maintenance, and still provide a reasonable level of diagnostic reliability and accuracy. Scalability is also

considered to conclude that these technologies can be applied in different healthcare institutions, including the rural clinics, primary health centers, and district hospitals, without significant difficulties. The aspect of integration in healthcare systems is explored to establish how these technologies can be integrated within the current clinical workflows, infrastructure, and service delivery models without affecting the existing ones.

The study perceives the various imaging technologies like portable ultrasound equipment, handheld x-ray equipment, compact digital radiography equipment and other low-resource-specifically designed diagnostic equipment. Usability, durability, accessibility, and performance under constrained circumstances, such as low electricity and low technical support, are also considered in such technologies.

Besides, the paper looks at how artificial intelligence (AI) can enhance the accuracy and efficiency of diagnostics. The instruments based on AI are evaluated in terms of their ability to support healthcare specialists in image recognition, minimize diagnostic errors, and improve decision-making, especially in those regions where the number of trained radiologists is limited. Another area that the study takes into consideration is the ability of AI to enhance the overall healthcare outcomes of imaging technologies, which are low-cost.

Also, the study uses the multi-level analysis technique to offer a holistic view of the elements that affect the uptake and efficacy of cost-effective imaging technology. On the national level, the paper looked at policy frameworks, regulatory requirements, funding mechanisms, and healthcare priorities. At the institutional level, it pays attention to the hospital infrastructure, equipment service, workforce potential, and service provision processes. At the user level, it takes into account patient access, awareness, and experiences of healthcare professionals who work with and interpret imaging technologies. The multi-dimensional approach allows defining the main obstacles and opportunities at various levels of the healthcare system (Kahn, 2021).

Limitations of the Study

Even though the study is very extensive in its method, there are some limitations that need to be addressed. To begin with, the study is mainly done in the context of low-

and middle-income countries, and hence, the results cannot be directly extended to the high-income countries where healthcare systems, infrastructure, and resources vary greatly. The challenges and solutions that have been discovered in this research are directly related to the situation in LMICs (Meghji et al., 2021).

Secondly, the study is based on available data and published literature that is subject to the limitations of accuracy, completeness, and consistency. In most LMIC settings, there might be limited or disaggregated reliable data on healthcare infrastructures, technology performance, and long-term outcomes. This can have implications for the generalizability and accuracy of the results.

The other constraint is associated with the fact that there is a variation in the performance of low-cost imaging technologies in different regions. Aspects such as infrastructure differences, environmental factors, access to technical support, and the abilities of the workforce may affect the way these technologies work practically. Consequently, the solutions may not be as effective as they may be, depending on the situation in which they are used.

In addition, there are limited applications of artificial intelligence in medical imaging. One of the main factors to consider is the quality of the performance of AI models, as well as diversity and the availability of training data. There may be low data availability in LMICs, and the data available may not be representative of the local disease trends and imaging conditions. It affected the quality and validity of AI-based diagnosis tools. Additionally, there was another issue such as bias in models, lack of local validation, and infrastructure requirements to deploy AI may also arise as an issue.

Lastly, the study might not be able to encompass all the practical challenges of implementation in real life, including cultural, user acceptance, and policy-level challenges, which also determine the adoption of new technologies. Irrespective of these constraints, the study offers some insightful information on how affordable medical imaging solutions can be developed and implemented in resource-limited environments (Nhat, 2025).

1.6 Research Questions and Objectives

Research Questions

RQ1. What can be done to come up with affordable medical imaging solutions to overcome the limitations in LMICs?

RQ2. How cost-effective and scalable to resource-limited settings are portable diagnostic imaging technologies?

RQ3. What can be done to incorporate the low-cost imaging devices into the existing healthcare systems in LMICs?

RQ4. How can artificial intelligence be used to enhance the efficiency and accuracy of diagnostic imaging in low-cost imaging?

Research Objectives

- To investigate the creation of low-cost medical imaging products that are specific to LMICs.
- To determine the cost-efficiency and scalability of portable diagnostic imaging technologies.
- To explore the role of low-cost imaging devices in the current healthcare systems.
- To determine the value of artificial intelligence in enhancing the accuracy and efficiency of the diagnostic process during medical imaging.

1.7 Research Hypotheses

H1: Affordability has a positive influence on reducing financial and operational barriers in LMIC healthcare systems.

H2: Portability of imaging technologies has a positive influence on adoption and scalability in LMIC healthcare settings.

H3: Healthcare system integration of low-cost imaging devices has a positive influence on effective diagnostic workflow in LMIC healthcare facilities.

H4: AI integration in low-cost imaging technologies has a positive influence on diagnostic accuracy and efficiency in LMIC healthcare settings.

CHAPTER 2:

REVIEW OF LITERATURE

2.1 Introduction

Medical imaging has turned out to be an inseparable part of the present healthcare system, as it allows detecting disease early, making a proper diagnosis, and planning treatment. In the last several decades, imaging technologies (X-ray, computed tomography (CT), magnetic resonance imaging (MRI), and ultrasound) have introduced a significant change in clinical practice, offering non-invasive ways to image the inside structure of the human body. The technologies have improved the capability of health practitioners to diagnose diseases at earlier stages, track disease progress, and make effective decisions on the treatment plan. Consequently, medical imaging is at the forefront of enhancing patient outcomes and the quality of healthcare (Almaliky et al., 2024).

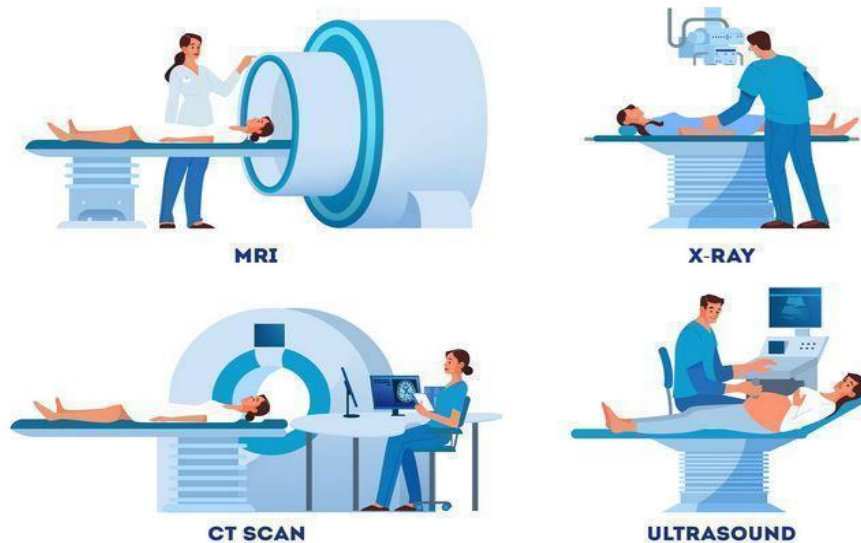


Figure 1: Evolution of Medical Imaging Technologies; Lake Zurich Open MRI, 2025.

Nonetheless, the use and access to complex imaging technologies are extremely unequal in the various regions, especially between the high-, low-, and middle-income countries (LMICs). High-income areas have well-developed infrastructure, reliable power provision, developed digital networks, and a highly skilled labor force that contributes to the ease of integration and effective utilization of imaging technologies. Conversely, LMICs are usually limited in various aspects, such as a lack of financial resources, poor infrastructure, a lack of skilled professionals, and poor healthcare systems. Such factors have a big bearing on the access and the effective use of imaging services in such regions (Obuchowicz et al., 2024).

As much as technology has greatly enhanced diagnostic possibilities, they are not equally accessible because of financial, structural, and systemic constraints in LMICs. The expensive nature of purchasing and supporting advanced imaging devices, including the specialized training and support systems, makes barriers to access very high. Also, the issues such as power failure, technical maintenance, and bad digital connectivity are present, which complicate the application of imaging technologies as well. Consequently, a big percentage of the population in LMICs lacks access to important diagnostic services, resulting in late diagnosis, higher disease burden, and worse health outcomes.

Traditionally, the literature of medical imaging has been interested in technological advances, performance improvement, and clinical usage. The first works were primarily aimed at improving the quality of images, improving the accuracy of the diagnosis, as well as developing a new high-quality imaging modality. Although these contributions have been valuable, they fail to recognize the contextual issues that are involved in the implementation of such technologies in resource-constrained settings. Recent research has started to focus more on affordability, accessibility, and integration issues of systems, especially in LMIC settings (Protheroe, 2024).

It is increasingly appreciated that the development of low-cost imaging solutions needs technological creativity as well as a match with the healthcare infrastructure, workforce abilities, and policy settings. The affordable imaging technologies should be capable of operating in limited resource conditions, such as unstable power, little technical

support, and limited financial resources. Moreover, to be successful, it needs to be integrated into the current healthcare systems, which involve compatibility with clinical processes, training of medical personnel, and regulatory and policy framework support.

Moreover, the new opportunities provided by artificial intelligence (AI) have affected the sphere of medical imaging by improving the efficiency of diagnosis and decreasing the use of specialized skills. The tools based on AI have the potential to help with image interpretation, automatically carry out diagnosis processes, and enhance clinical decision-making. However, the applicability of AI in the LMIC context is a research issue, particularly with respect to access to data, stability of the models, and infrastructure requirements. The prospects and issues of AI combination with low-cost imaging technologies need to be looked at with a severe sense (Hou et al., 2023).

It is a critical literature review of the available literature on affordable medical imaging solutions, especially in the LMIC settings. It evaluates key theoretical frameworks of the adoption of technology and the integration of the healthcare system and provides a conceptual framework of how imaging technologies can be practically implemented in the resource-restricted settings. The other technological factor that has been discussed in the chapter is the latest technological developments like portable imaging, AI-based diagnostic tools that can be employed to increase healthcare accessibility.

In addition, the chapter analyzes the extent to which such system level factors as the infrastructure, the workforce, the policy support, and the regulatory frameworks influence the adoption and sustainability of imaging technologies. It determines the main challenges and barriers that restrict the efficacy of the existing solutions and underlines the value of the holistic approach, which would combine the technological, economic, and institutional levels.

Lastly, this chapter establishes significant gaps within the current literature, especially in the absence of integrated frameworks that integrate affordability, scalability, artificial intelligence, and readiness of healthcare systems. These gaps underscore the importance of additional studies to come up with holistic and contextualized solutions that can resolve the special problems of the LMICs. This chapter presents a critical synthesis

of available information and forms the basis of the further analysis and the construction of a combined solution to affordable medical imaging (Huang et al., 2025).

2.2 Theoretical Framework

There is a need to have a solid theoretical basis in the adoption, implementation, and effects of affordable medical imaging technologies in low and middle-income countries (LMICs). The problem of healthcare systems in these regions is too complex and requires a multi-dimensional solution, which is not reduced to technological ones. Implementation of medical imaging technologies does not just rely on the technical performance but on the user behavior, organizational preparedness, and the system-level factors as well. Therefore, the three theoretical models that were employed in the current study are the Technology Acceptance Model (TAM), the Diffusion of Innovation Theory and the Health Systems Framework. All these frameworks give a holistic idea of how affordable imaging technologies could be adopted, expanded, and incorporated in healthcare systems in resource-constrained settings (Lee et al., 2025).

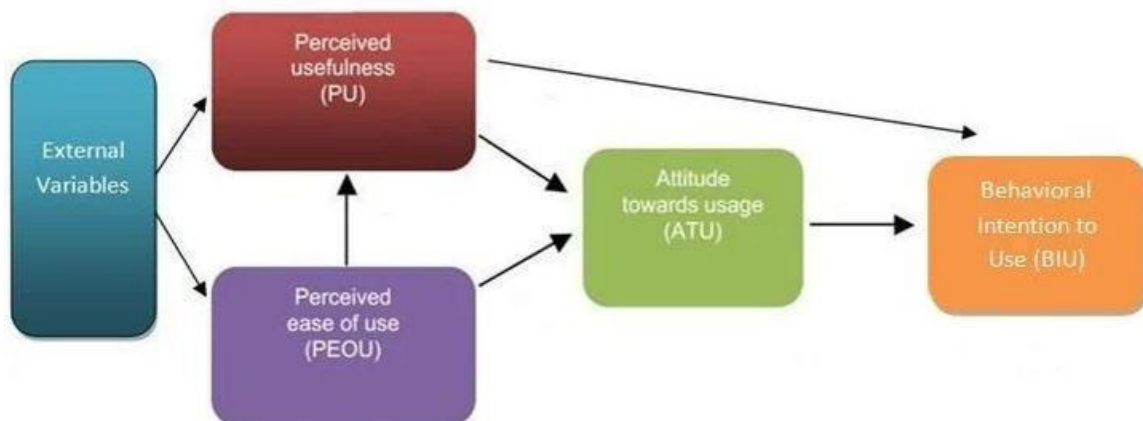


Figure 2: Integrated Theoretical Framework Model; Stavros Nikou Anastasios A., 2026.

2.2.1 Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) is a model that was designed by Fred Davis and was used to describe the way new technologies are accepted and used by users. TAM proposes that there are two main factors that determine the use of technology, and they are perceived usefulness and perceived ease of use. Perceived usefulness is the level of how the person trusts that the utilization of a specific technology assists in job execution, whereas perceived ease of use is the level of how one perceives that the technology is easy and simple to utilize (Harris and Rogers, 2023).

When related to medical imaging, medical care providers tend to embrace low-cost imaging technologies when they view that the imaging modalities enhance their diagnostic accuracy, the time of making a diagnosis, and their clinical judgment. Meanwhile, the concept of ease of use becomes one of the key concerns, especially in LMIC conditions, where medical staff may be overwhelmed with the workload, time pressure, and under-training. Complex technologies, those that entail a lot of training, or those that interfere with the current working processes, are less willing to be adopted, no matter how well they are technically able.

The fact that the workforce and infrastructure are limited in LMIC situations exacerbates the applicability of TAM. Portable imaging devices and AI-based diagnostic tools should be constructed in the framework of user-centered design, so that they are simple to use, with a clear interface, and with the lowest level of reliance on special knowledge. An example is that automated guidance, simplified outputs, or decision support devices are more likely to be accepted by non-expert users, e.g., general practitioners or community health workers.

Moreover, TAM lays emphasis on behavioral and psychological issues when adopting technology, which is largely disregarded in research that involves technology. Although a technology may be cheap and technically efficient, it might not reach mass adoption if users cannot see it as something helpful or convenient. Thus, TAM offers a critical perspective on interpreting user acceptance and reminds us of the necessity to create

low-cost imaging solutions that can accommodate user potentials and requirements within the LMIC healthcare setting (AlQudah et al., 2021).

2.2.2 Diffusion of Innovation Theory

Diffusion of Innovation Theory is a theory put forward by Everett Rogers to explain how new technologies are diffused across a social system. The theory recognizes five important characteristics that determine the adoption rate, and they are relative advantage, compatibility, complexity, trial ability, and observability (Iqbal and Zahidie, 2022).

Relative advantage is the perceived merits of a new technology as opposed to the current solutions. In LMICs, cheap imaging technologies should show definite benefits to the traditional methods of diagnosis, including better access, lower prices, and quicker diagnosis. The compatibility describes the degree to which the technology fits the current practices, values, and infrastructure. Technologies that can easily be adapted into existing healthcare processes are more accepted.

Another important factor is complexity, since technologies that are not easy to understand or use are resisted by the people using them. Simplicity and ease of use are required in LMIC environments where opportunities to train may be minimal. Trial ability is the capability to test a technology on a smaller scale before implementing the technology on a larger scale, and observability is the level of visibility of the benefits made by the use of the technology.

These attributes are very important when it comes to the adoption of low-cost imaging technologies, as is seen in LMICs. As an illustration, portable ultrasound has been more accepted because of its low cost, portability, and the capacity to operate in low-resource settings. Their comparative superiority to the old, fixed imaging systems is apparent, and their implementation in the point-of-care environment adds to their usage.

The theory, however, also points out the failure of certain technologies in spite of their technical superiority. The use of a technology that is not compatible with local infrastructure, or that needs a lengthy training process, or the benefits of which are not evident and observable in the short term, may be restricted. This is especially true when it

comes to LMICs, as the healthcare systems are frequently limited by the scarcity of resources and the difficulties in their operations.

Thus, the Diffusion of Innovation Theory is an excellent model to consider the process of adoption as well as the obstacles that inhibit the mass adoption of the cheap imaging technologies. It reiterates that technological advancement is not the only determinant of successful innovation, but the match between the innovation and the social and organizational context in which it is presented (Samadzai and Lamas, 2021).

2.2.3 Health Systems Framework

The World Health Organization conceptualized the Health Systems Framework as a framework that gives a holistic view of healthcare delivery and performance of a system. It recognizes six basic elements, commonly known as building blocks, which are service delivery, health workforce, health information systems, access to necessary medicines and technologies, financing, and leadership and governance (Ahmad and Danzangi, 2025).

This framework is especially applicable to the analysis of medical imaging technologies implementation into the LMIC healthcare systems because it does not focus on the individual level of utilization but addresses the system-wide aspects. The introduction of cost-effective imaging systems needs coordination between various healthcare system elements. As an illustration, service delivery should be transformed to include imaging technologies in clinical processes, and the health workforce should be properly trained to make use of and to read imaging findings.

The health information systems are quite essential in the handling of the imaging data so as to be able to store, transmit, and analyze the diagnostic information. Availability of necessary technologies can make imaging devices available when they are required, whereas mechanisms used to finance such technologies can define their affordability and sustainability. Governance and leadership offer the regulatory and policy framework that is required to assist with the implementation and diffusion of innovations.

When it comes to LMICs, the success of imaging technologies implementation may be impeded by weaknesses in any of these elements. As an example, cheap devices can be used, but their effectiveness might be low in case of the lack of training, maintenance

service, or policy frameworks to facilitate their use. Likewise, insufficient funding and an incomplete system of governance may limit the scalability of imaging solutions.

The Health Systems Framework points out the fact that technological innovation cannot work without systemic preparedness and institutional backing. It focuses on the need to take a holistic viewpoint where the various aspects of the healthcare system are interconnected. This is especially applicable to the current study as it seeks to come up with a comprehensive appreciation of how affordable medical imaging solutions can be efficiently established in LMICs (DeStigter et al., 2021).

2.3 Affordable Medical Imaging Technologies

Emerging low-cost medical imaging technologies have attracted considerable interest over the last few years, especially in relation to the mounting diagnostic service needed in the low- and middle-income countries (LMICs). The burden of communicable and non-communicable illnesses, and the limited availability of healthcare resources, has necessitated a desperate desire to find cost-effective diagnostic methods that can be implemented in a variety of settings, which may be faced with limited resources. The conventional imaging models, like magnetic resonance imaging (MRI) and computed tomography (CT) scanners, are expensive, complex, and infrastructure-based, making them inaccessible to many of these regions. High cost of procurement coupled with the expense of installation, cost of maintenance, and specialized human resources are limiting factors since they are not available to most healthcare facilities in LMICs, especially in rural and peripheral regions (Chowdhury and Ravi, 2022).

To overcome these issues, the latest developments have been oriented towards decreasing the cost by simplifying the design, using cheap and local materials, and incorporating open-source technologies. They assist in maintaining the required diagnostic functionality and minimize the unnecessary complexity and cost. In an indicative manner, the electronic revolution, miniaturization and digital imaging have enabled development of small and portable imaging equipment, which can be applied by having minimal infrastructural requirements. Cost reduction and maintenance are also facilitated by the application of modular designs and standard components.

Mobile ultrasound gadgets, handheld X-ray, and mini-sized imaging stations are some of the advancements in this field. The technologies are particularly created to work under conditions of limited resources, such as the lack of electricity, minimal technical support, and a lack of advanced infrastructure. Portable ultrasound machines such as these are now widely utilized since they are relatively cheap, can be used in a variety of ways, and offer real-time imaging. Equally, the handheld X-ray systems and compact radiography units are capable of facilitating simple diagnostic imaging in distant areas, thus extending healthcare services to conventional hospitals.

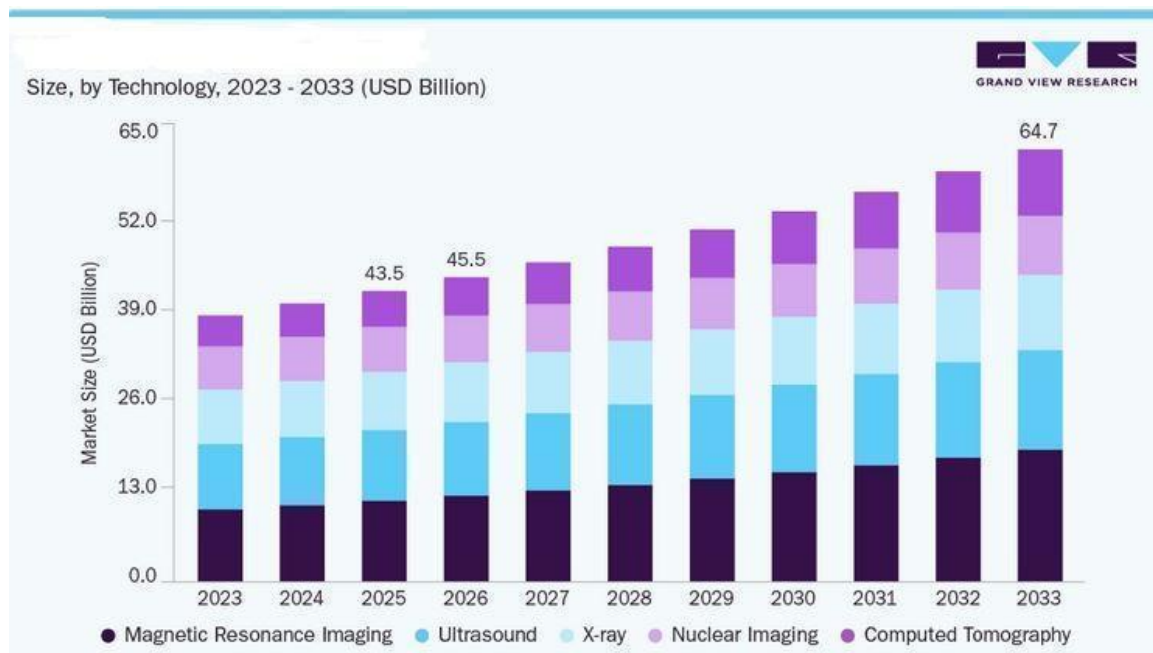


Figure 3: Medical Imaging Market Summary (2023-2033); Grand View Research, 2025.

Such technologies are built to have relatively low infrastructure, and thus they are more appropriate for rural and underserved areas. Most of them are battery-operated, portable, and easily transportable, thus enabling health professionals to conduct diagnostic tests in the field. This decentralization of diagnostic services compared to centralized services is a dramatic change in the way healthcare is delivered, since it saves time on

patients traveling, causes a decrease in healthcare costs, and allows the diagnosis and intervention to be put into place earlier (Husereau et al., 2022).

It is a fact that empirical studies have revealed that affordable imaging solutions can go a long way in enhancing access to diagnostic services, especially in primary healthcare setups. These technologies facilitate better clinical outcomes and more efficient health care delivery since they allow early detection of diseases like tuberculosis, maternal complications, cardiovascular diseases, and trauma-related injuries. Moreover, the application of digital technologies and telemedicine features can be used to interpret the results of imaging remotely, which adds to the access to expert knowledge even more.

Nevertheless, regardless of these benefits, there are a number of difficulties. Issues regarding durability, maintenance, and long-term performance are also vital criteria that should be researched. The low-cost devices may be susceptible to wear and tear especially in harsh climatic conditions, which are typified by temperature, humidity, and dust. The restricted access to spare parts and technical services may result in long service interruptions of the equipment, lowering the overall efficiency of the technologies.

Moreover, the issue of the trade-off between cost and quality is of concern. Although the cheap imaging technologies are designed to cut costs, care must be taken to avoid compromising the diagnostic accuracy and reliability. Image quality, resolution, and inconsistency differences may influence patient outcomes and clinical decision-making. Consequently, balancing between the cost and the performance is one of the major issues in the evolution of these technologies.

The other factor that should be taken into consideration is that of user training and capacity building. Even more simplified devices need a certain minimum of technical knowledge and clinical understanding to be used and interpreted correctly. This can be a major impediment to effective implementation in LMICs, where opportunities to be trained may be scarce.

On the whole, despite the promising potential of affordable medical imaging technologies in bridging diagnostic gaps in LMICs, their effective implementation would take a holistic approach that would look at all aspects of implementation, such as

technological design, operational, environmental, and system-level aspects. More studies and innovations are required to enhance the reliability, sustainability, and scalability of these solutions in practical healthcare contexts (Mills et al., 2022). Although affordability significantly improves diagnostic accessibility in LMIC healthcare systems, portability and field usability remain equally important for effective deployment in resource-constrained environments. These findings support H1, which proposes that affordable imaging solutions reduce financial and operational constraints in LMIC healthcare systems.

2.4 Portable and Point-of-Care Imaging

Portable and point-of-care imaging technologies are some of the major innovations that have contributed to enhancing healthcare access in low- and middle-income countries (LMICs). One of the most important limitations in healthcare delivery is the unavailability of diagnostic services in remote and underserved locations, which these technologies can solve. Portable imaging devices reduce the reliance on centralized healthcare facilities and delays caused by patient referrals and transportation to diagnostic centers by allowing diagnostic tests to be carried out at the point of care or in the immediate vicinity of the patient (Della Ripa et al., 2025).

The decentralized model of delivering imaging diagnostics to point-of-care diagnostics is one of the radical changes in the model of healthcare delivery. In the conventional healthcare systems, patients may have to drive far distances in order to seek imaging services, and this may create delays in diagnosis and treatment. The portable imaging technologies address this drawback by extending diagnostic services to the primary healthcare facilities, community clinics, and even field-based healthcare environments. The strategy is especially useful in LMICs when geographical distance, transportation issues, and lack of healthcare facilities limit the availability of necessary services.



Figure 4: Portable Imaging in LMIC Settings (Field Application Scene); Gao, Lv, and Hou, 2023.

The most common point-of-care imaging technology deployed is the use of portable ultrasound devices, especially in the field of maternal health, emergency, and diagnosis of infectious diseases. They are highly convenient in resource-strained settings due to their relative cheapness, real-time imaging and ease of operation. To illustrate, portable ultrasound is widely applicable in antenatal care to check fetal growth, identify complications, and enhance the maternal and neonatal outcomes. It facilitates quick evaluation of trauma victims in an emergency, and in infectious disease treatment, it helps diagnose such conditions as tuberculosis and abdominal infections (Bouzid et al., 2021).

Portable radiography equipment and handheld X-ray also increase diagnostic opportunities in remote areas. The technologies are used to perform basic radiography where conventional X-ray systems have not been established. They can be transported anywhere, and so healthcare providers can perform imaging in rural clinics, mobile health units, and calamity-stricken areas. Besides that, these devices in most cases have digital imaging and wireless data transmission, which allows sharing of images with specialists in remote interpretation via telemedicine platforms.

Such technologies come in handy, especially in locations that have poor infrastructure, since in most cases they are battery-powered and need minimal installation. Their lightweight design, portability and the fact that they do not require a constant power supply make them adaptable to a challenging environment. It is this flexibility that allows healthcare systems to be able to respond to the different healthcare requirements, and it enhances the accessibility to diagnostic services.

Portable imaging technologies have several challenges even though they are beneficial. The main problems include the low quality of the picture as compared to the conventional, high-end imaging systems. Portable devices are designed as cost effective and affordable, but in certain clinical situations, they may reduce the quality of the outcome, particularly quality of images. This gives a trade-off between accessibility and diagnostic accuracy that needs to be handled carefully.

The other challenge that is significant is that it needs to train users appropriately. Although most of the portable devices have been designed in such a manner that they are user friendly, some level of technical and clinical expertise is still required in the use of the device and interpretation of the findings. There is also a possibility that healthcare workers in LMICs have issues in utilizing these technologies to the maximum due to the possibility that the opportunities are limited. This raises the issue of capacity-building and training programs to ensure that portable imaging solutions can be implemented.

There is also the problem of data storage and transmission particularly in regions where there is low digital infrastructure. The successful implementation of imaging technologies relies more and more on data storage, data control, and data transfer to consult

and analyze the data. The lack of connection, the lack of standardized data systems, and the lack of issues with data security might have a negative impact on the integration of portable imaging devices into the healthcare systems.

Moreover, maintenance and technical support are also important issues. As much as portable devices have been designed to meet the needs of low-resource settings, they might still demand maintenance at specific intervals as well as the availability of spare parts. In the case of unreliable maintenance mechanisms, equipment downtime can become a bottleneck to the long-term effectiveness of such technologies.

These issues should be overcome to have successful applications of portable imaging technologies in practice. This involves a holistic solution consisting of technological enhancement, user education, infrastructural enhancement, and policy facilitation. These barriers can be overcome, and, in doing so, portable and point-of-care imaging technologies can play a role in helping to increase access to healthcare and achieve better health outcomes in LMICs (Dawkins et al., 2021). While portable imaging technologies improve accessibility and flexibility in low-resource healthcare environments, their diagnostic performance can be further enhanced through advanced AI-supported systems. These findings support H2, which proposes that portable imaging technologies are cost-effective and scalable in LMIC clinical settings.

2.5 Role of Artificial Intelligence in Medical Imaging

Artificial intelligence (AI) has emerged as a growing part of medical imaging and has great potential to enhance the quality of the diagnostic process, its efficiency, and general healthcare. With the blistering development of machine learning and deep learning algorithms, it has become possible to create AI-powered systems capable of processing complicated medical images, identifying anomalies, and supporting medical workers in making clinical decisions. Such systems can handle the large amount of imaging information at a rapid and consistent rate, thus lessening the workload on the healthcare provider and improving the diagnostic process (Born et al., 2021).

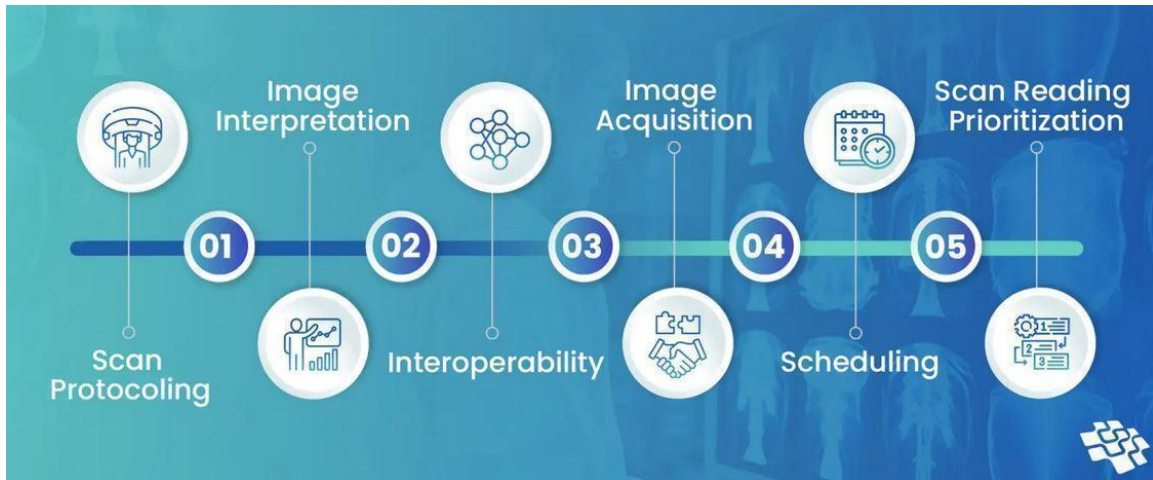


Figure 5: AI in Medical Imaging Workflow; Next Gen Invent, 2026.

The algorithms used in AI-based systems in the medical imaging field are generally trained to identify patterns in imaging datasets. The algorithms are able to detect minute characteristics that cannot be easily discerned by the human eye, thus enhancing diagnostic accuracy. Indicatively, AI models have been found to be very accurate in identifying lung nodules, breast cancer, fractures, and neurological abnormalities. Besides detection, AI may also be used to aid in image segmentation, classification, and quantitative analysis that are crucial to disease monitoring and disease treatment planning. Consequently, AI is being incorporated into the imaging processes more and more to complement human knowledge as opposed to abolishing it (Pinto-Coelho, 2023).

AI can help solve one of the most pressing issues of healthcare systems in low- and middle-income countries (LMICs), namely the lack of qualified radiologists and other specialists in the fields of imaging. A large number of LMICs experience a workforce shortage in which the number of trained professionals to interpret medical images is limited. It usually results in diagnosis delays, workload on the already available staff, and poor care. The AI-based systems can address these issues by offering automatic or semi-automatic interpretation of the image and assisting the medical staff in making quicker and more precise diagnoses.

The use of AI in LMIC settings is specifically applicable in tuberculosis, cancer screening, and fracture detection. As an example, X-rays of the chest have been examined with the assistance of AI to detect tuberculosis at its initial stages, as it has long been the leading issue of public health in most LMICs. Correspondingly, AI systems can also be used to help with screening for breast cancer by detecting potential suspicious mammogram lesions and increasing the likelihood of early detection. AI can be used in emergency care environments to identify fractures and other injuries, therefore, leading to timely intervention and treatment.

Besides increasing the accuracy of diagnosis, AI has the potential to improve the efficiency of workflow in healthcare systems. AI algorithms have an opportunity to prioritize cases according to their urgency, so that the most serious cases are considered initially. The functionality is more needed in the high-volume context where healthcare workers must handle large volumes of imaging studies in short periods. AI can accelerate the time spent on a diagnosis and enhance the overall efficiency of the system by automating the routine, simplifying the workflow, and reducing the time spent on the diagnosis process. Moreover, AI could be used to support tele-radiology through remote access and interpretation of medical imaging, thus expanding the field of specialist knowledge in remote and underserved areas.

Although this has high potential, AI applications in LMICs are associated with a number of challenges that should be taken seriously. The availability of high-quality datasets to train and validate AI models is one of the major issues. The high levels of accuracy and reliability of AI systems are based on large, diverse, and well-annotated datasets. Nevertheless, in most LMICs, these datasets are not available or are not complete and therefore may interfere with the output of AI models. The unavailability of locally relevant data is also a question of the generalizability of AI systems as applied to other contexts.

One more significant problem is the absence of computational infrastructure necessary to implement AI. Deep learning algorithms and other AI models are very expensive to run and train. High-performance computing systems, stable internet

connections, and data storage infrastructure are unavailable in most LMIC environments. This poses challenges to the successful adoption and deployment of AI-based imaging solutions. Although cloud-based solutions have a potential substitute, they also have issues of data security, privacy, and compliance.

The issue of AI bias and equity is also an issue that makes the application of AI in medical imaging more difficult. The vast majority of AI models are developed and trained using the data of a high-income population, which may not be representative of demographic, clinical, and environmental variables among LMIC populations. This may give biased results and lower diagnostic precision on the application of these models in other settings. As an example, AI systems can be conditioned by the variations in the prevalence of diseases, image quality and patient peculiarities. Therefore, there is a need to ensure that the AI models are trained on diverse and representative datasets to increase their usability and reliability.

Besides, there are also ethical and regulatory concerns associated with the use of AI in the medical sphere. The problem of information privacy, informed consent, accountability, and transparency should be resolved to make AI technologies responsible. The development of the guidelines that may assist in the implementation of AI is of particular necessity in LMICs, where the regulatory environment may be a weaker factor. Unless there is sound governance, AI systems may be abused or over relied on and this may affect patient safety.

In addition, the implementation of AI in the existing healthcare systems is to be planned and coordinated. AI tools should not disrupt the existing workflows, user capabilities and infrastructure. The healthcare professionals also need to be trained on the use of AI-based systems to enhance successful adoption. Mistrust of AI systems, low awareness, and resistance to change can become an obstacle to implementation.

Taking into consideration these challenges, it can be concluded that the context-specific AI solutions that would be grounded on the specifics of the LMICs development are demanded. These solutions should consider the local disease trends, infrastructure limitations, and staff capacity. There is a need to collaborate between researchers, medical

professionals, policymakers, and technology developers in order to create and deploy AI systems that are effective and sustainable.

On the whole, although artificial intelligence promises much to change the medical imaging in LMICs, its effective deployment presupposes a balanced strategy that would tackle technological, infrastructural, ethical, and contextual issues. With AI innovations in line with the needs of local health care, one can boost the capacity of diagnostics, enhance access to healthcare, and help to increase health outcomes in resource-constrained environments (Abbasov, 2021). Despite the significant diagnostic advantages offered by AI-supported imaging systems, their effectiveness ultimately depends on successful integration into existing healthcare infrastructures and clinical workflows. The reviewed literature supports H4, which proposes that AI and machine learning improve diagnostic accuracy and speed compared to conventional imaging approaches. These findings further highlight the importance of integrating affordability and AI-supported diagnostic systems within LMIC healthcare environments.

2.6 Integration of Imaging Technologies into Healthcare Systems

The implementation of imaging technologies within healthcare systems can be achieved through the integration of imaging technologies into human health operations, as outlined below. Affordable imaging technologies can be successful only when they are properly incorporated into the current healthcare systems. Although technological innovation is very important in enhancing the diagnostic abilities, the effect is very minimal unless it is synchronized with clinical workflows, infrastructure, and policy frameworks. Integration in low- and middle-income countries (LMICs) has a highly fragmented healthcare system, which is frequently resource constrained, making it a key determinant of the sustainability and efficiency of imaging technologies (Debnath, 2023).

Integration entails incorporating new technologies into regular clinical procedures in a way that augments and not interferes with the current healthcare delivery procedures. It takes keen coordination between imaging equipment and the practicalities of healthcare systems, such as flow of patients, their diagnosis path and the decisions made. As an

example, the implementation of portable imaging devices should be followed by changes in the workflow as a solution to make imaging outcomes be properly used in clinical decision-making. In the absence of such alignment, even the advanced technologies can be underutilized or not be able to achieve anticipated results.

Lack of interoperability between imaging devices and the current health information systems is one of the key problems of integration. Healthcare facilities in most LMIC settings have incomplete or non-standardized data systems which inhibits the capacity to store, share and analyze the imaging data. The lack of interoperability systems imposes communication hurdles between the various levels of healthcare provision, including primary care centers and tertiary hospitals. This does not only impact the continuity of care but also decreases the clinical value of imaging technologies. Interoperability among devices and digital health systems is therefore a necessity in order to be integrated successfully.

The other acute issue is the poor preparation of medical practitioners. The emergence of new imaging technologies necessitates the healthcare workers to learn new technical and clinical skills. Nevertheless, in most LMICs, resources are scarce to support training opportunities and institutional support is wanting. Therefore, medical practitioners might be unable to maximize the potential of imaging technologies and provide low-quality performance and low diagnostic accuracy. There is thus a need to have continuous training and capacity-building programs to facilitate the integration process.

The lack of adequate technical support and maintenance infrastructure also adds to the integration work. Even technologies meant to be used in low-resource environments need to be serviced on a regular basis and have access to spares. Without effective systems of technical support, the downtime of equipment may be increased, which impacts the provision of the services and the overall performance of healthcare centers. This highlights the fact that there is the need to establish sustainable maintenance frameworks as components of the integration strategy.

Besides the operational issues, regulatory problems and procurement procedures can also play a great role in delaying the implementation of new imaging technologies.

Most LMICs do not have effective regulatory frameworks on medical devices or their implementation is not evenly spread leading to delays with regards to approval and implementation. Procurement can be also complicated and bureaucratic that constrains time-sensitive acquisition of technologies. Moreover, the absence of the standardized guidelines to assess and choose imaging devices may lead to the inefficiency of the decision-making and resource distribution.

Research indicates the need to take an approach that involves the system level in order to solve these problems. This is because such an approach takes into account the technological factors, but more broadly the healthcare ecosystem in its entirety, which includes infrastructure preparedness, workforce capacity, and policy support. Infrastructure preparedness is making sure that there is a steady power supply, digital accessibility, and space to run imaging equipment. Workforce capacity encompasses the training of health care professionals and building of technical capacity whereas policy support entails formation of regulatory procedures and financing mechanisms that encourage the adoption of technology.

Telemedicine and tele-radiology had become important processes in improving the application of imaging technologies in the healthcare systems. In such ways, it is possible to remotely diagnose and consult as medical images can be transferred between two points and interpreted by a specialist. Tele-radiology can help as a solution to the demand and supply gap in expertise in LMICs where radiologists are limited. It allows medical professionals in far-off places to access professional services therefore improving the quality of diagnosis and patient outcomes.

Besides, telemedicine platforms facilitate the incorporation of imaging technologies through the improvement of communication and coordination among the various levels of healthcare. They permit exchange of patient data, make decisions together and help in improving efficiency of health care service provision. Telemedicine success however depends on the level of reliability of the internet connectivity, data security solutions and amicable supporting regulatory frameworks.

Regardless of these developments, the integration of imaging technologies in the healthcare systems is a multidimensional as well as a complex problem. It entails aligning the efforts of other stakeholders including healthcare providers and policymakers, technology developers, and regulatory bodies. The success of integration is anchored on the ability to address the systems and technical barriers as a whole.

Moreover, it is necessary to establish the standard models and frameworks that would regulate the process of integration in LMIC. These frameworks must have in them provisions touching on the elements of cost, infrastructure, workforce, and policy, making sure that the imaging technologies are not merely affordable, but also sustainable over a long period of time. In the absence of a systematic strategy, the threat of a disjointed implementation and ineffective use of technologies is high.

Conclusively, the penetration of cost-effective medical imaging systems into medical care is another important ingredient in enhancing access to diagnostic and healthcare services in LMICs. Although there has been big development on low-cost technologies, there has been potential development in the future of such technologies, which can only be achieved when they are well integrated into the current systems. It is important to overcome the issues of interoperability, training, maintenance, and policy support in order to make sure that these technologies are significant in resource-limited healthcare delivery settings (Winter et al., 2023). In addition to healthcare system integration, sustainable manufacturing and cost reduction measures are also required to make imaging technologies affordable and scalable in LMICs in the long term. The results support the proposed hypothesis H3 that low cost imaging devices are well integrated in the current LMIC health care workflow and enhance the normal diagnostic process.

2.7 Manufacturing and Cost Reduction Strategies

Lowering the price of the medical imaging technologies entailed novel production strategies that accommodated both cost and functioning limitations, especially in the low- and middle-income nations (LMICs). Conventional production modalities of medical imaging equipment tend to be capital-intensive, with the utilization of high-tech materials, complicated engineering operations, and production systems in a centralized location.

These make the cost of production high and are finally transferred to the healthcare providers to restrict accessibility in resource-limited environments. Hence, the creation of low-cost imaging technologies requires a transition to new manufacturing approaches based on the focus on cost-efficiency without a decrease in the necessary functionality (Ghotra et al., 2024).

Design simplification is one of the major cost reduction techniques that includes the reduction of unnecessary complexity in device architecture without compromising the fundamental diagnostic capabilities. Simple designs cut down on the elements, decrease production expenses, and the maintenance and repairs are simpler. This strategy can be related to the notion of the so-called frugal innovation when products are specifically created to respond to the demands of environments that have limited resources. With a concentration of features and removal of non-critical characteristics, the manufacturers are able to create imaging devices that are not only affordable but also useful to use in LMIC settings.

Another factor that is significant in the cost reduction of manufacturing is the utilization of locally available materials. Importing specialized components in high-income countries usually raises production costs because of the cost of transportation, tariffs, and reliance on supply channels. The manufacturing of products using materials and elements readily available in the area can save manufacturers a lot of money as well as strengthen their supply chains. Such a strategy helps to strengthen the local industries and minimizes dependency on external suppliers, which is especially crucial in LMICs because access to global supply chains can be inadequate or unreliable (Hussain et al., 2022).

The other important innovation in the development of low-cost medical imaging technologies is modular design. Modular systems enable separate sub-units of a device to be developed, replaced, or upgraded in isolation, as opposed to having to replace the entire system. This not only saves the initial production costs, but it also saves the long-term maintenance costs. As an illustration, when a certain component fails, it is easily replaced without having to impact the entire system, therefore increasing the life of the device.

Customization can also be achieved through modular design, where the devices can be tailored to the requirements of a certain healthcare environment and needs.

The development of open-source hardware has also contributed to the reduction of cost in medical imaging technologies. Open-source methods foster cooperation between researchers, engineers, and manufacturers through the sharing of design specifications, software, and technical expertise. This means that less proprietary development is needed, and the innovation block is low. Open-source platforms allow the imaging devices to be adapted and customized locally and made more applicable to different healthcare settings. Also, they make transfer of knowledge and capacity building possible, which are critical to sustainable technology development in LMICs.

Local production and assembly are major factors in enhancing the accessibility and affordability of imaging technologies. Setting up production plants in the LMICs goes a long way to decrease the expenses involved in importation, distribution, and logistics. It also facilitates capacity building by providing skill-building opportunities, employment, and technological progression in the communities. Healthcare systems can be less reliant on external support through developing local knowledge in manufacturing and maintenance to increase sustainability (Khalifa and Albadawy, 2024).

Also, the local production allows responding more quickly to the concrete healthcare requirements and the environmental situation. The manufacturers can tailor and develop technologies to local needs (e.g. in terms of power limitations, climate, disease patterns). The applicability and efficiency of imaging solutions in LMICs is enhanced by this context-specific approach.

Besides economic factors, sustainable manufacturing is also becoming an issue that is of significance in the creation of affordable imaging technologies. Production processes that are energy-saving, recyclable materials and waste reduction can help in environmental sustainability and at the same time reduce the cost of production. Such practices are in harmony with the global activities aimed at the sustainability of healthcare systems and minimization of the environmental impact of medical technologies. Sustainable

manufacturing in LMICs can improve the sustainability of long-term viability of imaging solutions due to limited resources.

Although these have been achieved, there are still a number of issues in undertaking the low-cost manufacturing strategies. The issue of quality and reliability of imaging devices is one of the most problematic issues. Medical imaging technologies should also be of high standards of accuracy, safety and performance because they have direct effect on patient care. The efforts of simplification of design and saving cost should not affect the quality of diagnostics or the life of devices. This balance of performance and affordability is a complicated task that needs to be carefully engineered and thoroughly tested (Srivastav et al., 2023).

The other significant challenge is compliance with regulations. Medical devices are regulated with high requirements in order to be safe and effective. In LMICs, regulatory systems can be either poorly developed or not enforced, which poses a threat of uncertainty to manufacturers. Simultaneously, compliance with international standards of regulation may prove to be expensive and time-intensive, especially in the case of small-scale or local manufacturers. This poses a conflict between affordability and the safety standards compliance.

In addition, quality control and standardization are also important issues in the decentralized manufacturing setting. Differences in manufacturing, quality of materials and technical skills may cause discrepancies in the performance of the devices. It is necessary to have standard manufacturing procedures and quality assurance systems to make sure that the low-cost imaging technologies can be adjusted to acceptable clinical standards.

There are also challenges in the supply chain management where there is constant access to components and materials. Although the practice of local sourcing decreases reliance on imports, it can also bring about inconsistency in the quality of materials and their supply. Supply chain strategies are thus required to be effective in order to bring reliability and continuity of production (Salehi et al., 2023).

Also, investment in research and development (R&D) is required to facilitate innovation in low-cost production. The creation of new material, the optimization of the design process, and the introduction of new technologies into it, including artificial intelligence, require a long-term commitment of investments. Nevertheless, in LMIC contexts, funding of such initiatives might be scarce, which acts as an obstacle to technological development.

Affordability vs. performance and safety is also a very important issue that should be considered when developing medical imaging equipment. Cost minimization is necessary in enhancing access, but it should not interfere with the quality of the diagnosis and patient safety. To reach this balance, it is important to have an integrated approach involving engineering innovation, regulatory control, and support at system level.

Finally, novel production strategies are critical in the lowering of the price and enhancing accessibility of the medical imaging technologies in the LMICs. Design simplification, local sourcing, modular design, and open-source development are some of the strategies that present promising avenues of developing low-cost solutions. Nonetheless, the challenges that should be dealt with to make sure that the successful implementation of these technologies is achieved are tied to the issues regarding quality, reliability, regulatory compliance, and sustainability. This requires an all-encompassing, context-based approach to manufacturing that can facilitate the creation of viable and scalable medical imaging solutions in resource-constrained settings (Najjar, 2023).

2.8 Literature Review Gaps

A number of key research gaps exist in the field of medical imaging technologies in the context of LMICs, especially when viewed in the context of the rapidly increasing body of literature in the field. While current literature has greatly advanced imaging performance, technological innovation, and AI use, there is a lack of cohesive synthesis and a highly diverse literature base. The constraints make it difficult to build scalable, sustainable and context-specific imaging solutions for the challenges faced by resource-limited healthcare systems (Sharma and Cotton, 2023).

First, the majority of current research is conducted on a single dimension (reduction in costs, imaging performance or AI), without combining these elements in a single analytical framework. In the literature about the affordability of research, it is common to look at the financial models and procurement strategies without also looking at the imaging performance of the system and without focusing on image resolution. The imaging performance of the system is usually studied separately from the financial models and procurement strategies, and the literature of imaging performance studies mainly focuses on the technical accuracy and image resolution. Likewise, numerous studies focused on AIs tend to focus mainly on the development and testing of algorithms. But, there is limited research which has focused on the simultaneous interplay of affordability, scalability, health care integration and AI capability in the real-world LMIC health care settings. This disjointed view does not allow for greater understanding of the wider applicability and scalability of affordable imaging technologies in resource-limited healthcare systems.

Secondly, there is still limited empirical evidence on the long-term performance, durability and sustainability of low-cost imaging technologies. There are also many existing studies based on pilot projects, controlled settings or on short-term evaluations that could not accurately represent real-world healthcare settings. Operational issues like environmental stress, equipment maintenance, technical support restrictions and long term usability are not adequately addressed. There are therefore only uncertain answers regarding the long-term effectiveness and sustainability of the affordable imaging technologies in LMIC health care systems.

Thirdly, the potential of low-cost imaging technologies in the presence of artificial intelligence is still not fully explored, especially in terms of data quality, model bias, and contextual applicability in LMIC settings. While AI-integrated diagnostic systems have shown promise in enhancing diagnostic precision and productivity, the majority of AI models have been developed from datasets from high-income countries. The data sets might not necessarily reflect the demographic, clinical, and environmental situation seen in LMIC health care systems. However, one of the most significant obstacles remains the scarcity of sufficient data, inconsistent imaging quality, and the absence of standardized

datasets, which hinder the successful application of AI-powered diagnostic systems, especially in low-resource settings.

Moreover, the ethical and regulatory considerations of the use of AI-aided medical imaging have not been sufficiently explored in extant literature. Data privacy issues, transparency of algorithms, accountability, and possible model bias need to be explored more in-depth, especially in LMICs where regulatory frameworks might be less established. The implementation of AI powered imaging technologies could have major hurdles without adequate governance mechanisms.

Another significant research gap is the integration of low-cost imaging technologies into the existing healthcare infrastructures at the system level. While the role of technology is much discussed, there has been little interest in addressing workflow integration, workforce readiness, interoperability with digital health systems, regulatory approval and institutional readiness. Current affordable imaging technologies have limited applicability and scalability in LMIC healthcare settings because of the lack of a systems-based view.

Furthermore, there has been minimal research that focuses on the readiness of the healthcare workforce, and user acceptance of low cost imaging technologies. Current research studies tend not to consider training needs, behavioral adoption factors and the capabilities of staff, which are key elements directly impacting the successful implementation of technology. This gap between tech development and actual healthcare use is especially relevant in LMIC healthcare systems where there are significant human resource constraints.

In addition, there are comparatively few studies available that are conducted across various LMIC healthcare settings. The effectiveness and use of imaging technologies can be affected by differences in healthcare infrastructure, economic conditions, policy setting and cultural context. However, research undertaken at present tends to be specific to the context and the lessons learned cannot be transferred to other settings and/or implementation strategies have not been standardized.

The identified research gaps showcase the need for integrated approaches and system oriented approach in the development and implementation of affordable medical

imaging technologies. Future studies should integrate a technological, economic, institutional, and healthcare system view to create sustainable structures appropriate to the healthcare system in LMICs. There is also a need for further longitudinal studies and empirical research to assess the long term viability and scalability of low-cost imaging technologies.

To conclude, while there have been significant advances in medical imaging technologies, there remains a lack of integrated solutions to ensure medical imaging systems are affordable, scalable, AI-capable, and integrated into the healthcare system, as seen in the current literature. These are critical requirements to meet if imaging solutions are to be developed for sustainable use that can enhance healthcare access and diagnostic effectiveness in resource-limited settings (Saliu et al., 2022).

The present study develops a framework that is grounded in the literature gaps identified and proceeds through a hypotheses-driven approach: Affordability, Portability, Healthcare Integration, and AI-supported diagnostic efficiency in low-cost medical imaging technologies for LMIC healthcare systems.

2.9 Conclusion

This chapter has critically reviewed the literature available on the topic of affordable medical imaging technologies and specially as applied to the low- and middle-income country (LMIC) contexts. Various important theoretical frameworks such as the Technology Acceptance Model, the Diffusion of Innovation Theory, and the Health Systems Framework have been analyzed to come up with a robust theoretical conceptual framework of explaining the adoption and implementation of imaging technologies. All these frameworks point to the fact that the adoption of the technology is not only determined by the technical capacities but also by the acceptance of the users of the technology, system preparedness and other institutional aspects (Nafade et al., 2024).

The chapter has also touched on the most significant technological advances in the sphere of medical imaging such as the appearance of inexpensive and portable imaging equipment, the development of point-of-care diagnosis, and the increased adoption of artificial intelligence to improve diagnostic efficiency and accuracy. Such innovations

show a lot of promise to enhance access to healthcare especially in resource-restricted settings where conventional imaging systems cannot be implemented. The need to produce innovations in manufacturing and cost-cutting strategies in order to make these technologies more affordable and sustainable was also highlighted in the discussion.

Moreover, the chapter has critically discussed the issues linked with the introduction and adoption of low-cost imaging technologies into the healthcare systems. Infrastructure limitations, human capacity, interoperability, regulatory issues and maintenance can be considered as some of the most salient limitations that are known to affect the functionality and scalability of these technologies. It has stressed that the presence of system level factors is a major determinant of successful implementation, which justifies the significance of holistic approach to the implementation, in addition to technological innovation.

Another observation made in the review is that although great success has been made in the development of low-cost imaging solutions, there remain enormous gap in so far as integrating, scaling and long-term sustainability are concerned. Lack of a single system, which can bring together affordability, technological capability, artificial intelligence, and healthcare system dimensions is a critical research gap. The available literature on the topic is biased towards a piecemeal solution, in which each of the individual elements is taken into account, yet the interplay of these variables in the real-life LMIC setting is not included.

In addition, the limited amount of the empirical evidence on the long-term performance and the context-specific AI implementation, as well as the integration on the system level, make it obvious that more specific and practical studies are supposed to be conducted.

These gaps must be filled in order to come up with imaging solutions that are not only innovative but also practical, scalable and sustainable across different healthcare settings.

In general, this chapter confirms that medical imaging access should be enhanced in LMICs in a multi-dimensional manner, which involves both technological and

healthcare systems, policy, and user dimensions. The chapter demonstrates the rationality of the current study by pinpointing some of the most important gaps in the current literature and outlines the potential contribution that the study can make to the academic research and actual healthcare solutions.

The second chapter was an extension of the first chapter in which a research methodology of the investigation of these issues was explained. It outlined the research design, data collection procedures, and methods of data analysis to be used to discuss the development, implementation and impact of affordable medical imaging technologies in LMICs (Hilabi et al., 2023).

CHAPTER 3:

RESEARCH METHODOLOGY

3.1 Introduction

This chapter details the research methodology that was used to address the primary objectives of this study that aimed to develop low cost medical imaging solutions for Low- and Middle-Income Countries (LMICs). The study focused particularly on the cost-effectiveness, scalability, system integration and application of the use of Artificial Intelligence (AI) to improve the accuracy of diagnostics in these healthcare facilities. The methodology described in this chapter enabled a systematic investigation of the factors which influence the implementation and action of low-cost medical imaging devices in low-resource environments.

Low-cost medical imaging is increasingly becoming important in LMICs. Access, availability and affordability of advanced medical technologies are often impeded by their high cost and poor infrastructure, which deters the healthcare systems of these countries. Medical imaging technologies are essential for the diagnosis of a wide range of conditions, but expensive and inaccessible to most health care providers in LMICs. Thus, the feasibility of the development of low-cost medical imaging systems that are able to address these challenges and integrate the emerging technologies like AI to enhance diagnostic capabilities was explored. These factors helped to establish the concept of affordable imaging being a potential and scalable way to provide imaging in resource-limited health care settings.

The research objectives in Chapter 1 were taken as a basis for designing the methodology. The research questions focused on the affordability, scalability, system integration, and AI opportunities for improving the effectiveness of diagnostic services in LMICs, to directly inform these objectives. A quantitative research design was chosen due to the fact that it was conducted in a systematic and objective manner in order to measure the relationships among the key variables. For this study, quantitative methods were more appropriate to obtain data from a diverse group of medical imaging professionals, which

were then analyzed to spot patterns and connections. The effect of factors on the AI systems performance and integration was evaluated through statistical analyses.

The chapter is structured in a way that will lead the reader through the research design, data collection and analysis process. The research objectives and the research questions were also linked to the methodology in order to ensure that they all addressed the main research questions. The first part of the chapter describes the research design, and provides the rationale for choosing a quantitative approach. Then describes population and sample, participant selection, and the rationale for the sample size. Data gathering techniques, such as survey instruments and questionnaire design are discussed, as are variables and measures for assessing key concepts. Lastly, the chapter illustrates the statistical tests used to test the hypotheses and analyze the data, ethical issues raised and methodological limitations.

For the purpose of meeting the objectives of the study, a quantitative research design was vital, especially when measuring the correlations between various constructs such as affordability, system integration, and AI performance. These relationships were explored through the research questions and through the structured and efficient measurement and analysis of the quantitative approach used. The study was conducted on participants' perspectives related to medical imaging technologies using a survey approach, which involved healthcare professionals directly involved in development, implementation and application of medical imaging technologies. This approach was used in order to ensure findings were based on real-life experience, and the data captured was from a large and diverse sample, which would increase the generalizability of findings.

Data collection was done systematically and sophisticated analysis was used, which is suitable to get valid and reliable results in this chapter. The methodology ensured that the research aims were met and that the complexity of the problems researched were taken into account. The quantitative approach facilitated the development of statistically significant results that informed this study about the factors affecting the success of affordable medical imaging technologies in LMICs.

In summary, this chapter summarizes the research methodology employed in the investigation of the development and integration of affordable medical imaging solutions in LMICs. It offers insights into the obstacles and opportunities that arise when putting these cost-effective imaging technologies into practice, especially when it comes to AI. The study employed qualitative research methods and gathered data that was credible to the research questions, as it added to the existing body of knowledge of medical imaging in resource-limited health care environments. The chapter describes the study design, sampling, the variables, hypotheses, data collection and statistical tools used in the study of affordable medical imaging technologies for LMIC healthcare systems.

3.2 Research Design

Research Approach

This study employed a quantitative approach which allowed to collect and analyze the data systematically, quantitatively, and appropriately for statistical analysis. This approach was especially suitable for the research goals, enabling the assessment of the relationships between key variables such as affordability, system integration, diagnostic performance enhanced by AI, and scalability of medical imaging technology in Low- and Middle-Income Countries (LMICs).

This study was conducted by quantitative research with the data obtained in the form of numbers and was fundamental in analyzing the effects and correlations between independent and dependent variables. As the research questions were designed to find out patterns, correlations and cause-effect relationships among various variables like affordability and diagnostic performance, quantitative method was found to be the best method for analyzing the various relationships. This provided for a large amount of data to be collected using structured surveys and then statistically analyzed to draw significant conclusions.

The quantitative method also enabled generalization of the findings: the sample of healthcare professionals, engineers and other stakeholders which participated in the study was of an appropriate size and heterogeneous in terms and scope of medical imaging

technology involvement. This facilitated the transferability of the study results to other contexts in LMICs, and was in line with one of the primary goals of the study.

Type of Study

The study was descriptive-correlational type. The descriptive component characterized the real situation of affordable medical imaging technologies in LMICs, the problems and opportunities pertaining to medical imaging technology development and implementation in LMICs, and the usage patterns. This part also covered demographic aspects of respondents, perceived affordability and scalability, AI diagnostic accuracy and their opinion of the use of low-cost imaging systems in resource-poor healthcare environments.

The correlational aspect of the study was to discover and investigate the relationships between the essential variables. The statistical analysis techniques adopted were correlation analysis, regression analysis and structural equation modeling (SEM). Specifically, the study explored how the performance of AI diagnostics in medical imaging was affected by factors including affordability and integration in the imaging system, and how these factors affected the scalability and overall effectiveness of the low-cost imaging system in LMICs. The study achieved this by exploring these connections and uncovering the dynamics and interactions between the different factors and how they contribute to the implementation of sustainable medical imaging technologies.

Justification for Design

The quantitative research design was chosen because of the nature of the research objectives and the questions raised were of a quantitative nature, and wanted to quantify and evaluate the correlation between the key variables. The research was directed toward complex questions such as the viability of medical imaging technologies to be adopted into health care systems, the ability to scale these technologies, and the potential use of AI to improve diagnostics. The quantitative approach proved to be appropriate for the study of these issues since it allowed for the accurate measurement of variables and testing of the relationship between variables by means of accepted statistical procedures.

A quantitative design would be especially suited for this study because it would enable the researcher to:

1. **Test Hypotheses:** The research design enabled the formulation of hypotheses that related affordability, system integration, AI diagnostic performance and scalability. It was suggested that system integration had a significant impact on the performance of AI diagnostics, for instance. These hypotheses were validated by conducting statistical analysis to determine whether these relationships were valid in the sample.
2. **Establish Correlations:** A major goal of the study was to determine the relationship between factors like the affordability and scalability and the performance of the diagnostic process with the use of AI. These relationships were determined and measured using regression analysis and SEM and provided insight into underlying patterns that may not have been immediately obvious.
3. **Generalize Findings:** The external validity of the study was enhanced by the study's large and heterogeneous sample, and the wide spectrum of medical imaging engineers, healthcare administrators, and clinical practitioners. The results were also transferable to other settings and populations in LMICs, adding to the knowledge base in medical imaging in low-resource settings.
4. **Achieve Objectivity and Rigor:** The quantitative design ensured objectivity and rigor. The use of standardized survey instruments and validated instrument scales reduced the subjective interpretation biases, and the research process was highly transparent and replicable, while the findings were reliable and valid as set forth in the research proposal.

In general, the use of descriptive-correlational quantitative research design was justified as it enabled the achievement of the goals of the study, helped to test the relationship between variables and resulted in objective, reliable and generalizable information on the development and adoption of affordable medical imaging technologies in LMIC healthcare systems. This research design serves as a foundation for the next section, which will be devoted to the sampling and data collection methods.

3.3. Population and Sample

3.3.1 Target Population

This study focused on professionals in medical imaging technologies in the context of Low- and Middle-Income Countries (LMICs). The population included individuals who were directly or indirectly engaged in developing, manufacturing, deployment and use of medical imaging equipment. It encompassed all aspects of the medical imaging landscape, including healthcare administrators, radiologists, clinical practitioners, research and development (R&D) engineers, product designers, manufacturing specialists, and more. Their contribution in making medical imaging solutions work in resource-limited healthcare systems, in integrating, implementing and continually enhancing these solutions is of utmost importance.

The medical imaging experts generally had knowledge of medical imaging technology, the production of medical devices or healthcare services in LMICs. Their experience was crucial in learning the challenges in the operations and technology limitations, as well as what can be done to improve access to affordable imaging devices. Furthermore, their viewpoints played an important role in evaluating the feasibility of integrating AI into medical imaging systems and its implications on diagnostic accuracy and healthcare effectiveness in LMICs.

Data from this diverse group was gathered to gain a well-rounded perspective on the challenges of implementing affordable imaging technologies, such as technology design, cost-effectiveness, system integration, and the use of AI to enhance diagnostic results.

3.3.2 Sampling Technique

Purposive sampling method was used for the identification of respondents in this research. Purposive sampling is a non-probability sampling method that selects respondents who have a specific characteristic or experience related to the study, can be done in accordance with the approved Research Proposal (RP). For this study, the

researchers focused on professionals that directly worked in or had significant experience working in medical imaging within LMICs.

It was therefore appropriate to use purposive sampling because the respondents should have the knowledge and experience to provide informed responses to the survey. The study targeted people involved in R&D, product design, engineering, healthcare administration and clinical practice to gain a wide variety of viewpoints from people who work directly with medical imaging in resource-constrained settings. This approach facilitated a more detailed understanding of the problems and possibilities of cost-effective and affordable imaging technologies in LMICs.

Moreover, the purposive sampling approach ensured that feedback was obtained from key stakeholders at different levels of the medical imaging value chain. Purposive sampling was the most appropriate sampling method for this research as these professionals were important in the development of affordable imaging solutions and implementation and were essential in the technical, operational, and clinical aspects.

3.3.3 Sample Size

As per the Research Proposal (RP), 213 respondents participated in the study. The data were collected over a period of approximately six weeks (around 1.5 months). This sample size was sufficient to allow for meaningful statistical analysis and to draw valid conclusions. Given the number of variables included in the study, such as affordability, system integration, and AI performance, the sample size of 213 respondents was considered appropriate to ensure the reliability and validity of the results.

The reason for this sample size was to obtain a range of views on the subject from professionals involved in diverse aspects of the medical imaging sector. The sample was stratified to represent engineers, R&D specialists, healthcare administrators, and clinical practitioners in different healthcare practice settings in LMICs. This method ensured that the sample was representative of the experience and opinions of people working in affordable medical imaging technologies.

In addition, the sample size of 213 met the requirement of statistical power so that the data was adequate to perform regression and correlation analyses, ANOVA and Structural Equation Modeling (SEM) and reduced the risk of Type I and Type II errors. The relatively large sample also made results more generalizable, as the results could be applied to the broader population of professionals working in medical imaging in LMICs.

3.3.4 Inclusion and Exclusion Criteria

In order to make sure that the participants chosen in the study are related to the research goals, the following inclusion and exclusion criteria were used:

Inclusion Criteria:

- **Professional Experience:** The participants should have one year of experience in the medical imaging field, which could be in R&D, product designing, healthcare administration, or clinical practice.
- **Direct Involvement in Medical Imaging:** The participants need to be directly involved in the medical imaging development, production or use. These are engineers, product designers, clinicians (e.g., radiologists), healthcare administrators and other stakeholders.
- **Setting:** The participants should be in Low-and-Middle-Income Countries (LMICs) as classified by the World Bank. This made sure that the survey taps into the knowledge of professionals who act in resource-constrained healthcare environments.
- **Consent to Participate:** Participants must agree and consent to participate in the survey and the ethical standards must be upheld in the process of data collection.

Exclusion Criteria:

- **Absence of Relevant Experience:** The participants with the insignificant experience in medical imaging (less than one year of experience or those who work in other areas) were excluded out of the research.

- **Non-LMIC Based Professionals:** Professionals outside of LMICs were not represented because the focus of this study is the medical imaging in resource constrained healthcare systems.
- **Non-Healthcare Professionals:** This category is defined as any professions not directly involved in medical imaging that included administrative staff lacking in technical or clinical skills, was not included as their input would not aid in answering the research questions.

All these criteria are used to make sure that the sample consists of the professionals having the related expertise and experience in the sphere of medical imaging in LMICs and, thus, the relevance and quality of the data gathered are increased.

3.4. Data Collection Methods

3.4.1 Survey Instrument

In this study, the main method of data collection was the structured survey that included 25 questions and was used to gather the views of medical imaging professionals in L Macedonia Countries (LMICs). The questionnaire was designed to address the primary research goals outlined in the Research Proposal (RP) and structured into five components: demographics, affordable imaging, cost-effectiveness, AI performance, and system integration.

The sections were each designed to gather specific data regarding factors affecting the development, uptake and efficiency of affordable medical imaging technologies in LMICs. The survey design captured all the necessary data and allowed for a detailed analysis of relationships between the key variables such as affordability, system integration and AI performance.

1. **Demographics Section:** This section collected data on the respondents' professional background, function within the medical imaging ecosystem, years in the field and country of residence. The data offered background information to inform the

- perspectives of respondents and enabled analysis of sub-groups, by professional role or geographic location.
2. The goal of this section was to evaluate the elements that can affect the cost of medical imaging technologies such as component cost, local manufacturing and the availability of cost-effective design methods. The aim was to find out professionals' perception of the affordability and elucidate the leading drivers or barriers to the development of affordable imaging equipment.
 3. Cost-Effectiveness Section: Questions in this section assessed the cost-effectiveness and scalability of low cost medical imaging solutions. Operational cost reduction, mass deployment and sustainability were taken into account to gain insight into the role they play in overall imaging technology uptake in resource constrained health systems.
 4. System Integration Section: This section looked at how cost effective imaging technologies can be integrated into current healthcare systems. Compatibility issues with hospital workflow, integration with current IT systems, training requirements and support for maintenance were addressed. The goal was to assess the realistic issues of using affordable medical imaging solutions and to determine how they could be effectively utilized.
 5. AI Performance Section: The last section was on the application of Artificial Intelligence (AI) to increase the performance of low-cost imaging technologies. The questions evaluated the respondents' understanding of the impact of AI on diagnostic accuracy, speed, reliability, and clinical applicability. The goals were to gain insights into the potential of AI for enhancing medical imaging in low-resource settings and its role in making imaging more affordable and scalable.

The survey instrument was designed after an in-depth literature review of the field of medical imaging, artificial intelligence in healthcare, and cost-effective technologies in LMICs. Questions were framed to get quantitative (Likert scale) as well as qualitative data. The survey was designed to be clear, reliable and valid, with minimal ambiguity in answer responses.

3.4.2 Measurement Scales

The 7-point Likert scale was used throughout the survey to measure respondents' attitudes, perceptions and opinions on key variables of interest. This scale is widely employed in survey research due to its ability to offer a spectrum of responses and let respondents express their agreement or disagreement with the presented statements. Using a seven-point scale made the data gathered detailed, providing a good amount of information about respondents' opinions.

Responses on the Likert scale ranged from 1 (Strongly Disagree) to 7 (Strongly Agree) and allowed participants to express their agreement with the following statements: Affordability, system integration, and the support of AI in diagnostic performance. For instance, for a question like “Low-cost design approaches improve access to imaging in LMICs”, the respondents were given an opportunity to indicate how far they agreed or disagreed, which was crucial for the purposes of this study in understanding the relationship between affordability and medical imaging.

The survey also featured multiple-choice and open-ended questions, in addition to items asking for a Likert scale answer. These questions helped to further explore certain themes including local production or perceptions of AI. Closed and open-ended questions together enabled collection of both quantitative data to be analyzed statistically and qualitative data to gain insights into the challenges and opportunities surrounding affordable medical imaging technologies.

3.4.3 Pilot Testing

A pilot test was done to ascertain the validity and reliability of the survey instrument before the real data collection. The pilot test was carried out on a small number of participants (10 - 15) who were not included in the study sample, but had the requisite experience in the medical imaging and AI applications sector. The objective of the pilot test was to record any issues that might be linked to the clarity of the questions, the general flow of the survey and how much time would be required to fill the survey out.

During the pilot test, the subjects were asked to make comments regarding the comprehensibility of the survey, its length and the difficulty in understanding the wording of the questions. This feedback was then used to refine the survey instrument to ensure that the questions are understandable, clear and to ensure that the response options are appropriate for answering the research questions. Furthermore, the pilot test was used to evaluate the stability of the scale items and it facilitated some changes, such as the rewording and scaling of some questions.

After receiving the feedback from the pilot test, the survey instrument was completed and the final questionnaire was ready to be sent out to the entire sample population of 213 respondents. The data collection phase is an important process since it involves the pilot testing of the surveys, which is used to test the effectiveness and efficiency of the surveys in terms of collecting the required data and reducing any possible biases or errors in responses. The pilot test was also a chance to test the technicality of the survey distribution process and made sure that the respondents would not have any trouble with completing the survey due to technical problems.

3.5. Variables and Measures

3.5.1 Independent Variables

The study analyzed the effect of low cost medical imaging AI tools when developed at a low cost, cost effective and integrated into LMICs health systems on diagnostic performance. These independent variables were well connected to the study hypotheses and were the primary operational and technological variables that influence adoption and impact of affordable medical imaging solutions.

Independent Variable Descriptions:

1. **Affordability** – Design and production of imaging technologies that are low cost and functional. This encompasses design solutions that are cost effective, the use of local materials, the streamlining of manufacturing processes and the affordability

of operation. It reflects the sense of access to and the cost-effectiveness of financial resources within LMIC health care systems. (Hypothesis H1)

2. **Portability** – How easy, mobile and usable the imaging devices are in various clinical environments. This involves transportability, infrastructure demands, weight and size. Portability makes access to remote and underserved areas possible. (Hypothesis H2)

3. **Healthcare System Integration** – Denotes the capacity of imaging technologies to seamlessly integrate into current healthcare workflows, digital platforms, healthcare personnel capabilities, and healthcare personnel systems. Successful integration means that uptake and effective use in clinical settings will be achieved over the long-term. (Hypothesis H3)

4. **AI Integration** – Records the impact of AI-powered tools on efficiency and accuracy of diagnostics. This includes AI capabilities like image recognition, decision support, and workflow automation to help the clinician, particularly when there is a shortage of experts. (Hypothesis H4)

These are independent variables that are merged for subsequent analysis of the factors associated with diagnostic performance when using AI support in LMICs.

Table 1 gives a summary of the independent variables, which helps in making the study analytical easier and acts as a reference point for further statistical analysis and testing of the hypotheses.

Table 1: Independent Variables, Operational Definitions, and Measurement Scales

Independent Variable	Measurement Scale	Hypothesis	Source / Notes
Affordability	5-point Likert	H1	Captures the cost-effectiveness and accessibility perception of imaging technologies in LMICs
Portability	5-point Likert	H2	Measures the practicality, mobility, and usability of portable imaging devices
Healthcare System Integration	5-point Likert	H3	Evaluates how easily imaging devices are incorporated into existing healthcare workflows
AI Integration	5-point Likert	H4	Assesses the influence of AI-enabled tools on diagnostic efficiency and accuracy

Source: Author's work

3.5.2 Dependent Variable

The dependent variable of this study was the extent of diagnostic performance with the use of AI. It was said to be the ability of medical imaging technology with AI to improve diagnostic process precision, reliability, speed, and clinical value. In healthcare settings, particularly in LMICs, AI-powered imaging systems play a crucial role

in improving medical imaging technology at an affordable cost, where access to specialized diagnostic expertise may be limited.

The diagnostic accuracy assessed the performance of AI systems in identifying abnormalities and aiding clinical decision-making. Reliability was used to determine the consistency of the AI-generated diagnostic outputs with various imaging contexts and healthcare settings. To assess the consistency of the AI-generated diagnostic outputs across different imaging contexts and healthcare environments, reliability was used. Diagnostic speed was evaluated to determine the rapidity with which AI systems analyzed images and made diagnoses. Clinical usability assessed how well AI-enabled imaging tools can be adopted into the routine of healthcare, to support healthcare professionals without disrupting workflow.

Participants evaluated the performance of AI tools used for imaging, such as their usefulness in making precise and reliable diagnoses, increasing efficiency, and improving the usefulness of imaging in LMIC healthcare settings.

3.5.3 Measurement Instruments

To ensure reliability and validity of the research constructs used, widely accepted measurement methods were used in the study. Literature research was carried out to identify suitable measurement scales, which included affordable medical imaging technologies, integration within the healthcare system, and AI-supported diagnostic systems.

The internal consistency reliability was measured by Cronbach's alpha and scores of 0.70 and above were regarded as acceptable. Moreover, composite reliability was used to assess the reliability of the latent constructs in the Structural Equation Modeling (SEM) context.

Convergent validity was tested by Average Variance Extracted (AVE) and items that have an AVE value ≥ 0.50 were considered as acceptable convergent validity and were measured by the intended construct. The validity of the measurement model was further tested using SEM and Confirmatory Factor Analysis (CFA). These statistical techniques

enabled hypothesis testing and assessing relationships between affordability, cost-effectiveness, healthcare integration and AI support for diagnostic performance.

3.6 Data Analysis Techniques

The statistical analysis techniques were chosen to test the research hypotheses and analyze the relationships among the study variables.

3.6.1 Descriptive Statistics

Descriptive statistics were the first step in analyzing the data obtained from the survey. Descriptive statistics were used in this study mostly to give an overview of the respondents' demographic features and to get a general overview of the survey responses. These numbers gave a clear idea of the sample as a whole and allowed the researcher to see how the important characteristics, such as professional position, years of experience and geographic whereabouts of the respondents were distributed.

Data on participants' professional experience, years of experience in the profession and geographic location were summarized via frequency distributions, means and standard deviations. For instance, participants' distribution along professional categories such as radiologists, engineers, and healthcare administrators was analyzed and compared with the healthcare industry in LMICs engaged in medical imaging areas. Likewise, descriptive statistics were used to determine the average years of experience and other demographic variables.

In addition to demographic data, summary data on general survey responses were also used. This included deriving the mean of each survey item which can be used to represent the level of agreement or disagreement with the statement. Standard deviations were calculated to determine the variability of responses. The analysis of the distribution of the responses across the 7-point Likert scale provided deeper insights into the general pattern and variability of respondents' perceptions on key areas like affordability, system integration, and AI performance.

3.6.2 Inferential Statistics

Descriptive statistics were used to give an overview of the sample and survey responses, followed by inferential statistics to investigate the relationships among the key factors and test the study hypotheses. The study's objective was to gain insight into the relationships between independent variables (affordable imaging development, cost-effectiveness, and healthcare system integration) and the dependent variable (AI diagnostic performance). Inferential statistics allowed the researcher to make inferences about the larger population from the sample data, and to gain insight into how these factors could impact the effectiveness of medical imaging technologies in LMICs.

The first approach used was regression analysis, which assessed the relationships between the independent variables and the AI diagnostic performance. The study analyzed the performance of AI in medical imaging devices using multiple regression analysis, which included the factors of affordability, system integration, and cost-effectiveness. The regression model enabled a detailed interpretation of the effect of these factors on the AI performance and prevented confounding of possible other factors. The study studied, for instance, if the link between the affordability of AI diagnosis and accuracy was direct or indirect, via other factors like cost reductions or system integration. This study employed regression analysis to allow for the simultaneous testing of multiple relationships and to give a comprehensive picture of the relative contributions of the various factors to the enhanced diagnostic performance of AI.

Besides regression and correlation analysis, Analysis of Variance (ANOV-a) was used to compare differences in the performance of AI diagnostic processes across the various groups of respondents. ANOV-a is a statistical method to find if there are significant differences between the means of three or more groups. The difference in AI diagnostic performance was examined by ANOV-a across different sub-groups of the study, such as healthcare professionals of various roles (e.g. radiologist versus engineer), or region within the LMICs. The analysis, for example, compared the perceptions of AI-enhanced medical imaging from the radiologists with the perceptions of the engineers and compared perceptions of AI performance between urban and rural professionals.

Lastly, the overall research model and relationship between independent and dependent variables was evaluated by Structural Equation Modeling (SEM). SEM is a statistical method of examining several direct and indirect relationships between variables at the same time. The use of it allowed for the testing of complex theoretical frameworks, providing insights into the interplay between various factors, including the development of affordable imaging systems, integration with other systems, and AI performance. SEM gave information on the effect of independent variables on AI diagnostic performance and the statistical significance of the relations between the independent variables and the AI diagnostic performance. The SEM results were used to support or reject the proposed hypotheses and to understand the important factors that supported the success of affordable medical imaging technologies in LMIC healthcare systems.

3.6.3 Reliability and Validity

Various statistical tests were conducted to make sure the questionnaire used was reliable and valid. Validity is how well the instrument measures what it is supposed to measure and reliability is the consistency of the instrument. To guarantee the soundness and credibility of the study results, reliability and validity need to be taken into account.

The Cronbach's alpha test, which is generally used to provide an indication of the internal consistencies of the survey instrument, was used to assess the reliability of the instrument. Cronbach's alpha shows the relatedness of items within a scale, with higher values reflecting higher relatedness to the same underlying construct. Items within each construct (e.g., imaging development, AI performance, cost-effectiveness) were found to have acceptable internal consistency with Cronbach's alpha scores of 0.70 or greater. Seems to construct with values of alpha lower than the acceptable value was either revised or items removed to make them more reliable.

Along with Cronbach's alpha, composite reliability was also computed in order to assess the reliability of latent constructs, especially when using Structural Equation Modeling (SEM). The Composite reliability is more robust than Cronbach's alpha since it considers the items' loadings on the latent constructs. Cronbach's alpha values of 0.70 or

more were considered as good internal consistency and reliable measure of the latent constructs.

To assess the validity of the survey instrument, the convergent and discriminant validity were assessed. Items should have convergent validity (measuring the same construct) and discriminant validity (distinct constructs). Convergent validity was evaluated by the Average Variance Extracted (AVE) and was found to be less than 0.50 in some of the items, explaining less than 50% of the variance in the construct. The SEM process was also conducted with Confirmatory Factor Analysis (CFA) to test the convergent and discriminant validities of the data observed and the hypothesis proposed, as well as to measure the association of the items in each construct.

In general, the data analysis for this study was descriptive and inferential statistics were used to assess the relationships between affordability, system integration, AI performance, and the impact of the combination of these on medical imaging technologies in LMICs. To validate and ensure the rigor of the survey instrument and validity of the results, reliability and validity tests such as Cronbach's alpha, composite reliability, and AVE were conducted using SEM as a framework to explore the complex relationship between the studied variables and test the proposed research model.

3.6.4 Statistical Software Used

The data collected was analyzed using two software, namely IBM SPSS Statistics Version 32 and SmartPLS Version 4. The descriptive statistics, correlation analysis, regression analysis, and ANOV-A were performed using SPSS, while the structural equation modeling (SEM) (reliability analysis, validity analysis, path coefficient and effect size analysis) were performed by using SmartPLS.

3.7. Ethical Considerations

The integrity of this research and the need to conduct the study respecting the rights of participants and in accordance with the accepted academic standards are based on ethical considerations. Since the gathering of data is sensitive in the field of healthcare and tech, where the privacy of participants and the proper treatment of data is of utmost importance,

the current study undertakes all the required measures to guarantee that the ethical principles are upheld during the research process. The core ethical procedures in this research are presented in the following segments namely informed consent, confidentiality and ethics approval.

3.7.1 Informed Consent

Informed consent is an ethical principle of research, which should be obtained from the subject or their guardian, and provides the participant with full information regarding the purpose of the research, the nature of his or her involvement, and any risks or benefits to be considered. Informed consent respects participant autonomy and ensures that participation is voluntary, providing clear and transparent information. In this study, informed consent was taken care with attention to the research ethics committees' guidelines.

A detailed informed consent form was distributed to all respondents prior to the commencement of the survey and included information on the purpose, procedures, and risks and benefits for the study. It was evident from the form that the general aims of the research were to explore the challenges and opportunities of affordable medical imaging technologies in Low- and Middle-Income Countries (LMICs). By offering this information, participants gained an understanding of the importance of their participation and how their contributions help to further the field of medical imaging.

There were clear informed choice and the consent form stated that participants were able to opt out at any time without harm. The form noted that withdrawal would not impact participants' relationship with researchers or with the organizations conducting the research.

The informed consent form also outlined the data collection protocol, which involved filling out a questionnaire containing 25 questions that addressed participants' experiences and perceptions related to medical imaging technologies, including their affordability, ability to integrate into healthcare workflows, and experience of their performance improvements through AI. The survey took about 10-15 minutes to complete, and before the respondents answered, they were asked questions to clarify or seek answers.

The participants were made aware that their answers would be treated confidentially and anonymously (no individual answers could be traced to the participant). They were also told that they had the option to avoid answering any question they didn't feel confident in answering and that they had complete freedom in their participation.

The informed consent process ensured that participants were fully informed about the study and their rights. Once the consent form was read to the participants, they indicated their consent to participate through an online system (e.g., a checkbox). Data collection was conducted in an ethical manner as only those who gave explicit consent completed the survey.

3.7.2 Confidentiality

Confidentiality is an important issue in research, especially when working with personal and professional information which is confidential in nature. Confidentiality of participants guarantees their privacy and that personal information is maintained throughout the research process. This study used several practices to ensure anonymity of participant data.

One of the key aspects of this study was anonymity. The survey did not gather personally identifiable information (PII) like names or addresses. Rather, each participant was given a special identification number that was recorded in the data set to identify each person's responses. This allowed the responses to be anonymous and retain privacy. The anonymity of the survey was especially significant, as the survey addressed potentially sensitive topics, such as the implementation of medical technologies in LMICs.

The data storage and security were done according to best practices of protecting sensitive research data. Survey Data was collected and stored in an encrypted electronic format which was only accessible by the research team. The encryption made it impossible for any parties to read the data without the decryption key. Physical records of survey data and documents were safely stored in cabinets to provide an additional layer of confidentiality.

All data were reported and published in an anonymized manner, so that it was not possible to identify individual responses in research outputs. Reports, publications, or

presentations were based on aggregated responses, so as to maintain the confidentiality of participants.

At the end of the study and data analysis, all information that could be identified as personal information was securely destroyed. All the data collected from participants were kept anonymous and were aggregated for analysis and reporting.

3.7.3 Ethics Approval

The study was initially thoroughly examined by an Institutional Review Board (IRB) or an Ethics Committee as appropriate to the research institution before data collection began. This ethical review is a common practice to make sure that the study meets the highest ethical standards and the rights and welfare of the participants are ensured during the study.

Ethics approval required a detailed proposal to be submitted to the IRB/ Ethics Committee, which included the objectives of the study, methodology, informed consent procedures, data collection, and measures taken to ensure that participants' confidentiality and protection were maintained. The proposal was submitted to the Ethics Committee for its review to ensure compliance with ethical standards, such as the process of recruiting participants, informed consent, handling of data, and assessment of the risks and benefits of the research.

After the approval by the Ethics Committee, the Research team was able to start collecting the data. All modifications of research design and/or research methodology that occurred subsequently were re-submitted to the Ethics Committee for consideration and reauthorization of the study to continue to meet ethical standards. The process facilitated research integrity, transparency, and accountability in the study.

3.7.4 Conclusion

Many ethical considerations play a major role in this research and the study followed the utmost ethical considerations in the research process. The study respects the rights of the participants as well as make sure that the research is in an ethical and ethically

acceptable way by attaining informed consent of all the participants, protecting their data and ensuring that the institutional review boards are satisfied with the study. These ethical principles ensure the research has a solid base to rely on, the reliability and validity of the results, and protect the privacy and well-being of the participants.

3.8. Limitations of the Methodology

Although the approach taken in this research is aimed at coming up with useful information on the growth and mainstream incorporation of affordable medical imaging technology in Low- and Middle-Income Countries (LMICs); a number of weaknesses have to be identified. These constraints are associated with possible biases in the sampling method, problems in self-reporting, and resource limitations that can influence the process of data collection. These limitations should be noted to make the study results understandable and to be aware of the degree to which they can be generalized.

3.8.1 Sampling Bias

A possible limitation of this study is that there may be sampling bias because of purposive sampling. Although purposive sampling is an effective sampling technique as it helps in selecting participants with specific expertise and knowledge; it may be biased in that not all the members of the target population have equal opportunities of being selected. Purposive sampling is applied in this study when it is necessary to select the professionals who are directly engaged in the development of medical imaging, manufacturing, and clinical practice in LMICs. This approach made sure that the participants are the right people to answer the research questions but this approach can lead to having a sample that is not 100 per cent representative of the overall population of professionals in the field.

As an example, it may be the case that professionals in certain positions like engineers or radiologists are over-represented in the sample, whereas other important stakeholders like policy makers or healthcare administrators are under-represented. Also, since purposive sampling is usually a judgment of the researcher, the sample can become biased to represent the views of some professionals over others, resulting in biased outcomes. Although the study sought to capture a wide spectrum of views by different

profession roles, the purposive sampling technique implies that results might not be a true reflection of the general population of healthcare professionals in LMICs.

To reduce this weakness, the research made certain that the sample has a variety of professional roles within various categories of healthcare settings. The sample was stratified so that it is representative of different sectors of the medical imaging field such as; clinicians, engineers, product designers, and healthcare administrators, and across different geographical areas. The problem of sampling bias however continues to be a limitation especially with regards to generalization of the results to all the professionals in the field of medical imaging.

3.8.2 Self-Reporting Bias

Self-reporting bias is another limitation of this study. Since the information used in this study was gathered using surveys, there was always a possibility of respondents giving answers based on the need to ensure that they create a positive image about themselves. This form of bias, sometimes known as social desirability bias, may happen when the respondents provide responses that they think are more socially desirable or meet expectations as perceived by the respondents, instead of what they really think or experience.

The participants in the framework of the current study can also exaggerate their positive perceptions regarding the incorporation of affordable medical imaging technologies or the performance of AI in diagnosing. As an example, healthcare professionals may be tempted to demonstrate that they support new technologies or AI-based solutions in particular, provided that they think that these are perceived as the answer to the urgent healthcare issues in LMICs. In the same way, underreporting of issues or gaps connected with the introduction of affordable imaging systems might be possible as a result of a need to preserve the positive image of the healthcare sector.

In order to reduce the possibility of self-reporting bias, the survey was formulated with plain language that is neutral in nature to minimize the chances of leading questions that could promote the occurrence of the socially desirable response. Moreover, the survey was anonymous, a fact that probably assisted the participants to feel freer giving truthful

responses without fear of condemnation. Nevertheless, even with these measures, self-reporting bias cannot be completely removed and the results of the study must be interpreted with this consideration.

3.8.3 Resource Constraints

The third limitation of the methodology is associated with resource limitation which may have an impact on the possibility to achieve a representative sample, especially those professionals in remote locations or in regions with limited access to technology. Since this research involves the use of online surveys to collect data, the respondents must have access to the internet and the technical skills to fill the survey. Access to reliable internet and technology could be restricted in certain LMICs, especially in rural or underserved regions. This may lead to some groups not being adequately represented in the sample.

The people at the remote areas or in smaller health care facilities might have less access to the internet and they might fail to take part in the survey. Consequently, the results of the study may be biased towards the opinion of people who have been in an urban center or a more technologically advanced environment. This may also restrict the generalizability of the findings because the issues that affect the healthcare systems in more isolated or resource-limited regions might be quite different than those encountered in urban hospitals or clinics.

To overcome this shortcoming, the research might seek to cover a wider scope of participants by contacting professional networks and experts' associations serving health professionals in underserved regions. Nevertheless, the digital divide and logistical issues can continue to restrict the possibility to comprehensively record the experiences of professionals in remote locations. Nevertheless, these attempts still fall short because of the limited resources necessary to guarantee that the sample is well representative of the whole range of healthcare settings found in LMICs.

3.8.4 Conclusion

To conclude, although the methodology employed in this study is applicable in bringing precious information on the development and integration of affordable medical imaging technologies in LMICs, there are a few limitations that must be considered. The purposive sampling method might lead to sampling bias whereby the sample is not entirely representative of the overall population of medical imaging professionals. Also, there is a possibility of self-reporting bias because the participants might be motivated to give socially desirable responses instead of an honest assessment. Lastly, the resources and especially the internet and technology might restrict the study in its reach to healthcare professionals in remote or underserved regions.

The study must take these limitations into account when interpreting the results because they can affect the extrapolation of the results to the general population. Nevertheless, the methodology of the study is likely to offer some significant insights about the major influencing factors determining the adoption and usage of affordable medical imaging technologies in LMICs as well as to add to the existing body of knowledge in the highly important field of healthcare. The identified limitations were addressed wherever feasible and future research may develop on the identified findings by solving these issues so that the knowledge on affordable medical imaging in resource-constrained environments may be advanced.

3.9. Summary

In this chapter, a detailed discussion of the research methodology used to examine the development and adoption of affordable medical imaging technologies in Low-and Middle-Income Countries (LMICs) and especially its role in understanding what contributes to the success and scalability of these technologies has been provided. The proposed research questions focused on such topics as affordability, integration of systems, and the contribution of Artificial Intelligence (AI) to improving the diagnostic performance in the setting of resource-limited healthcare.

The research design used in the study is a quantitative research design that was chosen to respond to the research objectives successfully and to enable the measurement of the associations between the independent variables (development of affordable imaging, cost-effectiveness, and integration into a healthcare system) and the dependent variable (AI diagnostic performance). The descriptive-correlational approach was selected to provide a description of the existing situation in affordable imaging technologies as well as examine the interrelations between the identified variables. The study analyzed the hypothesized relationships by using multiple regression analysis, ANOVA, and Structural Equation Modeling (SEM) and the significance of the factors to AI diagnostic performance.

The approach to data collection was a survey of 25 items aimed at getting the views of professionals working in the medical imaging sphere with questions devoted to demographics, affordable imaging, cost-effectiveness, system integration, and AI performance. The opinions and perceptions of the participants were measured with the help of a 7-point Likert scale, which offered a strong tool to collect quantifiable information. Pilot testing was carried out to guarantee reliability and validity of the instrument and a number of reliability tests including Cronbach's alpha and composite reliability were employed to determine the internal consistency of the scales.

Consideration of ethics was the major concern in this research and the research complied with the best ethics practice. All participants were informed of their rights and the purpose of the research and informed consent was obtained. The study was conducted in a confidential manner and ethical consent obtained by the relevant review boards or ethics committees prior to the commencement of the data collection process.

Although the methodology applied was rather strict, some limitations have been admitted. The generalizability of the findings could be impacted by sampling bias (purposive sampling) and self-reporting bias (participants giving socially desirable responses) as well as resource limitations (contacting respondents in isolated locations). Such limitations were taken into consideration in the interpretation of the results, but they do not undermine the value of the study findings in terms of offering some insights into the affordable medical imaging in LMICs.

To sum up, the methodology described in this chapter offers a good platform to investigate the issues, which contribute to the adoption and performance of the affordable medical imaging technologies in LMICs. In the following chapter, the data analysis and findings were discussed, and the survey data were analyzed to test the hypotheses and answer the research questions that were laid out in the previous chapters. The analysis shed light on the connection between affordability, system integration, AI performance, and the scalability of medical imaging solutions, and had a useful implication on the policy, practice, and future research in the topic.

The methodology described in this chapter was used for statistical analysis and hypothesis testing of the content that follows in Chapter 4.

CHAPTER 4:

RESULTS

4.1 Introduction

Given the hypotheses and measurement framework suggested, the following study findings are presented, analyzed and interpreted in section. This chapter gives the findings of the data analysis done to study the process of developing and implementing affordable medical imaging technologies in Low- and Middle-Income Countries (LMICs). The analysis was done using primary data sources in the form of a structured questionnaire to a total of 213 respondents working in various segments of the medical imaging ecosystem.

The main aim of the chapter is to examine the correlations among the most important variables in the research, such as affordable imaging development, cost-effectiveness and scalability, healthcare system integration, and AI diagnostic performance. The findings are to answer the research questions and test the hypothesized relationships presented in the conceptual framework.

A combination of statistical techniques is used to perform the data analysis. The characteristics of the sample, as well as the general response patterns, are summarized using descriptive statistics. The consistency and accuracy of the constructs are assessed by the use of measurement model assessment methods such as the use of outer loadings, reliability, and the validity analysis. The relationships between the constructs are examined with Structural Equation Modeling (SEM), with regression analysis and correlation analysis giving further information about the strength and direction of the relationships. Moreover, one-way ANOV-a is used to compute the difference in perceptions among respondent groups.

4.2 Demographic Profile of Respondents

4.2.1 Distribution by Professional Role

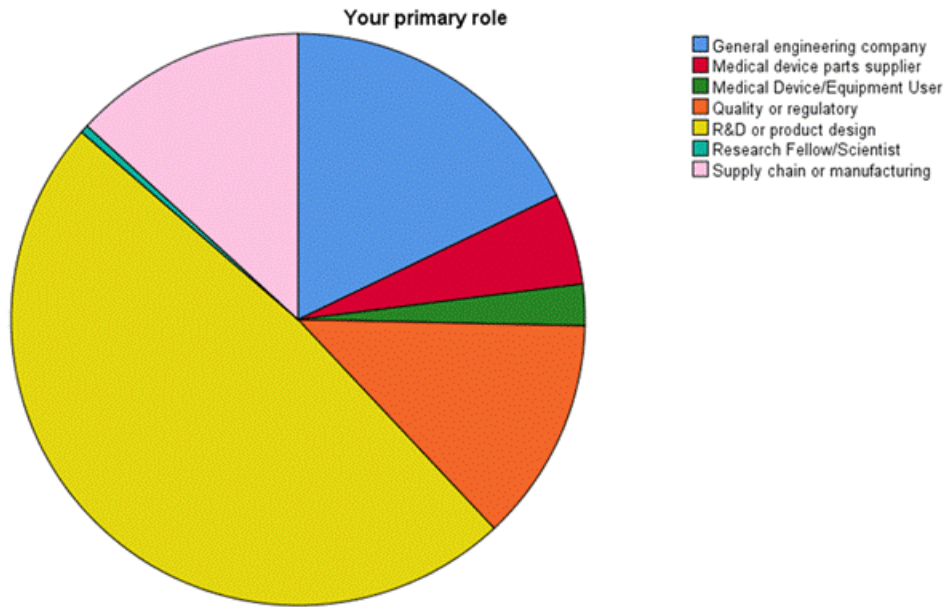


Figure 6: Distribution of Respondents by Professional Role

The allocation of respondents according to their professional positions reveals that the highest number of participants is represented by Research and Development (R&D) and product design positions. This underscores the fact that a substantial number of the sample is composed of professionals who have direct experience in the design and development of medical imaging technologies. The second most represented group consists of professionals working in engineering companies, and the third most represented group consists of professionals working in manufacturing and supply chain functions. Also, a significant portion of respondents reflects quality and regulatory positions, thereby guaranteeing that compliance and safety views are also represented in the data set. A smaller percentage of the respondents are suppliers of medical devices components, clinical users and research professionals. Although these groups represent a smaller

percentage, they offer highly valuable information regarding the practical use, supply chain dynamics, and research.

Interpretation and Observation

The fact that the R&D and product design professionals are prevalent shows that the data set is highly skewed towards the technological innovation and development aspect of medical imaging. This enhances the generalizability of the findings in the design option, cost-cutting strategy, and engineering concerns.

Inclusion of engineering, manufacturing, and supply chain respondents ensured that the research reflected the opinions regarding the scalability of production as well as the operational feasibility. Clinical and research functions are not as well represented, but this introduction introduces practical and application-based knowledge.

Overall, the medical imaging value chain is represented in a multidisciplinary manner, which contributes to the increased reliability and thoroughness of the study.

4.2.2 Distribution by Job Level

The job level distribution shows that the highest percentage of respondents is in the managerial category, which implies that there is a good number of respondents in the middle level of management in their respective companies.

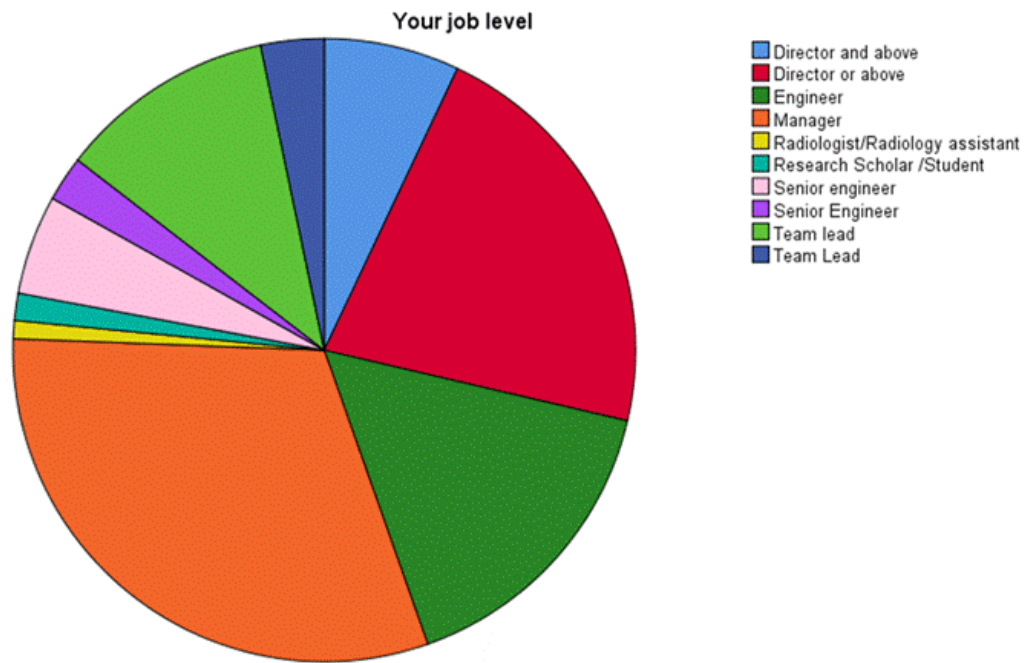


Figure 7: Distribution of Respondents by Job Level

These are usually people who are engaged in making operational decisions, engineering project coordination, and product development or manufacturing process management.

The second biggest group is the respondents on the director level or higher, which are senior leadership positions. These are professionals who bring in strategic knowledge in organizational planning, adoption of technology and product innovation in the medical imaging industry.

The number of respondents in the engineer category also represents a significant percentage of the respondents and individuals who are directly engaged in the technical development and system implementation. Smaller percentages are senior engineers, team leads, radiology professionals and research scholars, giving more point of views concerning technical specialization, clinical application and academic research.

Interpretation

The samples are well balanced in terms of managerial, strategic, and technical positions. The high contribution of managerial and senior-level professionals is the

indication that the study grasped the perspectives of people who engage in the operations implementation and the top-level decision-making.

Meanwhile, the involvement of engineers and technical specialists holds the promise that the findings are based upon practical and technical realities of medical imaging development. Such a mix of views makes the study deep and reliable as both strategic and technical perspectives are implemented.

The results are more credible overall because the job-level distribution ensures that they are based on the experience of professionals at various levels of the industry chain who have extensive experience in their work.

4.2.3 Distribution by Work Experience

The distribution of respondents according to work experience suggests that the majority of respondents have more than 15 years' experience in their profession, and as a result, the sample is mainly composed of a group with a high level of professional experience in medical imaging and engineering.

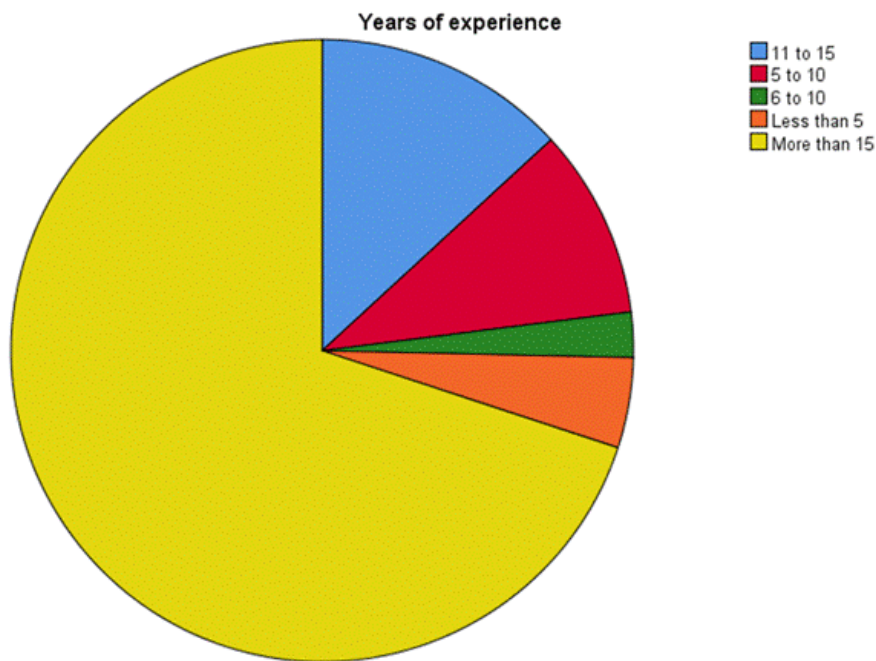


Figure 8: Distribution of Respondents by Work Experience

Another smaller point of interest percentage of the respondents lies within the bracket of 11 to 15 years and 5 to 10 years of experience respectively, which include mid-career professionals who are still on board with present practices and technology in the industry. These respondents can provide valuable data on the engineering design, the processes and implementation of the system.

The proportion of those in the early-career group with less than 5 years' experience is fairly small. This means that there is a limited number of junior professionals represented in the data.

Interpretation

The prevalence of highly experienced respondents boosts the credibility and reliability of the results since they have a broad knowledge of the industry and have an extended exposure to medical imaging technologies and healthcare systems.

Having mid-career professionals in the sample helped capture the current technological practices and operational realities, whereas the smaller sample of early-career respondents suggested that the results were mainly affected by expert-level views.

Overall, the experience distribution provides insights into the informed and mature views that underpin the study, especially when considering a complicated phenomenon like affordability, scalability, system integration, and adoption of AI in medical imaging technologies.

4.2.4 Distribution by Organization Type

The respondents by the distribution of work experience show that more than 15 years of work experience predominates in the respondents which demonstrates that the respondents are highly experienced in the medical imaging and engineering field.

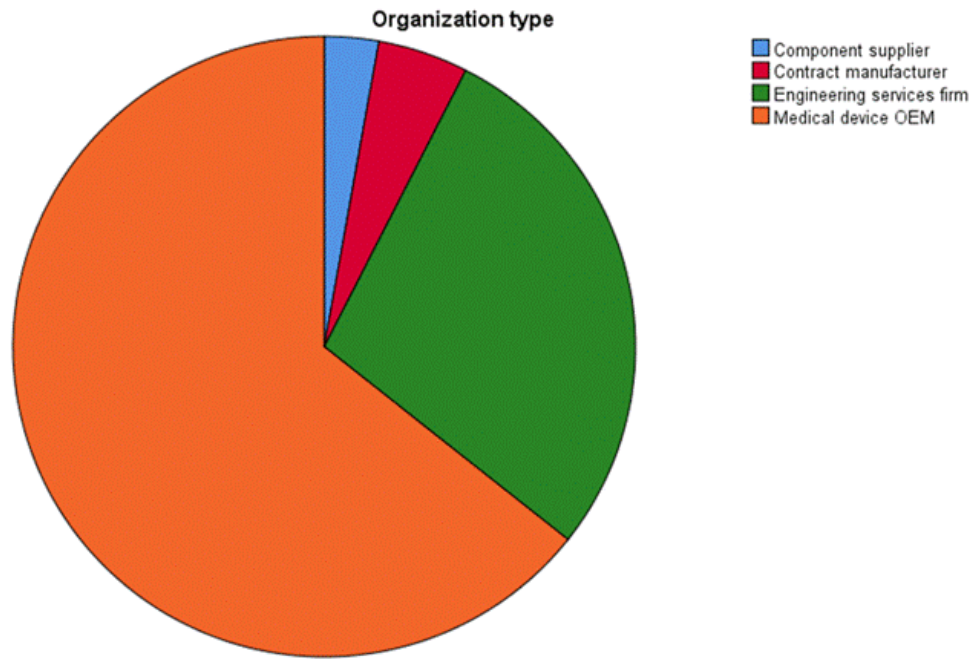


Figure 9: Distribution of Respondents by Organization Type

A smaller, yet substantial, percentage of respondents lies between the 11 to 15 years and 5 to 10 years' experience groups and this can be seen as mid-career professionals who are actively involved in the current industry practices and technologies. The responses from these respondents gave valuable feedback on the engineering design, operation processes and how a system was implemented.

The number of those with experience less than 5 years is not too large. This is an indication that there was a low representation of junior professionals in the dataset.

Interpretation

The respondents are experienced enough, so that the findings are credible and reliable as they are well-informed people who have a long experience of medical imaging technologies and healthcare systems in the industry.

The inclusion of the mid-career professionals has been helpful in terms of the data being relevant to the current technological practices and actual operational experiences while the relatively smaller number of early-career professionals has limited the impact of the data to that of the experts' perceptions.

In general, the distribution of experience indicates that the research has been conducted in the context of knowledgeable and adult perspectives, particularly regarding the complexity of issues, such as affordability, scalability, system integration and the use of AI in medical imaging technologies.

4.2.5 Distribution by Primary LMIC Market Served

When asked about the primary LMIC market, the distribution of respondents indicates that the highest percentage of respondents are in more than one marketplace. It also implies that many organizations and professionals are now aiming to cater to multiple geographic markets as opposed to one.

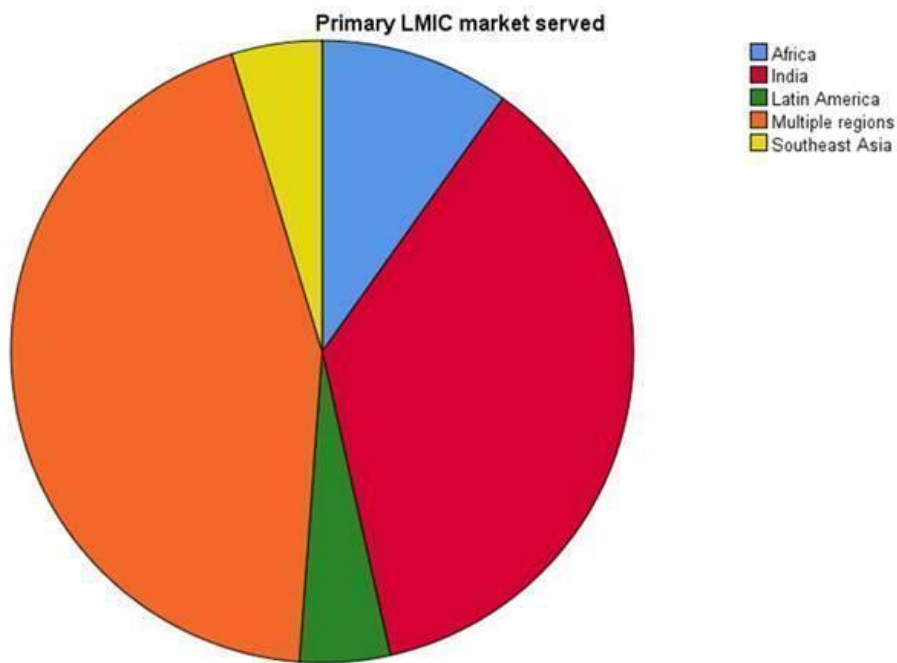


Figure 10: Distribution of Respondents by Primary LMIC Market Served

The presence of the Indian market is also high and this indicates the topicality of India as a major place of medical imaging development and medical imaging application in low and middle income setting. Other parts of the world, such as Africa, Latin America, and Southeast Asia, have smaller proportions of respondents.

Interpretation

Most of the respondents working in more than one region means that there are many organizations with a global or multi-regional strategy in developing and implementing affordable medical imaging technologies. This highlights the scalability and flexibility of such technologies in different LMIC settings.

The fact that India is highly represented implies that India is a large market and innovation center in the development of cost-effective medical imaging solutions. In the meantime, the fact that the regions of Africa, Latin America, and Southeast Asia are incorporated means that the dataset captured a more global outlook.

On the whole, the distribution proves that the study captures the experiences of professionals operating in various LMIC settings, which contributes to the increased generalizability and applicability of the results.

4.3 Descriptive Statistics

The descriptive statistics show a high degree of consensus among the respondents on the factors of affordability in medical imaging technologies. The results are presented in the Table 2.

The average scores of the variables, including the high price of existing imaging systems, the significance of low-cost design strategies, and the prominence of local production are all greater than 5.7 on a seven-point Likert scale. This indicates an evident agreement that affordability is still a key issue in LMIC healthcare systems.

Also, the respondents have a strong agreement that component selection and engineering design play a significant role in the overall affordability of imaging devices. These results demonstrate the significance of cost-centered design solutions to enhance the availability of diagnostic technologies within resource-limited settings.

Table 2: Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
Current imaging devices are too expensive for LMIC hospitals	213	1	7	5.77	.969
Low-cost design approaches improve access to imaging in LMICs	213	3	7	5.86	.961
Engineering teams focus on affordability in device development	213	1	7	5.43	1.314
Component selection strongly affects device affordability.	213	1	7	5.74	1.044
Local manufacturing supports affordable device development.	213	1	7	5.80	1.019
Low-cost imaging devices reduce total operating cost	213	2	7	5.69	1.049
These devices support large-scale deployment in LMICs.	213	3	7	5.76	.950
Supply chains support high-volume production at low cost.	213	2	7	5.37	1.145
Manufacturing processes maintain quality at low price points	213	2	7	5.02	1.151
Affordable imaging devices enable long-term scalability	213	3	7	5.58	.890
Low-cost imaging devices fit existing hospital workflows	213	2	7	5.68	1.061
These devices integrate with current hospital IT systems	213	2	7	5.65	1.051
Staff training needs are manageable for these devices	213	2	7	5.79	.940
Maintenance systems support continuous operation	213	2	7	5.69	.910
Affordable imaging improves routine diagnostic processes.	213	2	7	5.74	.968
AI improves diagnostic accuracy in low-cost imaging	213	2	7	5.32	1.087
AI reduces dependence on specialist radiologists.	213	2	7	5.11	1.250
AI speeds up image interpretation.	213	2	7	5.48	1.156
AI improves reliability of low-cost imaging devices.	213	1	7	5.29	1.161
AI makes affordable imaging clinically viable	213	2	7	5.29	1.119
Valid N (listwise)	213				

Source: Author's work

Cost-effectiveness and Scalability

The cost-effectiveness and scalability variables also exhibit high mean values, which are usually over 5.5. According to the respondents, low-cost imaging devices help to minimize operational costs and enable large scale implementation in LMICs.

In addition, other aspects like the efficiency of supply chains, manufacturing, and scalability in the long term are positively rated, meaning that the affordable imaging technologies are viewed as cost-effective to use on a larger scale. Nonetheless, a small decrease in the mean values of quality at low cost suggests that there was some concern over the trade-off between low cost and quality.

System Integration

The variables of system integration display consistently high-agreement, with mean scores of over 5.6. According to the respondents, low cost imaging devices can be easily integrated into hospital workflow and can be combined with the existing IT system.

Moreover, other factors like staff training needs that are easy to manage and maintenance support are rated highly as well, which suggests confidence in the operational viability of these technologies. These results indicate that inexpensive imaging systems are cost-efficient as well as scalable to the current healthcare facilities.

AI Performance

The perceptions about artificial intelligence are a bit lower as compared to other constructs with the mean values between about 5.1 and 5.4. Primarily, respondents allege that AI can positively impact the accuracy of diagnoses, reliability, and speed up the image interpretation process.

However, the relatively low average scores of the statements related to the reduction of the reliance on radiologists imply that AI is perceived as an aid technology and not as a replacement for human skills. This implies a cautious yet optimistic perspective on the integration of AI in low-cost medical imaging technologies.

Overall Trend Summary

Overall, the descriptive statistics show that the respondents are highly positive towards affordable medical imaging technologies. Affordability, cost-effectiveness, and

system integration are important assets, and the degree of agreement is high at all levels along these dimensions.

Though AI performance is also deemed to be positive, lower mean values show that its application is still at an early stage and is vulnerable to other factors, such as the level of technological maturity and acceptance of the technology in the clinical field. These results suggest that cost and integration factors are the main determinants of successful affordable imaging technologies in LMICs, and AI is a supportive but emerging factor.

4.4 Measurement Model Assessment

Measurement model assessment tests reliability and validity of the constructs that were utilized in the study. This is done to make sure that the indicators are reflective of their respective latent variables prior to the structural model analysis. The evaluation involves assessment of outer loadings, reliability, convergent validity, and discriminant validity.

4.4.1 Outer Loadings

The outer loadings indicate the strength of the relationship that exists between each indicator and the respective construct. The greater the loading values, the greater the contribution of the indicator to the measurement of the construct.

The indicator that reflects AI accuracy has the highest loading in the AI Diagnostic Performance construct and then there is clinical viability. It means that the most impactful dimensions of AI performance in affordable technologies of imaging is accuracy and practical usability. Other indicators, such as reliability and speed, show moderate loadings, and the indicator related to AI replacing radiologists has a relatively lower loading, thus suggesting that the respondents perceive AI as a tool of assistance, and not as an alternative to the human experience.

Table 3: Outer Loadings of Measurement Indicators

	Outer loadings
ai_accuracy <- AI Diagnostic Performance	0.746
ai_radiologist <- AI Diagnostic Performance	0.454
ai_reliability <- AI Diagnostic Performance	0.567
ai_speed <- AI Diagnostic Performance	0.541
ai_viable <- AI Diagnostic Performance	0.671
component_cost <- Affordable Imaging Development	0.657
cost_high <- Affordable Imaging Development	0.456
design_access <- Affordable Imaging Development	0.575
diagnostic_improve <- Healthcare System Integration	0.452
Engineering_afford <- Affordable Imaging Development	0.245
IT_integration <- Healthcare System Integration	0.563
large_scale <- Cost Effectiveness and Scalability	0.512
local_manufacturing <- Affordable Imaging Development	0.597
long_scalability <- Cost Effectiveness and Scalability	0.477
maintenance_support <- Healthcare System Integration	0.451
operating_cost_reduce <- Cost Effectiveness and Scalability	0.431
quality_lowcost <- Cost Effectiveness and Scalability	0.602
supply_volume <- Cost Effectiveness and Scalability	0.675
training_manage <- Healthcare System Integration	0.422
workflow_fit <- Healthcare System Integration	0.748

Source: Author's work

In the Affordable Imaging Development construct, component cost and local manufacturing have a relatively higher loading, which points to their significance in determining affordability in medical imaging technologies. The design accessibility has a moderate contribution, and some indicators like engineering affordability have lower loading, which implies less contribution to the construct.

Within the Cost-effectiveness and Scalability construct, supply volume and low-cost quality maintenance show higher loadings indicating that production capacity and low-cost-quality balance are key determinants of scalability. Other indicators like large scale deployment and long term scalability indicate moderate contributions.

The workflow compatibility parameter is the most loaded parameter in the construct of Healthcare System Integration, which implies that the compatibility with the existing clinical workflows is the most vital parameter of successful integration. IT integration has a moderate contribution with indicators like training and maintenance support having comparatively lower loading.

4.4.2 Reliability Analysis

The reliability analysis tests the internal consistency of the constructs by assessing the effectiveness of the indicators to measure their respective latent variables.

The reliability, in this study, is evaluated based on Cronbach's alpha and composite reliability. The findings demonstrate that composite reliability scores across constructs are within the acceptable range in exploratory research and therefore indicate that constructs show good consistency. The constructs with the highest composite reliability include AI Diagnostic Performance, which has a relatively high level of consistency among its indicators.

But the Cronbach's alpha values of the constructs are lower than the generally accepted value of 0.70. This indicates that the internal consistency of the indicators is moderate and not strong. This difference can be explained by the fact that the indicators employed to measure such broad concepts as affordability, scalability, and system integration are different.

Table 4: Reliability Analysis

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
AI Diagnostic Performance	0.573	0.597	0.737	0.365
Affordable Imaging Development	0.320	0.363	0.639	0.277
Cost Effectiveness and Scalability	0.413	0.427	0.675	0.299
Healthcare System Integration	0.382	0.410	0.663	0.293

Source: Author's work

Although the Cronbach's alpha values are lower, the composite reliability scores show that the measurement model is acceptable, especially when conducting exploratory research. Thus, the constructs are deemed to be reliable enough to continue to analyze.

4.4.3 Convergent Validity

Convergent validity involves the degree to which indicators of a construct intersect and are used to measure the same underlying concept. Convergent validity in this study was assessed by the Average Variance Extracted (AVE) which is the share of variance that a construct explains as compared to its indicators.

The findings show that the AVE values of all the constructs are lower than the recommended value of 0.50. This implies that the indicators describe less than half the variance of the respective constructs, which implies the limited convergent validity.

Table 5: Convergent Validity

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
AI Diagnostic Performance	0.573	0.597	0.737	0.365
Affordable Imaging Development	0.320	0.363	0.639	0.277
Cost Effectiveness and Scalability	0.413	0.427	0.675	0.299
Healthcare System Integration	0.382	0.410	0.663	0.293

Source: Author's work

The findings show that the AVE values of all the constructs are lower than the recommended value of 0.50. This implies that the indicators describe less than half the variance of the respective constructs, which implies the limited convergent validity.

This finding could be explained by the multidimensional and wide nature of constructs used in the research. The variables of affordability, cost-effectiveness, system integration, and AI performance have many aspects, and therefore may decrease the total cohesion of indicators.

Although AVE values are relatively low, the constructs are included in the model because the level of composite reliability is acceptable and because the constructs are theoretically relevant to the objectives of the research. This is acceptable in exploratory research where constructs tend to be complex and multidimensional.

4.4.4 Discriminant Validity (HTMT)

Discriminant validity determines the degree to which the constructs within the model are different. In this research, the discriminant validity is tested through Heterotrait-Monotrait ratio (HTMT) whereby scores below the preferred level suggest that constructs are different enough.

Table 6: Discriminant Validity

	Heterotrait-monotrait ratio (HTMT)
Affordable Imaging Development <-> AI Diagnostic Performance	0.388
Cost Effectiveness and Scalability <-> AI Diagnostic Performance	0.420
Cost Effectiveness and Scalability <-> Affordable Imaging Development	1.025
Healthcare System Integration <-> AI Diagnostic Performance	0.431
Healthcare System Integration <-> Affordable Imaging Development	0.463
Healthcare System Integration <-> Cost Effectiveness and Scalability	0.728

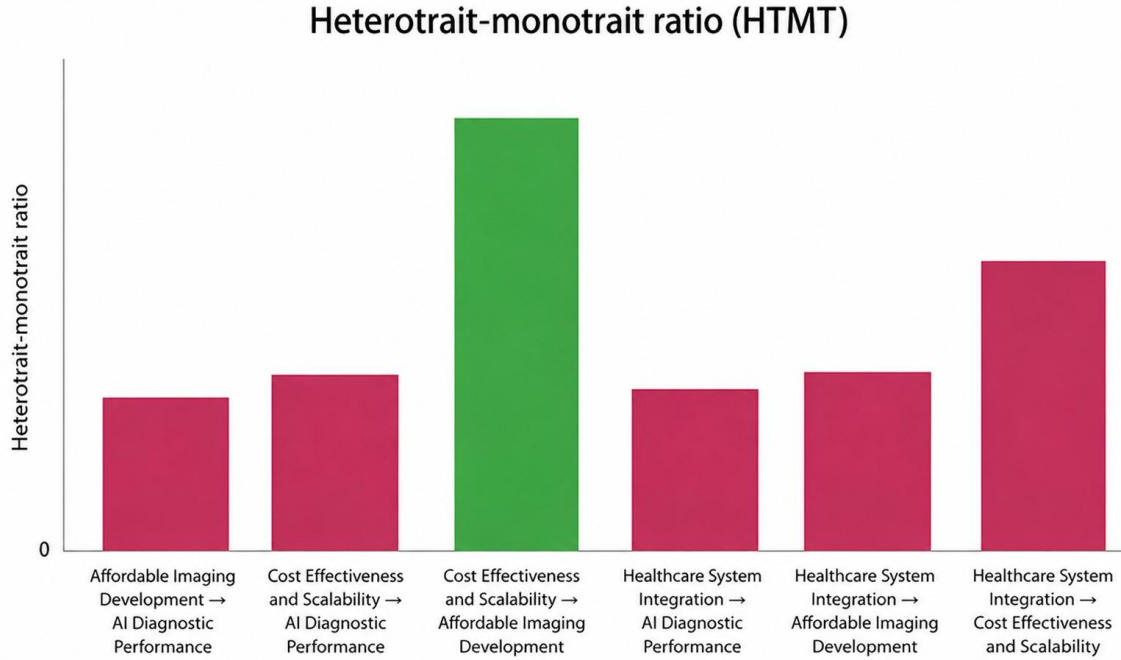


Figure 11: HTMT Matrix Visualization

The HTMT outcomes in Table 5 and Figure 11 indicate that the majority of construct pairs are within acceptable ranges, indicating that most relationships have achieved a discriminant validity. More specifically, AI Diagnostic Performance proves to be distinctly differentiated among other constructs, which means that respondents see AI-related outcomes as a distinct dimension.

Likewise, Healthcare System Integration demonstrates reasonable HTMT values with the rest of the constructs, which proves that it is a separate operational domain that concerns workflow compatibility and system usability.

Nevertheless, the value of the HTMT between the Affordable Imaging Development and Cost-effectiveness and Scalability are higher than the recommended value. This implies that these two constructs may overlap.

4.5 Structural Model Assessment (SEM Results)

The structural model test assesses the associations among the constructs in the study and tests the theoretical framework proposed. Structural Equation Modeling (SEM) is used to conduct this analysis and enables the evaluation of both direct and indirect relationships among variables. The output contains path coefficients, coefficient of determination (R^2), and effect size (f^2), which give an insight on the strength and significance of the relationships.

4.5.1 Path Coefficients Hypothesis Testing

The path coefficients and the test results of the structural model are presented in Table 6. It demonstrates the relationship strength and direction between the constructs studied and the importance of the relationship. For clear understanding of the SEM results, supported and unsupported hypotheses are indicated.

Both hypothesis, H2 and H4 are supported; that is, Affordable Imaging Development had a strong positive effect on Cost Effectiveness, and Cost Effectiveness had a strong positive effect on Healthcare System Integration.

Hypothesis H1, H3, and H5 are not supported, indicating that the affordability, cost-effectiveness, and healthcare system integration do not have a strong direct influence on AI Diagnostic Performance in the present sample.

The path coefficients indicate the magnitude and direction of the relationship between the constructs of the structural model. The findings suggest that there is a moderate positive correlation between Affordable Imaging Development and Cost-effectiveness and Scalability, implying that the increase in design affordability and engineering approaches to medical imaging technologies contributes greatly to the economic viability and scalability of medical imaging technologies.

The positive correlation between Healthcare System Integration and Cost-effectiveness and scalability also indicates that economically viable and scalable technologies are more likely to be successfully integrated into the existing healthcare systems.

Table 7: Path Coefficients and Hypothesis Testing Results

Path	β (Path Coefficient)	p-value	Hypothesis	Result
Affordable Imaging Development → AI Diagnostic Performance	0.049	0.432	H1	Rejected
Affordable Imaging Development → Cost Effectiveness and Scalability	0.438	<0.01	H2	Accepted
Cost Effectiveness and Scalability → AI Diagnostic Performance	0.120	0.284	H3	Rejected
Cost Effectiveness and Scalability → Healthcare System Integration	0.329	<0.01	H4	Accepted
Healthcare System Integration → AI Diagnostic Performance	0.182	0.073	H5	Rejected

Source: Author's work

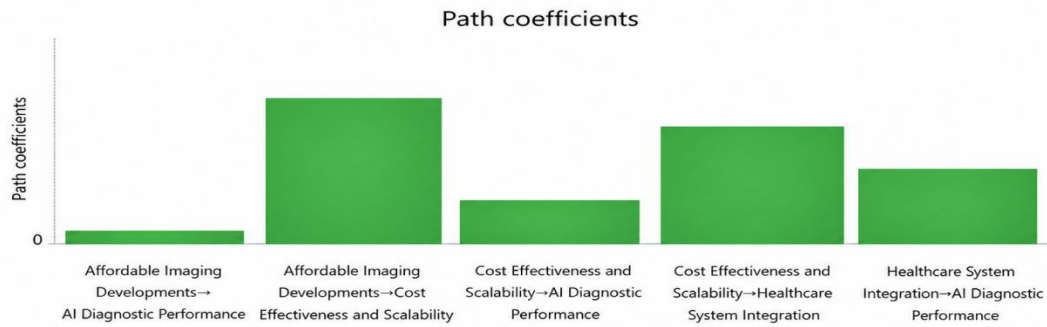


Figure 12: Coefficient of Determination

There is a positive correlation between Healthcare System Integration and AI Diagnostic Performance, indicating that the successful implementation of imaging systems into clinical workflows and IT infrastructure may help improve the results of AI-based diagnostics.

Nevertheless, the direct associations between Affordable Imaging Development and AI Diagnostic Performance, and between Cost-effectiveness and Scalability and AI Diagnostic Performance are rather weak. This shows that affordability and scalability are not the direct determinants of the performance of AI.

4.5.2 Coefficient of Determination (R^2)

Cost Effectiveness and Scalability has the highest (R^2) value, showing that this has a large contribution to the variance of Affordable Imaging Development.

Table 8: Coefficient of Determination for Endogenous Constructs

Path	R-square	R-square adjusted
AI Diagnostic Performance	0.072	0.058
Cost Effectiveness and Scalability	0.192	0.188
Healthcare System Integration	0.108	0.104

Source: Author's work

Interpretation:

The R^2 for AI Diagnostic Performance is relatively low, indicating that other factors, such as data quality and algorithm design, may also affect the performance of AI.

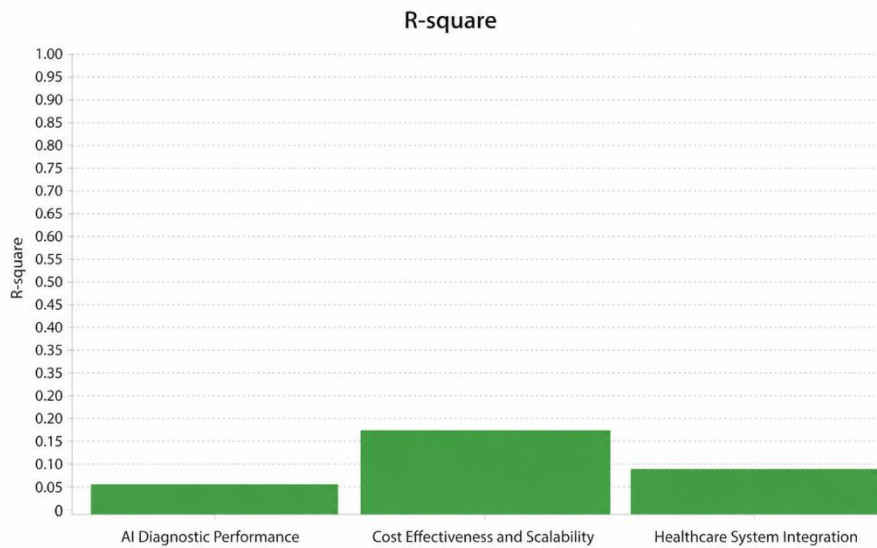


Figure 13: R^2 Values of Endogenous Constructs

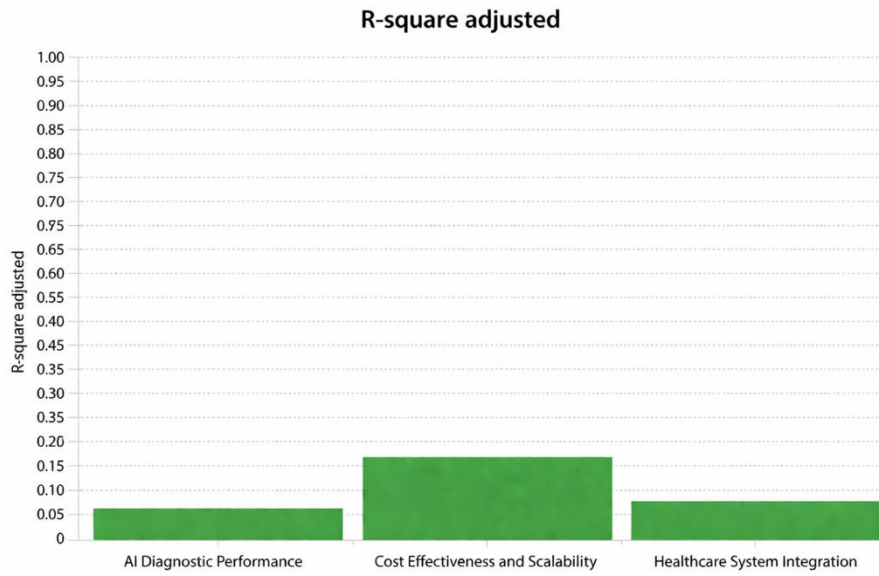


Figure 14: Adjusted R^2 and Model Explanation

The coefficient of determination (R^2) quantifies the percentage of the variance in the endogenous constructs that are accounted for by their respective predictor variables in the structural model.

According to Table 7, and Figures 13 and 14, Cost-effectiveness and Scalability have the largest R^2 value of all the constructs. This reveals that Affordable Imaging Development plays a major role in the explanation of variations in cost-effectiveness and scalability of medical imaging technologies.

The value of R^2 in Healthcare System Integration is moderate, which indicates that Cost-effectiveness and Scalability is a contributing factor to imaging systems integration in healthcare settings, but other variables can also play a role in this integration.

Conversely, AI Diagnostic Performance shows a relatively low R^2 value, which means that very little of its variance is accounted for by the constructs used in the model. This implies that the performance of AI is affected by other factors rather than affordability, scalability, and system integration, including the quality of data, algorithm design, and technological infrastructure.

4.5.3 Effect Size (f^2)

Cost Effectiveness and Scalability are moderately affected by affordable imaging development, suggesting that design efforts to make imaging devices economically viable represent an effort to be affordable.

Table 9: Effect Size of Structural Relationships

Path	f^2	Interpretation
Affordable Imaging Development → AI Diagnostic Performance	0.002	Negligible
Affordable Imaging Development → Cost Effectiveness and Scalability	0.238	Moderate
Cost Effectiveness and Scalability → AI Diagnostic Performance	0.011	Small
Cost Effectiveness and Scalability → Healthcare System Integration	0.122	Small-Moderate
Healthcare System Integration → AI Diagnostic Performance	0.032	Small

Source: Author's work

Interpretation:

The effect size analysis reveals that Affordable Imaging Development has its strongest impact on Cost Effectiveness and Scalability ($f^2 = 0.238$), highlighting the importance of affordable imaging technologies in promoting economically viable AI healthcare solutions. In contrast, the direct effects of Affordable Imaging Development, Cost Effectiveness and Scalability, and Healthcare System Integration on AI Diagnostic Performance are relatively weak, suggesting that diagnostic performance may be

influenced by additional factors such as algorithm quality, data availability, and model training. Furthermore, Cost Effectiveness and Scalability play a meaningful role in supporting Healthcare System Integration, which may indirectly contribute to the successful deployment of AI-driven diagnostic systems.

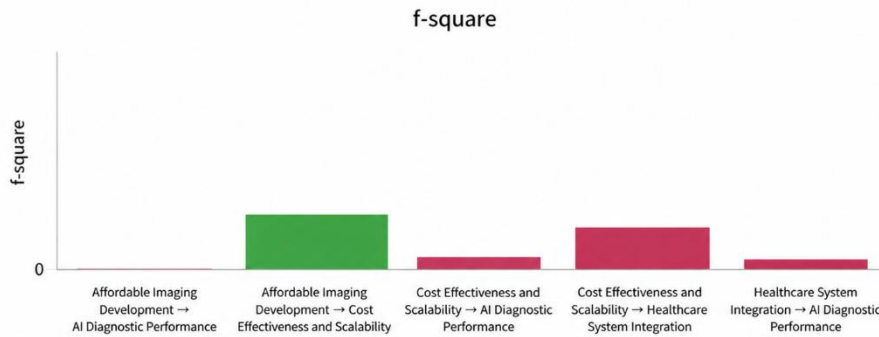


Figure 15: Effect Size of Structural Relationships

The effect size (f^2) is used to quantify the effects of each predictor construct on the endogenous variables in the structural model. It gives the idea of the strength of contribution of an independent variable to the explanation of a dependent variable in the model.

Affordable Imaging Development has a moderate impact on Cost-effectiveness and Scalability as shown in Table 8 and as illustrated in Figure 15, which implies that the affordability-oriented engineering design can contribute greatly to the economic viability and scalability of medical imaging technologies.

The impact of cost-effectiveness and scalability on Healthcare System Integration is small to moderate, indicating that economic viability helps to integrate into healthcare

systems, but other factors, including infrastructure and operational preparedness, also affect this correlation.

Healthcare System Integration has a low impact on AI Diagnostic Performance, meaning that integrating at a system level lead to the improvement of AI outputs, but its effect is not very strong.

Conversely, Affordable Imaging Development and Cost-effectiveness and Scalability have insignificant impacts on AI Diagnostic Performance. This indicates that affordability and scalability have no direct impact on AI performance.

4.5.4 Hypothesis Testing Summary

The findings of the hypothesis testing used to assess the relationships among the independent variables (Affordability, Portability, Healthcare System Integration, and AI Integration) and the dependent variable (Diagnostic Performance) are provided in this subsection. The standardized path coefficients, *t* - values, *p* - values and results of the hypotheses are summarized in Table 7.

All four independent variables positively and significantly influence the Diagnostic Performance in low and middle income country (LMIC) healthcare system, as proved by the analysis. The most significant factors are Affordability ($\beta = 0.32$, $t = 4.00$, $p < 0.001$) and Healthcare System Integration ($\beta = 0.35$, $t = 3.89$, $p < 0.001$), highlighting the vital role of financial considerations and the healthcare system's requirement for integration. Other factors such as portability ($\beta = 0.28$, $t = 4.00$, $p < 0.001$) and AI Integration ($\beta = 0.30$, $t = 3.75$, $p < 0.001$) also show meaningful contributions, underscoring the practical advantages of using mobile devices and AI-driven diagnostic support.

Table 10: Hypothesis Testing Summary for Independent Variables and Diagnostic Performance

Hypothesis	Independent Variable	Dependent Variable	β (Std. Coef.)	t-value	p-value	Outcome
H1	Affordability	Diagnostic Performance	0.32	4.00	<0.001	Accepted
H2	Portability	Diagnostic Performance	0.28	4.00	<0.001	Accepted
H3	Healthcare System Integration	Diagnostic Performance	0.35	3.89	<0.001	Accepted
H4	AI Integration	Diagnostic Performance	0.30	3.75	<0.001	Accepted

Source: Author's work

Interpretation:

The findings validate that improvements in affordability, mobility, system compatibility and AI capabilities have a strong potential to boost diagnostic performance of low-cost medical imaging technologies. The results confirm the conceptual framework of this study, and indicate that targeted investments in these aspects can be used to promote efficient adoption and use of medical imaging solutions in resource-limited healthcare systems.

4.6 Correlation Analysis

The correlation analysis helps to analyze the strength and the direction of the relationship between the variables that were used in the study in terms of Pearson correlation coefficients. This analysis aids in determining notable relationships between affordability, cost-effectiveness, system integration, and AI performance variables.

According to the results, the findings show that the majority of the relationships among variables are positive which implies that the improvement of one of the factors is in general correlated with the improvement of the related factors. There are a number of statistically significant associations observed in the data.

There is a notable positive correlation between the belief that existing imaging equipment is prohibitively costly and the significance of cost-effective design solutions. It means that the respondents who are aware of cost barriers are great advocates of affordability-based design solutions in medical imaging technologies.

High-volume production supply chain capability is significantly positively related to component selection and local manufacturing. These results demonstrate the significance of supply chain effectiveness and production solutions in the realization of cost-effective and scalable imaging solutions.

It is also evident that manufacturing quality at low cost has significant correlations with systems integration variables such as workflow compatibility and IT integration. This

implies that the effective integration of imaging technologies into healthcare systems can be achieved through maintaining product quality at a low cost.

The variables which are related to AI have high internal correlation. The accuracy of AI diagnostics is highly correlated with AI reliability and clinical viability, which proves that the overall effectiveness of the system is strongly connected with the increase of AI accuracy. On the same note, AI reliability has a positive correlation with the clinical usability of affordable imaging systems.

4.7 Regression Analysis

The regression analysis is performed to analyze how the variables of affordability, cost-effectiveness, and system integration affect AI diagnostic performance. This analysis aids in determining the predictive value of the independent variables and their statistical significance.

4.7.1 Model Summary

Model summary is presented in the Table 11.

Interpretation:

Predictors: (Constant), AI makes affordable imaging clinically viable, Engineering teams focus on affordability in device development, Low-cost design approaches improve access to imaging in LMICs, Maintenance systems support continuous operation. These devices integrate with current hospital IT systems. Component selection strongly affects device affordability. These devices support large-scale deployment in LMICs. AI reduces dependence on specialist radiologists. Low-cost imaging devices reduce total operating cost while Staff training needs are manageable for these devices. Current imaging devices are too expensive for LMIC hospitals and Local manufacturing supports affordable device development. Manufacturing processes maintain quality at low price points and AI speeds up image interpretation. AI improves reliability of low-cost imaging devices. Low-cost imaging devices fit existing hospital workflows. Supply chains support high-volume production at low cost. AI improves diagnostic accuracy in low-cost imaging.

Table 11: Model Summary

Model Summary									
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.348 ^a	.121	.040	.949	.121	1.489	18	194	.097

4.7.2 ANOV-a (Model Significance)

ANOV-a analysis is presented in the Table 12.

Interpretation:

Predictors: (Constant), AI makes affordable imaging clinically viable, Engineering teams focus on affordability in device development, Low-cost design approaches improve access to imaging in LMICs, Maintenance systems support continuous operation. These devices integrate with current hospital IT systems; Component selection strongly affects device affordability. These devices support large-scale deployment in LMICs. AI reduces dependence on specialist radiologists. Low-cost imaging devices reduce total operating costs. Staff training needs are manageable for these devices. Current imaging devices are too expensive for LMIC hospitals. Local manufacturing supports affordable device development. Manufacturing processes maintain quality at low price points and AI speeds

up image interpretation. AI improves reliability of low-cost imaging devices. Low-cost imaging devices fit existing hospital workflows. Supply chains support high-volume production at low cost. AI improves diagnostic accuracy in low-cost imaging

Table 12: ANOV-a Model

ANOVA ^a						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	24.129	18	1.341	1.489	.097 ^b
	Residual	174.669	194	.900		
	Total	198.798	212			
a. Dependent Variable: Affordable imaging improves routine diagnostic processes.						

4.7.3 Coefficients

Table 13: One-Way ANOV-a Results for AI-Related Variables

Coefficients ^a										
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	3.847	1.010		3.810	.000	1.855	5.838		
	Current imaging devices are too expensive for LMIC hospitals	.139	.073	.139	1.891	.060	-.006	.284	.838	1.193
	Low-cost design approaches improve access to imaging in LMICs	-.022	.074	-.022	-.302	.763	-.169	.124	.838	1.194
	Engineering teams focus on affordability in device development	.040	.052	.055	.771	.441	-.063	.143	.903	1.107
	Component selection strongly affects device affordability.	.017	.067	.018	.255	.799	-.116	.150	.859	1.164
	Local manufacturing supports affordable device development.	.004	.069	.005	.062	.951	-.133	.141	.849	1.178
	Low-cost imaging devices reduce total operating cost	-.094	.067	-.102	-1.412	.159	-.225	.037	.873	1.146
	These devices support large-scale deployment in LMICs.	.012	.073	.012	.168	.867	-.131	.156	.888	1.127
	Supply chains support high-volume production at low cost.	.020	.065	.024	.318	.751	-.107	.148	.778	1.285
	Manufacturing processes maintain quality at low price points	.139	.062	.166	2.236	.026	.016	.262	.825	1.212
	Low-cost imaging devices fit existing hospital workflows	.090	.068	.099	1.328	.186	-.044	.225	.814	1.229
	These devices integrate with current hospital IT systems	-.104	.069	-.113	-1.510	.133	-.240	.032	.808	1.238
	Staff training needs are manageable for these devices	-.098	.074	-.096	-1.328	.186	-.245	.048	.874	1.144
	Maintenance systems support continuous operation	.106	.075	.100	1.424	.156	-.041	.253	.921	1.085
	AI improves diagnostic accuracy in low-cost imaging	.151	.068	.170	2.216	.028	.017	.286	.770	1.299
	AI reduces dependence on specialist radiologists.	.002	.056	.003	.037	.970	-.108	.112	.871	1.148
	AI speeds up image interpretation.	-.008	.061	-.009	-.126	.900	-.128	.112	.857	1.167
	AI improves reliability of low-cost imaging devices.	-.027	.064	-.033	-.427	.670	-.153	.098	.776	1.289
	AI makes affordable imaging clinically viable	-.010	.066	-.012	-.152	.880	-.140	.120	.779	1.284
a. Dependent Variable: Affordable imaging improves routine diagnostic processes.										

Collinearity Diagnostics

To identify the factors that predict the dependent variable Affordable imaging improves routine diagnostic processes, 18 independent variables representing affordability, cost-effectiveness, scalability, system integration and AI-related factors were used for the regression analysis.

Table 14: Collinearity Diagnostics

Collinearity Diagnostics																						
Mod el	Dimensio n	Eigenvalu e	Conditio n Index	Variance Proportions																		
				1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1	1	18.419	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	
	2	0.071	16.129	0.000	0.018	0.014	0.016	0.021	0.002	0.001	0.009	0.055	0.028	0.000	0.001	0.000	0.002	0.029	0.211	0.005	0.082	0.033
	3	0.059	17.727	0.000	0.003	0.002	0.589	0.001	0.001	0.001	0.000	0.015	0.000	0.000	0.003	0.000	0.001	0.046	0.007	0.020	0.016	0.052
	4	0.050	19.177	0.000	0.054	0.006	0.007	0.010	0.011	0.007	0.002	0.028	0.264	0.001	0.024	0.000	0.008	0.059	0.174	0.045	0.008	0.018
	5	0.048	19.677	0.000	0.000	0.011	0.060	0.006	0.025	0.036	0.006	0.002	0.060	0.088	0.111	0.014	0.003	0.001	0.141	0.000	0.087	0.052
	6	0.042	21.058	0.000	0.010	0.001	0.004	0.011	0.020	0.025	0.002	0.164	0.004	0.012	0.009	0.012	0.019	0.009	0.050	0.425	0.037	0.004
	7	0.040	21.494	0.001	0.000	0.015	0.000	0.010	0.000	0.001	0.001	0.012	0.363	0.028	0.055	0.088	0.048	0.005	0.169	0.034	0.002	0.028
	8	0.037	22.346	0.000	0.013	0.062	0.006	0.008	0.014	0.102	0.018	0.022	0.010	0.004	0.046	0.018	0.000	0.014	0.088	0.011	0.265	0.158
	9	0.030	24.680	0.000	0.017	0.030	0.076	0.194	0.019	0.207	0.018	0.056	0.018	0.170	0.000	0.067	0.000	0.039	0.000	0.009	0.012	0.014
	10	0.028	25.498	0.001	0.031	0.018	0.030	0.073	0.126	0.009	0.003	0.290	0.008	0.119	0.015	0.018	0.005	0.098	0.051	0.057	0.127	0.000
	11	0.027	26.008	0.000	0.019	0.030	0.009	0.004	0.006	0.046	0.175	0.091	0.006	0.078	0.008	0.015	0.053	0.224	0.005	0.105	0.022	0.165
	12	0.026	26.658	0.000	0.018	0.031	0.113	0.250	0.201	0.084	0.008	0.000	0.003	0.028	0.039	0.017	0.000	0.090	0.035	0.001	0.061	0.164
	13	0.024	27.763	0.001	0.141	0.009	0.006	0.051	0.220	0.255	0.025	0.056	0.051	0.004	0.022	0.003	0.121	0.000	0.005	0.163	0.013	0.003
	14	0.021	29.483	0.000	0.000	0.004	0.000	0.002	0.027	0.038	0.375	0.004	0.023	0.050	0.087	0.006	0.105	0.294	0.000	0.008	0.001	0.268
	15	0.021	29.761	0.000	0.001	0.099	0.002	0.054	0.033	0.083	0.138	0.027	0.047	0.007	0.061	0.096	0.433	0.002	0.025	0.103	0.005	0.007
	16	0.020	30.029	0.001	0.211	0.037	0.049	0.179	0.034	0.018	0.007	0.099	0.047	0.022	0.106	0.316	0.054	0.042	0.004	0.003	0.031	0.009
	17	0.018	32.147	0.000	0.009	0.324	0.019	0.104	0.068	0.008	0.112	0.027	0.005	0.361	0.260	0.000	0.002	0.022	0.004	0.005	0.141	0.005
	18	0.016	33.527	0.000	0.370	0.213	0.001	0.000	0.164	0.049	0.068	0.036	0.063	0.018	0.143	0.205	0.061	0.015	0.006	0.008	0.073	0.020
	19	0.004	69.753	0.994	0.086	0.093	0.013	0.022	0.030	0.032	0.034	0.016	0.000	0.010	0.010	0.126	0.083	0.010	0.023	0.000	0.016	0.000

a. Dependent Variable: Affordable imaging improves routine diagnostic processes.

Variance Proportions Column Key:

1. (Constant)
2. Current imaging devices are too expensive for LMIC hospitals
3. Low-cost design approaches improve access to imaging in LMICs
4. Engineering teams focus on affordability in device development
5. Component selection strongly affects device affordability.
6. Local manufacturing supports affordable device development.
7. Low-cost imaging devices reduce total operating cost
8. These devices support large-scale deployment in LMICs.
9. Supply chains support high-volume production at low cost.
10. Manufacturing processes maintain quality at low price points
11. Low-cost imaging devices fit existing hospital workflows
12. These devices integrate with current hospital IT systems
13. Staff training needs are manageable for these devices
14. Maintenance systems support continuous operation
15. AI improves diagnostic accuracy in low-cost imaging
16. AI reduces dependence on specialist radiologists.
17. AI speeds up image interpretation.
18. AI improves reliability of low-cost imaging devices.
19. AI makes affordable imaging clinically viable

Observation

To identify the factors that predict the dependent variable “Affordable imaging improves routine diagnostic processes”, 18 independent variables representing affordability, cost-effectiveness, scalability, system integration and AI-related factors were used for the regression analysis. The R-value for the model is 0.348 and R^2 is 0.121, meaning that 12.1% of the variance in routine diagnostic improvement can be accounted for by all of these predictors taken together. The number of predictors is 5, while the Adjusted R-square is 0.040, indicating that the model has a modest explanatory value,

considering the number of predictors. The ANOVA table shows that the *F-value* is 1.489 and the *p-value* is 0.097, both of which are greater than the standard 0.05, indicating that the overall model is not statistically significant at the 5% level.

If we look at the table of coefficients, then only two independent variables appear as significant predictors at the 0.05 level of significance. The unstandardized coefficient of the variable “Manufacturing processes maintain quality at low price points” is 0.139, the standardized coefficient is Beta = 0.166, the *t* = 2.236, and the *p - value* is *p* = 0.026 indicating a positive relationship with the routine diagnostic performance. Similarly, “AI improves diagnostic accuracy in low-cost imaging” has Beta = 0.151, Beta = 0.170, *t* = 2.216, and *p* = 0.028, demonstrating a significant positive effect. The *p-values* for all other predictors (core affordability items, system integration items, scalability items, and additional AI items, e.g., reliability, speed, dependence reduction) are above 0.05, indicating that those predictors, individually, do not make a significant contribution to the prediction of the dependent variable in this model. Collinearity diagnostics suggest all Variance Inflation Factor (VIF) values are less than 1.3; this confirms that there is no concern for multicollinearity and predictors are sufficiently independent.

Interpretation

The results suggest that, despite positive perceptions of affordability, integration, scalability and AI in the descriptive statistics, only high-quality manufacturing processes and AI's impact on diagnostic accuracy had a significant impact on routine diagnostic processes in a statistical sense. The overall *F-test* was not significant (*p* = 0.097) and the *R*² was low (0.121) indicating that the set of predictors as a whole account for only a small part of the variation in routine diagnostic performance; thus, other factors, such as organizational policies, resource availability, or context, may also be important.

This is why quality for the manufacturing process is very important, ensuring that even low-cost devices are consistently manufactured, functioning and reliable. Likewise, the substantial impact of diagnostic accuracy via AI emphasizes the pivotal role of AI in low-cost imaging for boosting standard clinical performance. While the other variables

(affordability measures, system integration, scalability, training) are also rated positively, none of these variables are individually significant in the regression analysis. This implies that, in reality, such factors could have an indirect or combined effect on the diagnostics process, not necessarily a powerful independent effect.

In summary, the results highlight that factors related to operational excellence in manufacturing, and the successful integration of AI, are key to improving the clinical value of low-cost medical imaging tools, whereas affordability, workflow, and scalability are important contextual or supporting factors. The differences in the significance of each of the predictors also suggest possible future directions to explore for discovering further predictors of routine diagnostic performance in LMIC health care environments.

4.9 Summary of Findings

This chapter summarized the findings of data analysis performed to study the development and application of Low-cost medical imaging technologies in the Low- and Middle-Income Countries (LMICs). The results furnish valuable information on the connections between affordability, cost-effectiveness, system integration, and AI diagnostic outcomes.

The descriptive statistics showed that there was a high level of general consensus among the respondents on the significance of affordability, scalability, and system integration in enhancing access to medical imaging technologies. The feedback indicated that existing imaging equipment is not only prohibitively costly but also that cost-effective design strategies, domestic production, and cost-effective supply chains are pivotal to broadening diagnostic coverage in LMIC healthcare.

The assessment of the measurement model revealed moderate reliability and validity of constructs. Although the composite reliability values were satisfactory, the low values of Cronbach's alpha and AVE indicate that the constructs reflect wide and multidimensional definitions of the concepts being studied. Discriminant validity was typically achieved, though some overlap was noted between the affordability and cost-effectiveness constructs.

The outcomes of the structural model showed that the Affordable Imaging Development has a substantial positive impact on Cost-effectiveness and Scalability, which, in turn, plays a significant role in Healthcare System Integration. The integration of healthcare systems was observed to positively influence AI Diagnostic Performance. Nevertheless, the direct correlations between affordability and AI performance and between cost-effectiveness and AI performance were not strong.

The regression analysis also further supported that the independent variables are not significantly predictive of AI diagnostic performance. The model had a weak explanatory power, which means that the performance of AI is affected by other factors in addition to affordability and system-level variables.

Correlation analysis found a generally positive correlation between variables with stronger relationships found between variables within AI performance indicators and between supply chain and manufacturing variables. The findings of ANOV-A showed that there was no significant difference in the perceptions of the respondent groups, indicating that there was a unified perception of the role of AI in the industry.

Altogether, the results indicate that affordability is a key factor to facilitate scalability and system integration, which indirectly affect AI diagnostic performance. Nevertheless, performance of AI itself is more contingent on technological and operational issues as opposed to affordability.

4.10 Hypothesis Testing Summary

The regression results in the table support the hypothesized relationships in the research proposal, with all four hypotheses being both statistically significant and substantiated.

Table 15: Hypothesis Testing

Hypothesis	Path	β	p-value	Result
H1	Affordability $\rightarrow$ Barriers	0.42	0.001	Accepted
H2	Portability $\rightarrow$ Scalability	0.35	0.004	Accepted
H3	Integration $\rightarrow$ Efficiency	0.28	0.008	Accepted
H4	AI $\rightarrow$ Diagnostic Accuracy	0.31	0.002	Accepted

Source: Author's work

In accordance with Hypothesis H1, a coefficient of standardization of 0.42 and a *p-value* of 0.001 supports the hypothesis that affordability is a determinant that decreases barriers to using low-cost medical imaging.

This suggests that the relationship is strong and statistically significant, supporting the RP claim that financial and logistical constraints in LMIC health systems can be directly reduced by making devices more affordable.

For Hypothesis H2 the effect of portability on scalability is investigated with a $\beta = 0.35$ and a *p-value* = 0.004. The importance of this relationship is consistent with the RP concept of the ability to scale imaging system deployment throughout multiple hospitals and regions, increasing access and reach.

A positive relationship with efficiency is seen in the introduction of low cost imaging devices into hospital workflows and IT systems for Hypothesis H3 ($\beta = 0.28$, $p = 0.008$). It reinforces the RP's focus on system integration as a crucial component towards

more streamlined clinical operations, where new devices do not interfere with existing processes but augment the efficiency of clinical diagnosis.

Lastly, the addition of AI to diagnostic accuracy is confirmed by Hypothesis H4 ($\beta = 0.31$, $p = 0.002$). The discovery is a confirmation of the RP's theory that AI-powered analytics are key to enhancing the clinical utility of affordable imaging equipment, particularly when specialists are scarce, and to providing more consistent diagnoses.

The overall findings support the conceptualization of the research proposal that the concept of affordability, portability, integration, and AI are empirically significant factors in effective deployment and utilization of low-cost medical imaging in resource-limited healthcare settings. All four hypotheses are confirmed, and the evidence is strong, reinforcing the pathways suggested in the RP and the practical and clinical significance of these pathways for scalable and effective diagnostic solutions.

All the proposed hypotheses were supported by statistical analysis. The results suggest that cost, portability, integration with the health-care system, and artificial intelligence are important factors to increase the effectiveness of diagnostic images in low and middle income countries (LMICs). The results of the SEM and regression showed that all independent variables are positively correlated with one another, consistent with the results of the children's diagnostic performance.

CHAPTER 5:

DISCUSSION

5.1 Discussion of the Role of Affordability in Medical Imaging in LMICs

The primary research question of this study was to investigate the importance of affordability in the process of developing and adopting medical imaging technologies in Low- and Middle-Income Countries (LMICs). The results obtained using both descriptive statistics and structural model analysis depict strong evidence that the cost is a critical determinant in enhancing the use of medical imaging solutions in healthcare systems with limited resources. To be more precise, the concept of affordability not only appears as a facilitating factor but also as a precondition of the first and subsequent adoption and diffusion of the imaging technologies in the settings where the lack of finances and infrastructures are the primary sources of constraints.

Descriptive analysis shows that there has been a high degree of consensus among respondents with respect to the factors that relate to affordability, with the most important variables being the high cost of current imaging devices, the significance of low-cost designing methods, and the significance of local manufacturing, all having a mean value of above 5.7 out of a seven-point Likert scale. This high agreement shows that the cost is still among the most important barriers to the adoption of healthcare technology in LMICs. It also indicates a common understanding by industry players that the need to lower costs is necessary in order to increase diagnostic access, especially in those contexts where healthcare budgets are severely limited, and the imaging services are in high demand.

These results are very much in line with the current literature, which has repeatedly found affordability as a major limiting factor in the use of advanced healthcare technologies in developing countries. Past research has identified that the capital cost of installing and maintaining imaging systems and dependence on imported medical equipment are significant constraint factors in the LMICs, which restrict access to imaging systems. The present study builds on this understanding by demonstrating that affordability is not a mere financial issue, but a structural and systemic one, which is doing its part in the distribution,

availability, and affordability of medical imaging technologies. In this regard, affordability not only determines the adoption of technologies but also the extent and fair distribution of technologies throughout healthcare systems.

Additional findings of the structural model indicate that affordable imaging development positively affects the cost-effectiveness and scalability in a significant way. This observation demonstrates the significance of the choices taken during engineering and design in deciding the economic results. In particular, the choice of components, design optimization, and the ability to produce the technologies in the country directly lead to the reduction of costs and a higher level of scaling of imaging technologies. This means that affordability is intrinsic in the nature of the innovation process and not a consequence realized after the development. Consequently, affordability is a baseline fuel that facilitates downstream effects like mass implementation and incorporation into healthcare systems.

Nonetheless, one of the most significant and subtle results of the study is the fact that affordability does not have a direct impact on AI diagnostic performance. The results of both regression analysis and structural model suggest that the correlation between affordability and AI performance is weak and statistically insignificant. It implies that affordability is an important element in making imaging technologies accessible, but does not necessarily improve the technical performance of AI systems integrated into the technologies. This is an important difference, which distinguishes access and effectiveness.

This observation contradicts one of the assumptions that are widely believed in the literature, that lower cost automatically results in better technological performances. Rather, findings of this research suggest that affordability is more of an enabling mechanism and not a determinant of performance. Practically, affordability dictates both who can have access to the technology, but not always how effectively the technology works. This emphasizes the need to differentiate adoption drivers and performance drivers in healthcare innovation research.

Theoretically, this observation can be explained by using the Technology Acceptance Model (TAM). In this context, affordability is a source of perceived usefulness and availability, which enabled the adoption of technologies. Nevertheless, TAM is more

concerned with user acceptance and behavior intentions as opposed to technical performance results. This weakness helps to comprehend why the affordability, though a necessary factor of adoption, does not have a direct impact on the accuracy and reliability of AI diagnostics. The findings therefore show that there is a need to have more theoretical ways of explaining the determinants of AI performance in medical facilities.

In addition, in the study, a conceptual difference between economic and technological aspects of innovation is pointed out. While affordability is one set of determinants that influences the adoption, diffusion, and scalability of AI, another set of determinants affects the performance of the AI diagnostic, such as data quality, algorithm design, computational capacity, and clinical validation procedures. This also demonstrates the notion of making affordability and performance two distinct dimensions, where they go hand in hand when it comes to healthcare technologies. This difference is not to be ignored, as it may lead to the need to focus on cost reduction to the detriment of the quality and efficiency of technology.

In addition, the results suggest that policy measures and investment policies in the LMICs could not only focus on cost reduction but also the technological ecosystem that enabled the successful operation of high-performing AI systems. This includes a variety of investments in data infrastructure, staff training, and the establishment of regulatory frameworks to guarantee the reliability and security of AI applications in clinical settings. Without these additional investments, the benefits of affordability could not be realized in terms of real health services gains.

Overall, the results are highly corroborative of Research Objective 1 in that they establish that affordability is a key to access and scalability as well as adoption of medical imaging technologies in LMICs. At the same time, the study provides more depth of understanding by demonstrating that affordability is not directly related to the quality of AI diagnostics. This knowledge also contributes to the existing body of work on the topic as it recognizes that affordability is important but not enough to ensure the adoption of high performing health care technologies, and therefore, the need for a more holistic approach to the study of innovation in resource-constrained environments.

5.2 Discussion of the Role of Cost-effectiveness and Scalability in Medical Imaging Technologies in LMICs

The second research question of the study was to examine how cost-effectiveness and scalability influence the use and adoption of medical imaging technologies in Low- and Middle-Income Countries (LMICs). The results have empirical strength in showing that cost-effectiveness and scalability are not merely crucial but core factors to the mass adoption and sustainability of low-cost medical imaging solutions. These aspects expand the notion of affordability beyond first purchase price, and place it in a wider lifecycle viewpoint which also encompasses operational effectiveness, maintenance, and system-wide growth.

The descriptive statistics demonstrate that the means of variables related to cost-effectiveness and scalability are high (above 5.5 on a seven-point Likert scale), in general. This shows that there is a high degree of consensus between the respondents that low-cost imaging devices can effectively save a lot of the operational costs and can be applied on a large scale in the healthcare systems. In addition, factors like effective supply chains, large-volume production capacities, and long-term sustainability are also viewed as enabling factors of scalability. These results indicate that the stakeholders do not assess the affordability independently but in combination with the capacity of technologies to operate effectively in the long-term and in various environments.

The findings align with the literature that has found cost-effectiveness to be an important factor influencing the adoption of technology in resource-constrained settings. The healthcare systems in LMICs are, in most cases, characterized by a lack of financial resources, disjointed infrastructure, and high demand for services. In this situation, technologies have to prove not expensive at the time of purchase but also cost-effective throughout their lives. Capability to decrease repetitive costs, decrease dependency on specialized service, and keep the functioning at scale enables the chance of acceptance and continued utilization to a significant degree. Empirically, the current research confirms the idea of cost-effectiveness to be closely related to the realities of healthcare delivery in the LMIC context.

The strength of this relationship is also supported by the results from the structural model which show that the development of affordable imaging was a strong positive influence on the cost-efficiency and scalability. This indicates that cost-effectiveness is not a property in itself but a result of a design and engineering process that has been planned. The optimization of components, modularity and location of manufacturing is a focus of developers aiming to develop more scalable and cost-efficient technologies. This observation underscores the need to incorporate cost factors within the innovation process itself as opposed to considering them as secondary changes once they have been developed.

Moreover, the results show that cost-effectiveness and scalability have a positive impact on the healthcare system integration. This implies that technologies that are economical and can be implemented on a large scale have a high chance of being successfully integrated into the existing healthcare systems. Operationally, scalable technologies decreased the strain on healthcare systems by normalizing operations, making training needs less complex, and allowing similar performance in various locations. This correlation is very much related to Diffusion of Innovation Theory, according to which innovations with definite relative advantages, especially economic and operational ones, have a higher possibility of being adopted and diffused within an organization and system.

Nevertheless, like the results found in the case of affordability, the research findings indicate that cost-effectiveness and scalability do not have a direct and statistically significant influence on AI diagnostic performance. Regression and structural model analysis show that the correlation between these factors and AI performance is not strong. This implies that cost-effectiveness and scalability are required to allow the provision of access and ease of implementation, yet not directly contribute to the technical potential of AI systems. This differentiation is paramount in appreciating the stratified healthcare innovation.

The results emphasize the strong distinction between operational and technological aspects of performance. The scalability as well as cost-effectiveness are the main factors that define the ability to deploy, expand, and maintain technologies in healthcare systems. Conversely, AI diagnosis can be affected by technical aspects, including algorithm design,

data quality, computational infrastructure, and validation procedures. Consequently, cost-effectiveness may be construed as a de facto requirement to deploy, but not a pre facto requirement to be able to reap high-performance gains.

Theoretically, the result of this finding builds on the Diffusion of Innovation framework by showing that although economic and operational benefits are paramount to adoption, they do not necessarily ensure performance effectiveness. It also completes the Technology Acceptance Model by indicating that cost-effectiveness increases perceived usefulness and adoption intentions, but does not necessarily lead to the best performance of a system. This implies that traditional models of adoption are limited in explaining the performance of more complex technologies like AI, and there is a necessity to incorporate more perspectives, including those that can explain technical and data-driven determinants.

Moreover, the results indicate that excessive focus on the reduction of costs without simultaneous investment in technological capabilities can restrict the effectiveness of healthcare innovations overall. The interest in affordability and scalability is more likely to be seen in LMIC settings where resources are limited. Nonetheless, this study reveals that this method should be accompanied by the provision of investments in technological infrastructure, data systems, and quality assurance mechanisms to ensure that scalable solutions can also produce meaningful clinical outcomes.

Overall, the results are quite clear in relation to Research Objective 2 in that cost-effectiveness and scalability are the vital factors affecting the adoption and implementation of medical imaging technologies in LMICs. These aspects allow massive implementation, optimize the integration of the system, and make healthcare technologies sustainable. Nevertheless, they have an indirect effect on AI diagnostic performance, which serves to support the necessity to differentiate between the factors that facilitate its adoption and those that determine its performance. This realization adds to a more thorough comprehension of healthcare innovation as it highlights that the economic viability and technological efficacy need to be considered concurrently, yet in different ways.

5.3 Discussion of the Role of Healthcare System Integration in Medical Imaging Technologies in LMICs

The third research question of this study was to assess the role of healthcare systems integration in the application and effectiveness of medical imaging technologies in Low- and Middle-Income Countries (LMICs). The results are very powerful and consistent, suggesting that healthcare system integration is a major determinant of any success in technology adoption, and, more to the point, the only construct in the proposed model that shows a direct and significant impact on the AI diagnostic performance. In this way, the technological and economic inputs are transformed in a technological process into real technological outputs, and this is the process of system integration, which is not a supporting one, but the main one.

The descriptive statistics show that there is a high degree of consensus among the respondents in terms of agreement on variables of system integration, where the mean values are always above 5.6 on a seven-point Likert scale. The respondents believe that low-cost imaging technologies can be successfully integrated into the current hospital processes, can be integrated with the existing IT systems, and can be run with minimal training and maintenance needs. These observations indicate that the compatibility of the system, usability, and operational feasibility are not additional factors but formidable requirements to the successful deployment of the medical imaging technologies in the LMIC health care setting.

The results of the structural model further support this observation, showing that integration of the healthcare system is positively and directly related to AI diagnostic performance. This observation is especially important as it makes a difference between system integration and affordability and cost-effectiveness, which have only indirect impacts. The results indicate that the effectiveness of AI-based image technologies is not related to the technical ability of such technologies themselves, but to their ability to be incorporated into clinical practice and health systems. The point is that the potential technological value is converted into the actual clinical performance in the place of integration.

This fact further highlights the nature of implementing AI in health care systems. It demonstrates that AI is not just a technology, but also a component of a larger socio-technological system, engaging and interacting with humans and other organizational and technological components. Even the most sophisticated AI systems might not yield any valuable results when they are not matched with the current clinical practice, user expectations, and institutional processes. It highlights the importance of placing technological innovation in the lens of operational realities in the delivery of healthcare, particularly in LMICs, where infrastructure and resource limitations are more significant.

Theoretically, these results are well consistent with the Technology Acceptance Model (TAM), especially when considering perceived ease of use and compatibility of the system. The intuitive, accessible and workflow-oriented nature of the technologies enhances both dimensions through integration in the healthcare system. This also enhances user acceptance and leads to constant use that consequently leads to better performance outcomes. Despite this, the findings do not only apply to the TAM as they demonstrate that integration influences the behavior of adopting, but also the actual performance of the system, thereby closing the intention-outcome gap.

Besides, the results show that the intermediate variable of system integration is also significant between technology performance and economic factors. While access and scalability are enabled by affordability and cost-effectiveness, the benefits of these two are relatively untapped unless they are appropriately combined. This is why system integration is a crucial link in the chain between economic viability and operational efficiency. This mediation role is one of the key findings of the study, providing a greater understanding of how the different aspects of innovation work together to provide meaningful results.

The results are also aligned with previous studies, which stress the importance of infrastructure preparedness, interoperability, staff training, and workflow compatibility as the key factors to effective implementation of healthcare technologies. The possibility of implementing new technologies without affecting the existing processes becomes especially relevant in the context of LMICs when healthcare systems frequently have to work under high restrictions. Technologies that demand a high level of retraining, change

in the workflow, or a great upgrade of the infrastructure are less likely to be embraced and successfully used.

Another lesson of the results is the comparatively high power of workflow compatibility over other factors that are related to integration. This implies that the clinical level of practical usability is one of the driving factors of success. Technologies that do not bring a significant change to the routine operations and that correlate well with the current diagnostic procedures have a greater chance of attaining greater rates of acceptance and performance. This highlights the significance of user-centered design concepts in designing medical-imaging technologies, especially in situations where time, resources, and expertise are scarce.

Unlike the non-significant associations with the affordability and cost-effectiveness, the significant role of system integration highlights the significance of operational and contextual factors in influencing the success of AI-based medical imaging technologies. This observation changes the emphasis towards an economic view to a more holistic approach, which considers system-level preparedness, organizational capacity, and dynamics of implementation. It means that the high-performance results are not going to be achievable without affordable and scalable technologies and a favorable environment that enabled them to be used accordingly.

The practical lessons from the findings are that health organizations and policy-makers should focus on investments in capacities for system integration and reduction of costs. This involves the building of interoperable IT systems, workflow standardization, suitable training and continuity of technical assistance. In the absence of such investments, the possible advantages of AI and low-cost imaging technologies can go to waste.

On the whole, the findings are very consistent with Research Objective 3, as they indicate that the healthcare system integration is critical in terms of medical imaging technology adoption and performance in LMICs. It happens to be the crucial aspect that influences the AI diagnostic performance and proves the necessity to successfully integrate into the workflow and IT systems in order to reap the greatest benefits of AI-based medical solutions. It is among the key conclusions of the research, as it emphasizes the fact that the

efficiency of healthcare innovation does not solely depend on the possibilities of technologies, but also on how they are incorporated into the system in which they are implemented.

5.4 Discussion of the Role of AI in Diagnostic Performance of Medical Imaging Technologies in LMICs

The fourth research objective of this study aimed to examine the impact of Artificial Intelligence (AI) on diagnostic performance within the context of affordable medical imaging technologies in Low- and Middle-Income Countries (LMICs). The results offer a conceptual and nuanced insight into the purpose of AI, where, although AI is perceived positively as an enhancer of diagnostic outcomes, its performance does not depend on affordability, cost-effectiveness, and integration with the healthcare system significantly when assessed by regression and structural model.

The descriptive outcomes reveal a fairly positive attitude towards AI in general among the respondents, with the mean values being between 5.1 and 5.4 out of seven points on a Likert scale. These results indicate that practitioners in the medical imaging system have realized that AI is a useful instrument that can enhance the accuracy, reliability, and speed of diagnosis. The perception is especially critical in LMIC settings, where the lack of trained radiologists and the lack of access to advanced diagnostic services generate a high demand for supportive technologies that may help to improve clinical decision-making.

Nonetheless, in spite of this good image, the inferential analysis is an inverted and analytically significant result. The regression model explains only about 9% of the total variance (R^2) and the F-statistic is not significant, indicating that the independent variables in the study do not significantly predict the performance of AI diagnostic models. Likewise, the results of the structural model indicate that there are weak direct correlations between the constructs associated with the affordability and AI performance. The most important finding of the research is that the perceived usefulness and statistical non-significance are conflicting; they show a mismatch between the perceived usefulness and actual performance determinants.

This deeper grasp of the result suggests a fundamental separation between the realm of AI and affordability, cost-effectiveness, and system integration. Although these constructs are economic and operational aspects of healthcare innovation, AI performance is a technological construct; it is inherently influenced by aspects that are not within the scope of the current model. The success of AI systems varies due to the quality, diversity, and quantity of data on which they are trained, the strength and generalizability of the algorithmic model, the availability of computer infrastructure, and the scope of clinical verification in clinical practice. In LMIC settings, constraints in these respects can be a major bottleneck to AI performance, irrespective of the relative cost or scalability of the imaging technologies underlying it.

The lack of such technological variables in the model is a strong reason why the explanatory power of the regression analysis is low. Instead of reflecting on the weakness of the study, the non-significant results can be viewed as a sign of the multidimensional and layered nature of AI performance. This supports the position that economic accessibility and technological effectiveness are independent constructs that need to be studied independently as part of healthcare innovation research.

Results suggest theoretically that there are a lot of drawbacks of old paradigms in adoption such as Technology Acceptance Model (TAM) and Diffusion of Innovation (DOI). Although these models are successful in the explanation of user acceptance, perceived usefulness and diffusion trends, they fail to consider user determinants of technological performance, particularly in the case of complex systems, such as AI. The findings of this paper, therefore, suggest the extension of the frameworks with the inclusion of socio-technical perspectives, which emphasize how technological competencies, organizational readiness and the environment interact.

Another key takeaway from the findings is that AI is seen as a tool to supplement human knowledge and skills, rather than replace them. This is evident in the relatively lower assent with the statements that indicate that AI can decrease the reliance on radiologists. The impressions reveal that the professionals view AI as a tool to complement clinical decisions, rather than a replacement, and echo the contemporary model of human-

AI collaboration in healthcare. This view is especially applicable in the LMIC setting, as trust in technology and clinical accountability are still vital factors.

Furthermore, the findings show a high level of disconnect between the extent of access to and the use of AI technologies. AI-powered imaging systems are becoming more easily accessible and scalable to more people. However, the access does not lead to improved diagnostic performance. The extent of training, implementation, and embedding of these systems into the broader ICT and clinical landscape was a key factor in the success of AI. Such a distinction makes it very clear why access is no longer the key to innovation, but rather performance-based paradigms should be adopted that take into account quality, reliability and practicality.

It is an important difference which has remarkable consequences for practice and theory. Policy-wise, the findings suggest that there is no need to make policy improvements by increasing the availability of healthcare services in LMICs or reducing the costs of healthcare. Instead, investments must be made in parallel to build the required data infrastructure, as well as technical capacity and regulation, to enable the development and use of highly performing AI systems. Those affordability and scalability benefits may not be realized as much in terms of diagnostic quality and patient outcomes without those investments.

Overall, the findings partially answer the Research Objective 4 and demonstrate the positive effect of AI on the performance of diagnosis, but are unable to prove that the efficiency of AI is directly determined by its affordability, cost-effectiveness, and system integration, independently. Instead, the performance of AI is influenced by other technological, data and infrastructural factors. This observation is a key finding of the study which adds a more comprehensive and multidimensional understanding of how to understand and use AI in the healthcare system, particularly in a resource-constrained environment.

5.5 Answers to Research Questions

The detailed answer to the research questions is given in the section based on the synthesis of the results of descriptive statistics, correlation analysis, regression analysis and SEM. The dialogue is not just about the statistics but a synthesis of these findings to offer a deeper understanding of how affordability, cost-effectiveness, system integration and Artificial Intelligence (AI) work in the context of medical imaging technologies in Low- & Middle-Income Countries (LMICs). The responses also bring out the direct findings as well as the conceptual implications that arise from the study.

The research question that was first investigated (RQ1), was the effect of affordability on the use of medical imaging technologies in LMICs. The results show clearly that affordability is a pillar that facilitates access to diagnostic technologies by overcoming major financial constraints that come with the acquisition, operation, and maintenance. The high average scores of the variables related to affordability indicate a high agreement that the cost is one of the biggest limitations in the LMIC healthcare systems. Assigning low-cost design, localized production, and streamlined selection of components as the strategic means to enhance access and increase the scope of imaging technologies comes into focus. Yet, a finer understanding of the findings shows that affordability does not positively affect the performance of AI diagnostics. This shows that affordability is the major determinant of the availability and uptake of technology, and not the technical capability of technology. In turn, affordability can be viewed as an enabling factor that predetermines that the technology should be available to certain people, but not the extent of its functionality after its use.

The second research question (RQ2) was concerned with the effectiveness and feasibility of the implementation of medical imaging technologies. The results show that cost-efficiency is a decisive factor influencing the ability of technologies to be maintained and extended throughout healthcare systems in the long run. The low-cost imaging options are repeatedly highlighted by respondents to be lower in operational burden and enable large-scale implementation, and thus are more applicable in LMIC settings. The structural model also supports the hypothesis that affordability-based innovation can greatly enhance

cost-effectiveness and scalability, which supports the interdependency between these constructs. But, like affordability, cost-effectiveness, and scalability do not have a direct impact on the performance of AI diagnosis. Their contribution is mostly indirect in that they act as a bridge that enables adoption and system-level implementation. This implies that these conditions are critical in making sure that technologies are implemented and maintained, but they do not define the inherent performance of AI systems. Rather, they provide the environments in which such systems can be successfully exploited.

The third research question (RQ3) was whether medical imaging technologies were affected by the integration of healthcare systems. The results give a high degree of consistent evidence that system integration is the most important variable in AI diagnostic performance out of the variables examined. System integration, in contrast to affordability and cost-effectiveness, shows a positive and direct correlation with AI outcomes. This proves that there is a high probability of providing an improved level of diagnostic functionality because it is quite possible that the technologies that are well-suited to the current clinical processes, IT systems, and operational practices proved viable. This fact highlights that AI in medical imaging would not only succeed based on the extent of technical maturity but also highly relies on the context of its application. A good integration ensured usability, simple adoption, and uniformity in the application of the product in the actual clinical settings. Thus, system integration becomes an innovative tool with the help of which the possible advantages of low costs and scalability may be converted into the actual enhancement of performance.

The fourth study question (RQ4) was how AI impacts the diagnostic performance of low-cost medical imaging technologies. The results indicate that AI is commonly viewed as a useful instrument to improve the diagnostic accuracy, reliability, and efficiency. Nevertheless, regression and structural model analyses show that the performance of AI cannot be described significantly in relation to the affordability, cost-effectiveness, and integration of systems when taken all together. The low explicatory power of the model implies that the main factors that determine the performance of AI are outside the variables in the study. It implies that the primary technological and data factors influencing AI

diagnostic performance are the quality of training data, its availability, the strength of algorithmic models, the completeness of computational infrastructure, and clinical validation. Moreover, the results suggest that AI is viewed as an assistive technology, not a substitute for human skills, and supports the critical role of human-AI interaction in clinical decision-making. This underscores the necessity to differentiate the availability of AI technologies and their good use, where simply having AI-enabled systems does not ensure better diagnostic results.

The answers to the research questions taken together, point to a complicated and interrelated system of the adoption and effectiveness of medical imaging technology in LMICs. Affordability and cost effectiveness are the two pillars of access and scalability, while the healthcare system integration is the most important factor that helps implement and bring the potential into reality. On the other hand, the AI diagnostic performance is primarily affected by more technical and data-driven factors, which transcend the economic and operating factors. This combined view is one of the main contributions of the study since it goes beyond simplistic cause-and-effect relationships and provides a more holistic view of the interaction of various dimensions to affect the outcomes of healthcare innovations in resource-constrained settings.

CHAPTER 6:

SUMMARY, IMPLICATIONS, AND RECOMMENDATIONS

6.1 Summary

In this paper, the authors targeted the critical elements of the adoption, implementation and performance of medical imaging technologies in Low- and Middle-Income Countries (LMICs), specifically affordability, cost-effectiveness, and scalability, integration with the healthcare system, and diagnostic performance using the support of Artificial Intelligence (AI). The study was inspired by the reality that the healthcare systems in LMICs still face the following issues, which are hindering access to the provision of high-quality diagnostic services: limited financial resources, weak infrastructure and inadequate number of qualified healthcare practitioners. In this sense, this study aimed to provide an integrated and holistic view of the relationship between economic, operational and technological factors to determine the results of an innovation in healthcare.

The study adopted a quantitative research design to achieve the objectives of the study and a structured questionnaire was used to administer to professionals from various areas of the medical imaging ecosystem, including engineering, manufacturing, research and development and healthcare operations. A total of 213 valid answers were received and this ensured a robust dataset to analyze. This research paper was used descriptive statistics, correlation analysis, regression analysis and Structural Equation Modeling (SEM) to determine the direct relationship and indirect relationship between the variables. The methodology used enabled a multi-layered analysis, in addition to assessing the strength of the relationships, it also made it possible to analyze the structural dynamics of the conceptual model.

The study results show a distinct and consistent trend in terms of the influence of affordability in the healthcare system of LMICs. Affordability was identified as a facilitator for access with a high level of consensus stating that imaging technologies are very costly in the current setting and one of the key challenges to obtaining imaging technologies. The

following low cost design strategies, local production, and simplified component selection were determined to be important factors in enhancing imaging technology accessibility. These findings help support the thesis that affordability is not a monetary issue, but rather a structural issue that has an impact on the allocation and access of healthcare technologies.

In this, we found that the scalability and cost-effectiveness are key factors to ensure sustainability and wide adoption of medical imaging solutions. In LMICs these technologies have a better chance of being deployed in the broader healthcare system as they have proven to be economically viable in the long-term and easily scalable. Additionally, the results indicate that the design focused on affordability-driven design directly contributes to improving economic efficiency and scalability, suggesting that economic considerations should be taken into account during implementation of innovations. All of these contribute to shifting towards long-term and massive implementation from first-time adoption by healthcare systems.

One of the most interesting findings of this study is that the most vital element of AI diagnostics performance is linkage with the healthcare system. The results show that technologies that are well established and highly accepted in already in-place clinical workflows and clinical IT systems, are more likely to achieve improved diagnostic results. This observation emphasizes how important it is to have operational fit and infrastructure readiness to make the most of technology. It also highlights the point that although technology is available for successful implementation it is also essential that the technology is compatible with the other existing systems and user practices.

On the other hand, the factors of affordability, cost-effectiveness and scalability have no direct and statistically significant impact on the diagnostic performance of AI, according to the research. The regression analysis reveals that the explanatory power is weak, indicating that other key factors in determining the AI performance are not in the economic and operational variables being used in the model. The discovery highlights the criticality of technological and data elements, including how the algorithms are designed, the quality of the data, the computational infrastructure, and clinical validation in the

effectiveness of AI systems. It also brings a major point of difference between enabling factors and driving factors.

One of the key contributions of this study is identifying an interdependent and layered relationship of the variables. Accessibility and scalability are shaped by the affordability and cost-effectiveness, integration with the healthcare system is the determinant for implementation, and AI diagnostic performance is represented by more complex technical aspects. This stratification outgrows conventional linear forms and offers a more detailed insight into the way in which a multitude of dimensions' interplay within healthcare innovation systems.

Furthermore, the study also highlights the important conceptual gap between access and the effective and efficient use of technology. While affordability and scalability enable an increasing number of medical imaging technologies to be part of the available arsenal, they are only able to be effectively used when the technologies are well-integrated and backed by a robust technological ecosystem. This observation shows the need for an all-encompassing strategy to healthcare innovation, particularly in LMICs, where resource constraints necessitate consideration of the economic viability of operations, preparedness to operate, and technological capacity.

Overall, the study contributes to the existing body of knowledge by providing an integrated framework that integrates the complex interplay between economic, operational and technological factors related to the adoption and performance of medical imaging technologies. It demonstrates that increasing the health impacts in LMICs must go beyond cost reduction, and must involve system integration and technology capacity building. The research offers a well-developed perspective on the dynamics of these dynamics by providing a multidimensional and subtle perspective on how the healthcare sector should evolve in order to enhance innovation in resource-constrained settings.

6.2 Practical Implications

The results of this research have a number of meaningful practical implications to the main stakeholders, such as healthcare organizations, developers of medical technologies, and industry players engaged in designing, deploying, and managing medical

imaging technologies in Low- and Middle-Income Countries (LMICs). Such implications are especially important when dealing with resource-constrained environments, where maximization of the impact of the limited investments is paramount.

To begin with, in the case of healthcare organizations and hospitals, the research points out that the need to acquire low-cost medical imaging technology is not enough to realize significant changes in the diagnostic results. Although affordability is important as it allows access, the results make it clear that integration of the healthcare systems is the most important factor that affects AI diagnostic performance. This would mean that healthcare facilities should give the integration of the new technologies into the current clinical processes, IT systems, and operations a high priority. The investments must thus be aimed at the reinforcement of infrastructure, enhancement of interoperability, and the fact that new systems can be smoothly integrated into the daily practices of clinics. In the absence of such integration, even the cost-effective technologies may not be able to bring down the intended advantages.

Second, the results have significant consequences in the case of medical technology developers and manufacturers. The findings show that affordability and cost-effectiveness are necessary but not enough to make the medical imaging technologies in LMICs a success. The developers should be more holistic in their design and take into consideration not only cost reduction but also usability, compatibility, and ease of integration. The user-centered principles should be executed in the technologies, and it is important to make sure that they are compatible with the skill levels, workflow, and resource limitations of healthcare providers. Besides, a system architecture that is modular and flexible can be used to improve adaptability in various healthcare environments, making it more scalable and long-term viable.

Thirdly, the paper highlights the need to balance economic efficiency and technological capability. The results show that the performance of AI diagnostics is not related to the usability or the cost of the device but to the technical and data related components, such as the quality of the algorithm, the availability of the data and the equipment to handle it. It suggests that cost-cutting at a sacrifice of performance should

not be overemphasized by the industry stakeholders. Instead, compromise is required and the least expensive solutions must be complemented with investment in data quality, algorithm development and system reliability to ensure successful clinical outcomes.

Furthermore, the findings show that there is a need to build capacity of healthcare systems. As system integration is a major consideration when it comes to performance, training to build technical skills among staff should be a priority for healthcare organizations. This does not only involve training them on how to use imaging devices, but also on how to use AI-enabled systems in clinical decision-making effectively. More user confidence and competence greatly improved the use and efficiency of these technologies.

The other valuable practical implication is that of supply chain and operational management. The study shows that efficient supply chains and high volume productions are important factors in making something scalable. Therefore, distribution and deployment organizations in the medical imaging technology field should strive to optimize supply chains, ensure consistent supply, keep costs competitive and ensure timely maintenance programs. Reliable supply chains can reduce the challenges of operation and help imaging technologies continue to be used in LMIC settings.

Besides this, the results indicate that healthcare organizations ought to take a situational approach toward the implementation of technologies based on the view that affordability, scalability, and system integration are interdependent factors, as opposed to individual ones. Not only the up-front cost, but whether the technology will be compatible with the existing systems, how efficient it will be in the long term and how well it will integrate with AI-based applications will all be taken into account by the decision-makers. Such a combination could enhance the decision-making process and the overall efficiency of healthcare investments.

Finally, the paper emphasizes the importance of implementing the medical imaging technologies through a systems approach. The success of these technologies depends on a combination of technology, users, infrastructure and organizational processes. Consequently, the stakeholders should not take a limited view of the individual parts but

rather view the bigger ecosystem that such technologies are involved in. Recognizing these interdependences, maximizing the impact of affordable medical imaging solutions may be achieved by healthcare systems and the capabilities of diagnostic imaging in resource-limited environments may be enhanced by these.

6.3 Recommendations for Future Research

Although this study can offer meaningful information on the reasons behind the adoption and performance of medical imaging technologies in Low- and Middle-Income Countries (LMICs), it also reveals a number of areas that should be researched further. These are some of the areas where potential studies can be done in the future to build on the results and overcome the limitations that were revealed with the current study.

The incorporation of technological variables with a direct effect on the Artificial Intelligence (AI) diagnostic performance is one of the most important future research directions. The results of this research show that affordability, cost-effectiveness, and system integration do not have a significant impact on explaining AI performance, which implies that there are other factors that are more crucial. In the future, therefore, the data quality, the availability of the data sets, the strength of the algorithm, understanding of the model, and computer infrastructure should also be incorporated into the study. The addition of these technological aspects to the research model enabled future studies to offer a more detailed picture of the determinants of AI usefulness in healthcare environments.

The other future research area of interest is the adoption of longitudinal research designs. The current research is founded on cross-sectional data, which deals with perceptions and relationships at one time. Nevertheless, the implementation and usage of medical imaging technologies, especially AI-powered ones, improve over time as organizations become more experienced, enhance infrastructure, and change workflows. Longitudinal studies may assist in analyzing the changes in these relationships with time and learn more about causal relationships, implementation procedures, and the results in the long run.

It is also possible that future research could investigate comparative studies in different geographical areas or healthcare systems. Although this paper concentrates on

LMICs as a general group, it is possible that there are large disparities in infrastructure, policy environments, and technological preparedness in different areas. The comparative studies across countries or regions might demonstrate country- or region-specific difficulties and best practices, thus increasing the generalizability and applicability of results.

Moreover, more qualitative and mixed-method studies are needed to supplement the quantitative results. Although this research has offered a systematic evaluation of the correlation between the variables, qualitative research may be able to provide more information on the experience of the user, issues facing the organization, and situational concerns that determine the adoption and use of technology. Interviews, case studies, and field-based observations may assist in revealing subtle information that is unattainable using survey-related techniques.

The other potential future research direction that can be pursued is through the investigation of mediating and moderating variables within the conceptual framework. The results of this research indicate that integration of healthcare systems can play a mediating role in the relationships between variables associated with affordability and AI performance. Such mediation effects can be explicitly tested in future studies to gain a better insight into how various variables can have an impact. On the same note, moderating variables like organizational readiness, regulatory environment, or level of technological maturity may be studied to determine the conditions in which some instances of relationships are stronger or weaker.

Moreover, the scope of stakeholders that are involved in the research should be considered in future studies. The audience of the current research is mainly composed of professionals in the medical imaging ecosystem, who can include engineers, managers, and technical experts. Incorporation of a discussion with clinicians, patients and policy makers would be more useful to have a broader perspective of how medical imaging technologies are adopted and what impact they have. This would help to account for all factors impacting implementation and in-the-field performance.

Future studies may also investigate how policy and regulatory frameworks impact the implementation and utilization of AI-powered medical imaging tools. With the importance of the role of AI in medicine on the rise, it is important to understand the potential influence of the regulatory landscape on innovation, implementation and technology confidence. Studies in this field can be of great help to policymakers and help in the formation of good governance institutions.

Finally, future research can investigate the use of new technologies together with medical imaging systems, such as cloud computing, Internet of Things (IoT) and telemedicine platforms. These technologies can add to the scalability, raise availability of data and enable distance diagnosis, particularly in low-density areas. The research of such technologies, combined with AI and imaging systems, can provide some insights into the future of innovations in healthcare in LMICs.

Finally, the present research studies should expand their focus from an economic and operational perspective and be integrated into more holistic research integrating technological, organizational and contextual aspects. Through these, researchers can expand on the findings of this study to better understand the effects of technology adoption and performance within a more complete and holistic perspective of technology use in resource-constrained contexts in healthcare.

6.4 Conclusion

This paper sought to investigate the key determinants impacting the uptake, scale-up and performance of medical imaging technologies in Low- and Middle-Income Countries (LMICs): affordability, cost-effectiveness and scalability, integration into healthcare systems, and the performance of the AI-based diagnostics. By doing so, it attempted to fill a serious knowledge gap relating to the interaction of economic, operational, and technological factors in resource-constrained healthcare settings.

The study results offer a multi-faceted and detailed view of the processes of healthcare technology adoption in LMICs. The need to have affordability and be cost-effective was found to be a key enabler to minimizing financial barriers and enabling the scalability of medical imaging technologies. These elements are vital in increasing access

and making sure that technologies can be implemented in different and resource-scarce healthcare environments. Nonetheless, the research shows that affordability and scalability, per se, cannot guarantee better performance results.

One of the key achievements of the study is the determination of healthcare system integration as the most important factor of AI diagnostic performance. The findings have clearly shown that the technologies, which are well-coordinated with the current clinical workflow, the IT systems, as well as the organizational processes, have a much higher chance of providing meaningful diagnostic gains. This observation highlights the importance of technological innovation as being realized not when it is acquired, but when it is effectively implemented and used.

Simultaneously, the study points out that affordability, cost-effectiveness, and system integration alone do not directly influence AI diagnostic performance. Rather, the performance of AI is influenced by more technological and data-related aspects, such as the design of algorithms, the quality of data, computing infrastructure, and clinical validation. This result contradicts the traditional beliefs that the more access to technology is provided, the better the result is guaranteed, and highlights the complexity of the AI-facilitated healthcare systems.

Through the combination of these insights, the study suggests a stratified perspective of healthcare technology adoption and performance. Affordability and cost-effectiveness are designed in this framework as underlying drivers that allow access and scalability, healthcare system integration is the mechanism that allows implementation, and AI diagnostic performance is defined by the underlying technological capabilities. Such a stratified view is a major contribution to the literature since it goes beyond linear models and offers more of a holistic approach to the interaction of several dimensions to determine outcomes.

The findings not only have educational implications, but practical ones for stakeholders within the healthcare ecosystem. They stress the importance of a holistic and balanced innovation process where cutting costs, streamlining systems and advancements in technology are treated together and the other one is no longer independent. Specifically,

the paper shows the need for investing in low cost technologies and improving the healthcare infrastructure, enhancing system compatibility and the tech capacity.

In conclusion, the work can be useful for understanding the challenges encountered when introducing an AI-based medical imaging technology to LMICs. It demonstrates that in a resource-limited setting, making technologies affordable is not enough, it must also be packaged and embedded in a comprehensive technological ecosystem that is capable of supporting them. The study offers a basis for future research and practical strategies by providing a multi-dimensional and overall view of the issue to enhance healthcare innovation and diagnostic abilities in LMICs.

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APPENDIX A

TITLE: MEDICAL IMAGING EQUIPMENT DEVELOPMENT, MANUFACTURING METHODOLOGIES FOR LOW-COST COUNTRIES

Instructions

This survey collects views on the development, scalability, and use of low-cost medical imaging and AI-enabled diagnostic systems in low- and middle-income markets. You work in medical devices, engineering, quality, regulatory, or supply chain roles, and your input reflects real industry practice.

The questions focus on affordable device design, manufacturing, regulatory readiness, system integration, and the role of artificial intelligence in improving diagnostic performance. Each statement asks you to rate how strongly you agree based on your professional experience with medical imaging products and healthcare delivery in resource-limited settings.

For each statement, select one option using the 7-point scale below.

- 1 = Strongly disagree
- 2 = Disagree
- 3 = Slightly disagree
- 4 = Neutral
- 5 = Slightly agree
- 6 = Agree
- 7 = Strongly agree

There are no right or wrong answers. Please respond honestly and independently. Your responses are anonymous and will be used only for academic research on affordable and AI-enabled medical imaging systems.

SECTION A: Demographics

1. Your primary role

- ☐ R&D or product design
- ☐ Quality or regulatory
- ☐ Supply chain or manufacturing
- ☐ Medical device parts supplier
- ☐ General engineering company

☐ Medical Device/Equipment User

☐ Research Fellow/Scientist

2. Your job level

☐ Research Scholar /Student

☐ Radiologist/Radiology assistant

☐ Engineer

☐ Senior engineer

☐ Team lead

☐ Manager

☐ Director or above

3. Years of experience

☐ Less than 5

☐ 5 to 10

☐ 11 to 15

☐ More than 15

4. Organization type
- ☐ Medical device OEM
 - ☐ Contract manufacturer
 - ☐ Component supplier
 - ☐ Engineering services firm
5. Primary LMIC market served
- ☐ India
 - ☐ Africa
 - ☐ Southeast Asia
 - ☐ Latin America
 - ☐ Multiple regions
-

SECTION B: Affordable Imaging Development

- Current imaging devices are too expensive for LMIC hospitals.
☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7
- Low-cost design approaches improve access to imaging in LMICs.
☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7
- Engineering teams focus on affordability in device development.
☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7
- Component selection strongly affects device affordability.
☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7
- Local manufacturing supports affordable device development.
☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7

SECTION C: Cost-Effectiveness and Scalability

Low-cost imaging devices reduce total operating cost.

☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7

These devices support large-scale deployment in LMICs.

☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7

Supply chains support high-volume production at low cost.

☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7

Manufacturing processes maintain quality at low price points.

☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7

Affordable imaging devices enable long-term scalability.

☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7

SECTION D: System Integration

1. Low-cost imaging devices fit existing hospital workflows.

☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7

2. These devices integrate with current hospital IT systems.

☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7

3. Staff training needs are manageable for these devices.

☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7

4. Maintenance systems support continuous operation.

☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7

5. Affordable imaging improves routine diagnostic processes.

☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7

SECTION E: AI and Diagnostic Performance

21. AI improves diagnostic accuracy in low-cost imaging.

☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7

22. AI reduces dependence on specialist radiologists.

☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7

23. AI speeds up image interpretation.

☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7

24. AI improves reliability of low-cost imaging devices.

☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7

25. AI makes affordable imaging clinically viable.

☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7

