An-Najah National University
Faculty of Graduate Studies

FACTORS INFLUENCING THE ADOPTION OF ARTIFICIAL INTELLIGENCE TOOLS IN THE PALESTINIAN HEALTHCARE SECTOR: AN EMPIRICAL STUDY

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Dedication

To the beacon of knowledge, the Chosen Imam... to the one who conveyed the message, fulfilled the trust, and advised the nation, to the Prophet of Mercy and the light of the world, our Master Muhammad, may God bless him and grant him peace. To those who honored us, to the souls of the martyrs in our beloved homeland, Palestine

To the candles that burned to light the way ahead of us, To those who colored our lives with the most beautiful colors, To those who illuminated our souls with the lights of guidance, To the shining stars in the sky, To the candles of our lives

To the angels in life... To the meaning of love, to the meaning of tenderness and devotion... To the smile of life and the secret of existence... To those who were the secret of my success and whose tenderness was the balm for my wounds, To the most precious of loved ones... My mother (Najah Hay Azzam)

And the one the heart cannot forget, To the soul of my late father, Adeeb Mohammed Azzam.

To precious coffee... Companion of the path and struggle

To my children and the apple of my eye (Adeeb, Ahmed, Ayoub)

To my colleagues at An-Najah National University

To ourselves, who have always dreamed of reaching this beautiful moment... You It deserves

To all lovers of science and knowledge

Everyone who contributed to the success of this work

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My God, the night is not pleasant without gratitude, the day is not sought except through obedience to You, and the moments are not pleasant without remembrance of You, and the afterlife is not pleasant without speaking to You, and Paradise is not pleasant without seeing You. So, thanks are due to God Almighty first, as He says in His perfect Book:

(If you are grateful, I will surely increase you [in favor]).

At such moments, I stop to think before I write the letters, to gather them into words. I stumble and fail to try to gather them into many lines, lines that are scattered in my imagination, and in the end, all that remains for us are a few memories and images of us with companions who were by our side. We extend our deepest gratitude, appreciation, and love to those who have delivered the most sacred message in life, to those who paved the way for us to learn and gain knowledge, and to all our distinguished professors.

Be a scholar... if you cannot, then be a learner. If you cannot, then love scholars. If you cannot, then avoid hating them.

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referred to all those who extended their support and assistance to this project. All those who sowed optimism along our path and offered us assistance, facilitation, ideas, and information have gathered. We honor and appreciate them, and may God reward them on our behalf.

And to our university, which has embraced us for all this time, we express our appreciation and gratitude for everything it has provided. It has been a light that illuminates the darkness for us.

An-Najah National University

Declaration

I, the undersigned, declare that I submitted the thesis entitled:

FACTORS INFLUENCING THE ADOPTION OF ARTIFICIAL INTELLIGENCE TOOLS IN THE PALESTINIAN HEALTHCARE SECTOR: AN EMPIRICAL STUDY

I declare that the work provided in this thesis, unless otherwise referenced, is the researcher's own work and has not been submitted elsewhere for any other degree or qualification.

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Date: 26/08/2025

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FACTORS INFLUENCING THE ADOPTION OF ARTIFICIAL INTELLIGENCE TOOLS IN THE PALESTINIAN HEALTHCARE SECTOR: AN EMPIRICAL STUDY

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Abstract

Recent years have witnessed rapid growth in the application of artificial intelligence (AI) in the healthcare sector. However, some developing countries, such as Palestine, have not seen significant interest in this field. This study aims to explore the key factors and barriers affecting the adoption of AI technologies in the Palestinian healthcare sector, focusing on the levels of trust and ethical concerns faced by healthcare workers. The Technology Acceptance Model (TAM) was adopted as the primary framework for explaining behaviors, given its ability to analyze the impact of perceived ease of use (PE) and perceived usefulness (PU) on intentions to use.

To gain a deeper understanding of technology adoption behavior, a mixed-methods approach was adopted, combining qualitative and quantitative methods (Venkatesh et al., 2016). The qualitative phase included semi-structured interviews with a group of physicians and healthcare professionals. The transcripts were analyzed using NVivo 14 software, employing coding and thematic analysis to identify key themes related to awareness, biases, and ethical barriers. The quantitative phase used a structured questionnaire distributed to a random sample of 186 participants from Palestinian hospitals, clinics, and healthcare institutions. The questionnaire was designed based on validated and reliable measures, and the data were analyzed using partial least squares structural equation modeling (PLS-SEM). The results showed that AI adoption is primarily influenced by organizational and ethical factors. In enhancing overall performance through PE, institutional pressure (IP), legal compliance, and ethical concern (EA) played a significant role, while financial readiness (FR) and top management support (TMS) had no significant impact. The results indicate that the availability of resources or management support, while important, are not sufficient on their own to boost trust or improve adoption intentions. The study also revealed that practical experience, quality of training, and external incentives play a crucial role in shaping healthcare professionals' perceptions of AI systems.

This study helps bridge the knowledge gap by examining the Palestinian reality, which faces resource and institutional challenges and is unique in this regard. It offers practical insights for enhancing self-awareness, reducing biases, and improving ethical decision-making regarding AI applications in the healthcare sector. Its findings offer valuable recommendations for policymakers, clinicians, and technology developers on how to accelerate the adoption of these technologies and optimize their use in similar resource-limited settings.

Keywords: Artificial intelligence, Intention to Adopt, healthcare sector, technology acceptance.

Chapter One
Introduction

1.1 Overview

Artificial Intelligence(AI) is defined as a branch of computer science that aims to develop engines that mimic human capabilities such as learning, reasoning, prediction, and problem-solving, using intelligent algorithms and processing. With the remarkable development of digital technologies, AI has been employed in a variety of distinct fields, including the healthcare sector. It contributes to analyzing important medical data, supporting predictions, predicting disease progression, and personalizing personal information, including income, based on each patient's condition.

In the Palestinian context, AI applications have begun to gain traction, being employed in education, smart agriculture, public administration, and the financial services sector. In the Palestinian healthcare sector, AI applications have emerged in the analysis of medical imaging (such as X-rays and CT scans), supporting early diagnosis of chronic health conditions such as cancer and diabetes, and managing health data standards at the hospital level, including the development of health services and advanced healthcare quality for patients, especially in light of the challenges related to scarce resources and the pressure on numbers targeting health care (Jebreen et al., 2024).

Artificial intelligence in Palestinian healthcare has remained an innovative tool for developing new healthcare products, which has become increasingly important as an alternative technological option to traditional non-surgical solutions. Artificial intelligence (AI) holds a prominent position in healthcare, representing a significant technological advancement amidst the ineffectiveness of traditional solutions. AI has made significant contributions to the medical field, underscoring the importance of adopting AI technologies in healthcare to enhance productivity and ensure high-quality care (Salam &Abhinesh, 2024).

1.2 AI in Healthcare

Artificial intelligence has become an essential component in various industries, including healthcare (Salam &Abhinesh, 2024). It encompasses a wide range of technologies, including computer vision, machine learning, and natural language processing. These technologies enable machines to recognize patterns, learn from data, and form opinions. Hospitals and other healthcare institutions are using AI to promote innovation in several contexts (Bothaet al., 2024). Artificial intelligence tools have been adopted in many areas within the healthcare sector, the most important of which are disease prediction and diagnosis (Kitsios et al., 2023). For example, radiologists use AI models to identify abnormalities in imaging scans, enhancing diagnostic accuracy and reducing human error (Pesapane et al., 2018). In addition, artificial intelligence can help prepare health plans by analyzing the patient's medical record, suggesting appropriate treatments, and achieving the best expected results(Karalis, 2024).

The use of AI technologies requires big data (a vast amount of complex data that is difficult for traditional systems to handle and store) (Ahmed, 2022). Due to its rapid evolution, variety (both structured and unstructured), and volume, this data requires the use of advanced analytical methods such as artificial intelligence and machine learning to extract useful information and make data-driven decisions. This helps the system train on analytics and machine learning to achieve high accuracy in medical predictions, improve service satisfaction, and detect diseases early, enabling efficient management of healthcare resources. AI-based predictive models can help prevent costly medical incidents, such as readmissions, by identifying at-risk patients and recommending preventive measures (Badawy et al., 2023). AI's role goes beyond diagnosing or treating patients; it also includes making healthcare more efficient and resource-efficient, which is essential for the system's long-term sustainability(Secinaro et al., 2021).

The use of artificial intelligence has shown great potential in healthcare, helping to deliver better services more quickly. For example, machine learning algorithms require large amounts of medical imaging data to identify simple symptom features associated with diseases such as cancer, diabetes, cardiovascular disease, and others (Topol, 2019). AI-enabled diagnostic tools help minimize human error, increase accuracy and efficiency, and assist healthcare providersin makinginformed decisions(Jiang et al., 2017).

AI is transforming modern healthcarein various ways, with one of the most impactful applications (Ghebrehiwet et al., 2024). In this approach, treatment is tailored to individual patients based on their genetic data, lifestyle, and medical history, allowing AI to identify the most effective treatment regimens (Ghebrehiwet et al., 2024). Additionally, AI plays a crucial role in streamlining healthcare services, including appointment scheduling, patient care coordination, and supply chain optimization (Shah et al., 2024).

Generative AI (GenAI) is a type of AI that creates new and innovative content, such as text, images, icons, audio, and video, by learning from and synthesizing patterns in large datasets. In healthcare, machine learning algorithms are used to generate new, synthesized data that closely mimics real-world medical data. This synthesized data is effective in training machine learning models, simulating clinical trials, and personalizing patient care. Generative AI has numerous applications in healthcare, ranging from improving diagnostic accuracy to optimizing treatment plans. By harnessing the power of generative AI, healthcare providers can deliver more accurate and effective care, improving patient outcomes and ultimately reducing costs (Reddy, 2024).

1.3 Challenges to AI Adoption in Healthcare

Some challenges are likely to be faced while implementing AI in the healthcare sector. One primary barrier is data-related; they need large sets of high-quality and diverse data (Petersson et al., 2022). Additionally, associated data privacy and security issues present daunting challenges, especially since privacy in health information is strongly protected (Shortliffe & Sepúlveda, 2018). Compliance with privacy laws, including but not limited tothe Health Information Protection and Accountability Act (HIPAA) laws in the USA andthe General Data Protection Regulation(GDPR) laws in Europe, is essential if users and healthcare professionals are to trust AI systems(Murdoch, 2021).

Ethical concerns are the two main factors that enhance the demand for AI but impede its growth. Prejudice in the machine learning libraries is valuable, as using training data containing prejudice will inevitably lead to prejudice in outcome, which may widen the health disparity gap (Obermeyer et al., 2019). In this regard, ethical concerns surrounding fairness or, more specifically, transparency and accountability are significant concerns that have become limiting factors. It is crucial for patients, the general public, and healthcare professionals not to trust all models whose workings are not explicable or where responsibility is not clear (Davenport & Kalakota, 2019).

This is especially the case financially, as implementing AI solutions is a problem for many healthcare organizations, at least for a few years, especially the small ones. Implementation costs, recurrent expenses, and necessary infrastructure requirements are typically expensive (Wolff et al., 2021). Another challenge is the regulation because the laws have not kept pace with AI advancement, since healthcare providers are unsure of the legal standing in using artificial intelligence (Shah et al., 2024).

1.4 The Role of Adoption Models in AI Implementation

Several approaches have been proposed to help address these issues, including the Technology Acceptance Model (TAM). Understanding these factors helps healthcare researchers and policymakers develop interventions that facilitate future adoption. (Venkatesh & Davis, 2000).

In addition, models developed for the healthcare sector have been expanded for new variables connected with AI use, including ethical concerns, financial status, and regulatory compliance (Rahimi et al., 2018). These factors are crucial in explaining the extent to which healthcare organizations are valuable and feasible in the perception of the AI technologies required to execute their work (Jiang et al., 2017).

1.5 Problem Statement

The efficacy of AI in the healthcare system depends on healthcare data. However, several obstacles have prevented AI from completely revolutionizing the Palestinian healthcare sector, including a lack of finance, inadequate frameworks, and other contextual obstacles (John Afolabi, 2024). Unfortunately, poorly maintained structural data also affects the Palestinian healthcare system (Abdoh & Salman, 2019). A lot of the time, patient data is unorganized, unclear, and unstructured. Healthcare data is shared by numerous care facilities, but many of them do not properly exchange or save information. The population of the West Bank is served by several public, private, and foreign healthcare facilities, which leads to ineffective data interchange (Alkhaldi et al., 2020). This poses a challenge in adopting AI tools, which require comprehensive data to provide accurate predictions and analysis. Furthermore, it has been found that a lack of standardization in data quality causes incomplete and inconsistent results, hence lowering the credibility of AI-based solutions (Isbeih et al., 2024).

On the other hand, the ethical and legal issues surrounding the application of AI in the Palestinian health sector are primarily the result of the political environment (Naik, et al., 2022). As patient information, privacy, and data security are always important globally, any particular country faces extra challenges when working with data that may have dramatic repercussions in conflict zones (John Afolabi, 2024). The West Bank region lacks a comprehensive data protection law that strictly regulates healthcare data, leaving patient information vulnerable to exploitation (Abdoh & Salman, 2019). Legal frameworks were not fully developed around the issues of data protection, which causes problems for the use of AI since healthcare organizations do not have regulations to adhere to concerning the privacy of the patient’s data (Da Silva et al., 2022).

Besides the compliance risks, AI triggers ethics-related issues, including fairness. Because of the scarcity of training diverse algorithms, there is a chance that AI systems will reproduce such biases and hence cause disparate healthcare delivery among diverse groups, especially those in remote or hard-to-reach areas (John Afolabi, 2024). The “black box” problem—another facet of AI’s decision-making—only serves to complicate matters as the clinicians in the West Bank may not be willing to go with AI systems they do not understand well, which may be a problem for patient trust and therefore AI utilization (Alkhaldi et al., 2020).

Another inevitable challenge in the Palestinian healthcare system is that of financial limitation, in part due to its conflicted history, which hampers its organization's capacity to integrate innovative technologies such as AI (Sofian & Samara, 2021). Small financial capabilities hinder the acquisition of the necessary technological resources, staff training, and constant AI system support.

The cost of AI also includes the belief that it entails a high amount of infrastructure expenditure, such as developing electronic health record (EHR) systems and acquiring consistent system upkeep. Palestinians in healthcare may, thus, face challenges of investing in AI, despite the benefits of efficiency and better quality in providing healthcare overall, due to the current urgent, attested healthcare needs.

Despite having theoretical frameworks to build on, such as the TAM, theoretical models need to be amended to consider the socio-economic and political context of the West Bank (Reddy et al., 2021). Theoretical frameworks can be used by policymakers and healthcare administrators in the West Bank to assess the value of AI and how it currently fits within the local environment (Kim, 2024).

A context-sensitive model for AI integration into Palestinian healthcare would enable the system's positive and responsible implementation; thus, the outlined factors must be considered. The model can promote a quality and efficient delivery of healthcare services and can further help the healthcare system of the West Bank address issues of equitable healthcare disparities between urban and rural settings. Hence, there isa need to develop and deploy a framework that addresses the realities of the healthcare context in the West Bank to build a sustainable model of AI application (Schlicht & Räker, 2023).

Healthcare in Palestine is highly organized, managed, and funded by local government organizations, ministries, international NGOs, and local NGOs (Alkhaldi et al., 2020). The Ministry of Health oversees most primary healthcare services, hospitals, and clinics in urban and rural areas. However, inadequate healthcare delivery has been achieved due to funding shortfalls and limited access to affordable resources, particularly in the West Bank (AlKhaldi et al., 2018). The World Bank reported that current government spending on health in Palestine (as a percentage of GDP) remains below the global average, at approximately 5.4% in 2022, and is, therefore,unable to meet the growing health needs of a population with a high prevalence of chronic diseases and limited access to medical care (World Bank Group, 2022).

A 2021 report by the Palestinian Central Bureau of Statistics highlighted some of the challenges facing the health sector. According to the report, despite the presence of more than 84 hospitals in the West Bank, with over 5,600 beds, specialized care and treatments, including MRI and CT scans, are scarce. Furthermore, the physician-to-population density ratio remains low, with one doctor currently estimated to serve a maximum of 1,200 people. This pressure increases the need to increase the number of health facilities and consultation clinics available and to introduce the latest technologies into the healthcare sector (PCBS, 2021).

There is a growing problem with waste management, particularly in the healthcare sector. Healthcare waste disposal in Palestine is not professionally managed, resulting in increased environmental impacts and health risks. According to the World Health Organization, half of the waste generated in healthcare facilities is non-infectious, and the other half is infectious; however, facilities have not implemented the necessary coordination to handle or dispose of the waste in a hazardous manner. The Palestinian Ministry of Health claims that 3,300 tons of medical waste are generated annually, half of which does not meet international safety standards for management. Eliminating these logistical challenges in the waste management system in healthcare facilities is critical to developing safer and more sustainable healthcare facilities in the future with the help of advanced waste management technologies.

1.6 Research Questions

This study focuses on AI adoption within medical organizations and aims to answer the following research questions: How do readiness factors and organizational forces, including institutional and regulatory forces, impact users' PE, PU, and behavioral intentions toward adopting AI technologies? All research questions are formed to examinethe effects of these factors on PE, PU, or attitude toward using AI. Through this exploration, this study contributes to a nuanced understanding of AI adoption drivers, offering actionable insights for organizations considering or implementing AI solutions.

- **RQ1:** What are the technological, organizational, and societal factors, as well as challenges, influencing the intention to adopt the AI tools in the Palestinian healthcare sector?
- **RQ2:** What are the relationships between organizational, technological, and societal factors and the adoption of AI tools in the Palestinian healthcare sector?
- **RQ3**: Is there a model that can be proposed and recommended for the adoption of AI tools in the Palestinian healthcare sector?

1.7 Objectives of the Study

The first research question of this study is to understand the relationships between readiness factors and organizational pressures on the users' perception and adoption intentions toward AI. Therefore, this research assesses the extent to which data, ethical and FR factors, and institutional and regulatory factors directly or indirectly affect AI applications' PE and usefulness. Further, this study examines the mediating effects of PE in these relationships. In pursuing these objectives, this study seeks to present organizations and decision-makers with specific information on factors that could enhance or constrain the use of AI, hence informing improvement strategies. This study aims to achieve the following objectives:

1. To identify and analyze the technological, organizational, and societal factors and challenges influencing the adoption of AI tools in the Palestinian healthcare sector.
2. To examine the relationships between the organizational, technological, and societal factors and the adoption of AI tools in the Palestinian healthcare sector.
3. To propose a model for using artificial intelligence tools in the healthcare sector in Palestine.

1.8 Research Significance

The significance of this research lies in its comprehensive review of the factors influencing the adoption of AI in healthcare systems in developing countries, with a particular focus on the West Bank. As previously mentioned, there is significant potential for the future development of AI and its global impact on healthcare. These elements include (data readiness, FR, TMS, EA, institutional pressures, and regulatory compliance), all of which are the focus of this study. These are valuable for uncovering the factors that determine AI adoption, particularly in a healthcare environment with limited resources and regulations.

This study aims to be an essential resource for policy-making within healthcare organizations. Palestinian healthcare administrators and policymakers can use it to focus on improving AI acceptance by analyzing the institutional pressures, regulations, and key readiness factors. The findings of this research can also help prioritize areas such as further development of the data infrastructure, addressing ethical issues, and overcoming financial challenges, whichoften affect PE and PU for healthcare professionals.

Furthermore, this study makes theoretical and empirical contributionsto the AI adoption literature in healthcare,particularly interms of the mediating roleof PE and PU in translating external pressures into adoption intentions. In doing so, the study enhancesthe theoretical understanding of technology acceptance and adoption in developing regions by contextualizing the TAM and its extensions. These findings could be helpful to IOs, NGOs, and AI solution providers working on developing and deploying equitable and environmentally friendly AI solutions in various healthcare contexts.

Finally, the findings of this study providea clearer path forimplementing AI technology in the healthcare sector. Understanding the main drivers that define healthcare professionals' perceived readiness to adopt AI tools creates the basis for producing specific educational interventions and strengthening efforts, and for partnerships with international organizations that may further support the sector. These conclusions serveas a baseline for further research insimilar contexts, contributing to a broader understanding of AI adoption in environmentsfacing economic and regulatory constraints. In summary, this study underscores the valuable role of AI in enhancing the Palestinian healthcare system and healthcare systems worldwide by offering practical approaches to address the challenges explored inthis research.

1.9 Thesis Outline

This study systematically introduces the reader to the topics of background, methodology, findings, and implications. The subsequent chapters are connected to offer a coherent discussion of the factors affecting AI adoption and, therefore, with the overall objective of providing a guide for the healthcare systems in Low and middle-income countries (LMICs).

The first chapter identifies and presents the main goals and research questions. It provides a review of the literature that looks at the theoretical underpinnings of AI, technology acceptance models, and the relevant challenges and opportunities of applying AI in the healthcare sector.

Chapter 2 describes the research method used to analyze the determinants of AI adoption within the healthcare sector in the West Bank. This chapter describes the sample selection process, data collection technique, tools used, and an example of a survey and interviews.

Chapter 3 presents the data analysis results of the study. It highlights key findings such as path coefficients and the mediation effects of data readiness, ethical and economic considerations, PE, and PU. In addition to highlighting new insights from the investigation, the last chapter compares the study's conclusions with those of other studies. It then looks at the key points and potential implications of the study, explaining how lawmakers, hospital administrators, and tech firms could apply the results to enhance the usage of AI.

1.10 Theoretical Background

In 1989, Davis proposed the TAM, which servesas a theoretical foundation for studying user acceptance of new technologies (Ursavaş, 2022). He describedthe TAM as the theory of animated action, proposing thattwo key factors, PU and perceived ease of use, shape an individual’s behavioral intention toward adopting specific technology. These determinants, which are influenced by external factors, pose a challenge to the decision to adopt advanced technology in healthcare (Ursavaş, 2022). The TAM has become one of the most widely used models for explaining technology acceptance in various application areas, including healthcare, where understanding the factors influencing adoption is critical (Ursavaş, 2022).

In healthcare, TAM provides a framework for understanding how practitioners adopt and integratetechnology, particularly AI (Rahimi et al., 2018). The increasing reliance on AI technologies and the rapid expansion of adoption have proven that the change management (TAM) methodology can identify the factors influencing users' willingness to adopt these technologies (Kim, 2024).

1.10.1 Technology Acceptance Model (TAM) as a Foundational Framework

The TAM model is based on PU and ease of use. PU suggests that job advancement will increase employee productivity and boost employee confidence, while PE refers to an employee's belief that adopting a technology is easy. The TAM model suggests that when these perceptions are positive, individuals are more likely to adopt and use the technology. The TAM model provides a clear and comprehensive framework for understanding the factors that influence healthcare workers' willingness to adopt new AI technologies (Nguyen et al., 2020).

1.10.2 Key Factors Influencing AI Tool Adoption in Healthcare Settings

The use of AI in the healthcare sector is strongly influenced by TAM, PU, and PE. However, because healthcare settings are difficult, additional factors that have an enormous impact on how valuable and useful people think about artificial intelligence must also be incorporated when using the model (Alqudah et al., 2021).

1. **PU:** Regarding the concept of job performance in the context of AI use in healthcare, this measure refers to how healthcare practitioners perceive the role of AI tools in their work practices, the well-being of their patients, and their optimistic decision-making. It was also noted that if physicians perceive the practical benefits of AI in terms of determining diagnostic times, treatment recommendations, and resource allocation for patients, they will rely on it. For example, algorithms that help interpret imaging data may increase the speed and accuracy of diagnosis, directly impacting job performance in the healthcare context (Nguyen et al., 2020).
2. **PE:**In the healthcare sector, PE is essential to enable professionals to work consistently in a variety of situations where time and accuracy are critical. For AI tools to be considered PE, they must be easy to use and learn, and compatible with existing healthcare technology systems. For example, an integrated AI system designed within an electronic health record should be intuitive enough that the user does not have to worry about interacting with the AI for more than a short period. PE is particularly important in healthcare because good interface designs significantly reduce support resistance when implementing new technologies (Nguyen et al., 2020).
3. Behavioral Intention to Use (BI): In the context ofBI in healthcare, the two perceptions, "PU" and "PE," are defined by additional contextually perceived factors, such as perceived organizational and regulatory support (Kim, 2024).

1.10.3 Application of TAM in Healthcare Technology Adoption

Research has revealed that both PU and PE influence healthcare users' decisions to adopt new technology systems (Nguyen et al., 2020). In healthcare, TAM models have been used to help identify factors that hinder technology adoption, such as complex interface design or low perceived benefit. Specifically, in AI applications, TAM models help determine how healthcare providers evaluate new AI tools in terms of ease of use and perceived benefits in terms of clinical effectiveness. However, this also highlights the weakness of asset management models in explaining AI adoption in healthcare, as these models typically need to be adapted to address healthcare-specific concerns and regulations.

This research relies on the TAM model to study AI adoption patterns in healthcare to address the specificity of healthcare systems. Thus, the improved TAM framework creates a useful bridge between traditional and more general theoretical schools of technology analysis and the realistic prerequisites for AI adoption in multi-layered healthcare environments (Rahimi et al., 2018).

1.11 Healthcare Sector in the West Bank

The healthcare system in the West Bank remains ineffective due to political and economic barriers, exacerbated by geographical restrictions and inadequate infrastructure within the Palestinian Authority (Sultan & Crispim, 2018). Several factors limit the population's access to quality and appropriate healthcare, for example, a lack of medical equipment, a shortage of specialized staff, and limited mobility due to political instability. Consequently, the healthcare delivery system is significantly impacted, and to address the gap resulting from insufficient government efforts and funding, the Ministry relies on international aid and non-governmental organizations (NGOs) (Shalash et al., 2024). However, there is growing concern about integrating modern technologies to improve healthcare operations and resource utilization. This concern, however, is associated with some obstacles, particularly regarding the implementation and adaptation of modern innovative technologies such as artificial intelligence, as confirmed by this study (Marie et al., 2016).

1.11.1 Emerging Technologies in Palestinian Healthcare

However, there is growing awareness of the adoption of emerging context-based technologies to improve healthcare standards in Palestine, given the challenging healthcare climate. Pilot projects have been implemented to provide facilities with eHealth solutions to address healthcare shortcomings, including electronic health records (EHRs) and telemedicine. Telemedicine has been promoted as a means for patients in a distant village or district to consult doctors in larger cities or other countries due to the current shortage of specialists in fields such as oncology or cardiology. The implementation of EHRs has also shown potential in improving the organization of patient information and the transfer of care from one care setting to another, as required in the fragmented US healthcare system (Contributors to Wikimedia projects, 2025).

Artificial intelligence holds great promise and potential for improving the future of healthcare delivery through innovations in diagnosis, decision-making, and patient care. Skills that cannot be uploaded to the cloud can be applied to AI in diagnostics to maximize the utilization of scarce medical staff and develop algorithms that adapt to working with medical data for imaging analysis or disease outcome assessment. Furthermore, by helping to predict demand for services, AI-based systems are instrumental in helping facilities maximize the use of their resources. However, the application of artificial intelligence in the healthcare sector in Palestine is currently limited due to the many obstacles that hinder the achievement of an ideal healthcare sector based on advanced technologies such as AI.

1.11.2 Challenges of Adopting AI in the Palestinian Healthcare Sector

The introduction of AI into healthcare institutions in Palestine, particularly in the West Bank, has unique implications. First, there are challenges related to the lack of facilities and equipment,that is, the technical base. AI technologies require adequate data capture and storage, significant processing power, and stable connectivity, all of which healthcare institutions in the West Bank often lack. Poor infrastructure development not only challenges the operation of AI systems but also impacts data security, a widespread issue in healthcare, where patient data is considered sensitive (Abdoh & Salman, 2019).

Another significant issue is the lack of experienced professionals in AI and data science in the healthcare context. Most Palestinian healthcare workers lack experience using AI technologies. These programs are expensive and typically require an international framework, which can be challenging given the current political climate in the region (Al-Worafi, 2023).

Artificial intelligence systems require operational budgets for adoption, but the limited financial resources in the Palestinian healthcare sector pose a significant challenge to the adoption of these systems. Furthermore, external healthcare funding sources are not suitable for long-term investments in technologies, and high-risk projects that rely on technologies such as artificial intelligence are unsustainable. (Dahleez et al., 2021).

Finally, regulatory and ethical issues pose a challenge to the adoption of AI tools in healthcare. Currently, there are no general legal rules governing the use of AI in Palestine, which has led many healthcare providers to be interested in adopting AI-based solutions. It is also clear that the transnational legal framework regarding data privacy and protection, accountability, and even liability for treatment decisions made by AI is not well-articulated. Ethical issues, such as data ownership and the degree of bias in algorithms, are also known to hinder acceptance and adoption. There are some general precautions necessary when applying AI in the healthcare context: the legal and ethical issues of using a safe, unbiased, and, most importantly, transparent AI system (Isbeih et al., 2024).

Indeed, case studies have shown that the healthcare sector in the West Bank suffers from a multifaceted lack of resources and physical infrastructure, as well as systemic barriers that hinder the healthcare sector from adopting emerging technologies such as AI (Eker & Imam, 2025). However, there is an emerging appreciation for the benefits of using AI and other digital tools to bridge the significant gap in healthcare service delivery and enhance individual benefits. However, this is not sufficient for the ultimate goal of ensuring the introduction and implementation of AI in the Palestinian healthcare sector, as Palestine, as a developing country, requires further investment ininfrastructure and technical and organizational development, such as developing human capital for AI, data management infrastructure, and AI governance and policy. Overcoming these barriers would enhance the quality of healthcare systems and achieve the goal of creating a healthcare system that specifically addresses Palestinian healthcare needs.

1.12 Gaps in the Literature

Previous research on the application of AI in healthcare has highlighted its many benefits, emphasizing its valuable impact on diagnostic and healthcare improvements, resource utilization, and patient care. A large number of research papers have demonstrated that AI can bridge existing gaps in healthcare by supporting and enriching the decision-making process of physicians and other medical practitioners and providing accurate treatment recommendations for each patient. Other work has also revealed the following factors that influence the use of AI technologies: healthcare workers' attitudes toward the use of AI tools, assessment methods, and AI.

Furthermore, the impact of organizational readiness on AI adoption has been studied, particularly in terms of technological and FR for businesses, beyond separate factors such as automation. Factors such as DR influence AI adoption, determining the feasibility of adopting these systems in terms of the availability of resources, such asFR. Ethics, such as patient data privacy and the fairness of AI-based healthcare decisions, have received similar attention as critical factors shaping perceptions of AI in healthcare, as patients and physicians raise concerns about data security and the potential biases of AI algorithms.

1.12.1 Identification of Gaps

Although previous research has demonstrated the many factors that influence the acceptance and implementation of AI in various settings, research gaps remain, such as the moderating influence of IP, EA, and RC on the acceptance of AI tools in healthcare settings. Compared to the substantial body of research devoted to internal AI readiness in healthcare organizations, concerning technological or financial support, there is a lack of understanding of how external conditions influence the practical implementation of AI solutions.

1. Institutional Pressure and AI Adoption: Although the impact of IP on technology adoption in healthcare settings has been identified, pressures from accreditation bodies, government regulations, and industry standards related to AI adoption have

not been adequately addressed (Bag et al., 2021). This is particularly evident in regions experiencing a changing regulatory environment or operating under stringent regulatory regimes, where healthcare providers are under pressure to adhere to local or international standards. This lack of extensive research focusing on these institutional factors contributes to understanding the dynamics of AI adoption.

2. Ethical Anxiety and Its Impact on Adoption: There is insufficient research on the detailed mechanism linking ethical sensitivity to AI adoption in healthcare. Some studies have addressed the ethical perspective, citing data privacy, patient rights, consent, and algorithmic openness as issues related to AI. Given the broad scope of ethical issues related to AI, the impact of ethical concerns on the awareness and application of AI technology remains a key area that has not been thoroughly investigated.
3. Regulatory Compliance as a Factor in AI Adoption: Regulatory compliance is another understudied area that warrants further study within the literature. AI integrates into a highly sensitive sector, making data privacy and healthcare guidelines vital for implementation. However, little research addresses regulatory compliance as a factor that ensures or hinders its adoption.
4. The combined effect of IP, EA, and RC: Previous research has focused on some of the challenges of adopting AI in healthcare, including IP, EA, and RC, as factors that influence healthcare users. However, it has not focused on other aspects of the challenges, such as understanding the internal and external pressures healthcare users face when adopting AI tools. This is due to the lack or absence of a comprehensive analysis of the complexities of AI by researchers and healthcare institutions.

1.12.2 Investigating the Role of Organizational and External Factors in AI Adoption

Previous research (Conduah et al., 2025) has highlighted the need for future focus on studying the relationships between institutional readiness (such as data reliability and financial resources) and external factors, including legal requirements for data privacy protection and healthcare users (WHO, 2023). Studying these interactions is particularly important in regions with complex institutional environments, such as

Palestine, where the increasing reliance on new technologies poses particular challenges for healthcare providers (Khatib et al., 2021).Studying the impact of AI itself on AI adoption decisions: Further research is needed to examine the ethical challenges of healthcare users, concerns about bias or data privacy exploitation, and explore potential solutions to these issues (Morley et al., 2020).Exploring regulatory compliance as a critical factor in AI adoption, one area that needs further research is regulatory compliance, as compliance is often a challenge in adhering to strict privacy laws and datasets accessed by healthcare providers. Further research could analyze the impact of different regulations on AI adoption and explore the most effective ways to comply with regulations and implement AI. This research could also help policymakers understand how to support healthcare organizations by developing more flexible, clear, and effective regulatory environments for AI adoption (Topol, 2019).

Develop a framework for adopting AI technologies so that future studies can focus on developing a unified framework that links healthcare organizations' readiness to adopt AI technologies and how to manage them (Dwivedi et al., 2021). This framework could also serve as a useful reference for policymakers to adhere to, providing them with an easy way to understand the issues hindering their organization's operations and the ethical aspects of AI adoption.

1.13 Intention to Adopt (IA)

Intention to Adopt (IA) is the willingness of healthcare professionals and organizations to use AI technologies in their operations. Adoption intent is a key factor in the TAM, representing both perceived behavioral control and actual behavioral intention to use new tools or perform new procedures (Wang & Li, 2024). In healthcare settings, the application of AI tools improves diagnostic accuracy, system functionality, and the overall efficiency of high-quality patient care, making AI critical for clinical settings (Khanfar et al., 2024).

TAM suggests that the two strongest predictors of AI adoption are a user's perceptions of the ease of interacting with an application, on the one hand, and their belief in their ability to use a particular application to achieve their work-related goals, on the other. Focusing heavily on the interplay between perceived PE and PU of AI technologies reveals that the more people are aware of these technologies, the more likely they are to adopt them because they help improve workplace performance. PE reduces the cognitive and operational "distance" people tend to have when encountering AI tools. PU reflects the extent to which these tools are perceived to contribute value that improves patient care and organizational practices (Nascimento & Meirelles, 2022). PE and PU together influence AI in the healthcare setting, increasing an entity's propensity to use it (Alqudah et al., 2021).

Previous studies lend credence to the following associations: PE, PU, and IA in the healthcare context. For example, Lee et al. (2025) indicated that PE and PU influence the use of technologies in the healthcare sector. Alqudah et al. (2021) also observed that healthcare professionals, in general, will use artificialintelligence tools and applications if they expect these tools to improve utility value and clinical benefit. These findings, based on PE and PU, reveal the importance of IA in the context of the often high-stakes and complex healthcare field (Kim, 2024).

1.13.1 Extension of TAM for AI Adoption in Healthcare

Although TAM is helpful in a basic understanding of technology adoption, it needs some extensions when adopting AI in healthcare. Therefore, AI implementation in health care depends not only on PU and PE but also on organizational factors and outside pressure, not addressed in the original version of TAM (Kim, 2024).

Data Readiness (DR): AI systems rely on big data to be as accurate and effective as possible. This perception depends on the organization's readiness to handle and integrate data in a manner compatible with the application of AI tools in the healthcare sector. Data readiness refers to having the necessary data sources, appropriate storage systems, and data protection methods, all of which influence the application of AI in the healthcare context (Rahimi et al., 2018). DR is the concept that defines the readiness of high-quality, available, and accessible data required by AI technology to operate in the context of healthcare systems. AI systems rely on high-quality, structured data to generate reliable outputs. In healthcare data, readiness is critical because it determines the accuracy with which AI tools can help identify and address health issues, gradually impacting positive patient outcomes and overall workflow (Devi & Bansal, 2024).

As previously mentioned, data analytics can play a key role in changing the work environment by removing many barriers and streamlining the process. Better-organized and easily accessible data reduces the time and repetition required for healthcare providers to interact with AI systems, improving the work environment. The relatively high data readiness also mitigates these technological challenges and enables the ease of use of most AI tools in the healthcare provider context (Subrahmanya et al., 2022).

Having more accurate and reliable data helps AI systems learn more effectively and produce more accurate outcomes. This improves performance, as there is evidence that decision-makers can adopt AI tools in healthcare as reliable tools. The more providers perceive that AI use leads to useful information and improved clinical decisions with accurate information, the greater its perceived utility (Ghaleb et al., 2023).

Financial Readiness (FR): Budgetary constraints or the inability to support AI technologies when used within healthcare organizations impact ease of use and perceived benefit.Financialreadiness (FR) refers to the extent to which healthcare organizations have the financial resources to invest in AI systems (Venkatesh et al., 2012). FR primarily influences AI adoption in healthcare, as organizations must assess their ability to bear the costs associated with AI adoption (Ramezani et al., 2023).

Financially empowered organizations can provide significant infrastructure and training programs, mitigating barriers to AI implementation. Abundant funding in the healthcare sector enables providers to easily interact with AI interfaces by creating conditions for learning and development. Thus, AI can enhance professional performance by creating an enabling environment for the technology's application (Santamato et al., 2024).

Organizations with a high response rate can afford to purchase improved AI tools, and thus, the perceived benefits of these technologies are high. Adequate funding enables healthcare organizations to optimally utilize advanced, superior formal AI systems. This increases the utility of use by considering the practical use of AI in improving patient outcomes and increasing the efficiency of organizational processes (Nikhil et al., 2022).

Scholars have repeatedly highlighted that financial resources are essential to technology implementation and adoption. Damschroder et al. (2009) note that financial support is a key driver of healthcare technologies. Alami et al. (2021) demonstrate that motivation and funding are the two defining factors influencing the success of AI technology adoption among organizations.

Top Management Support (TMS): It is the active involvement, commitment, and encouragement of senior executives and organizational leaders in the implementation and success of projects, activities, or organizational reforms. It is an essential component of success in both strategic and operational contexts.

Ethical Anxiety(EA): Subtopics related to ethical issues in AI-based healthcare, such as patient data privacy, algorithmic bias, and transparency, make it important to integrate EA into the AI adoption TAM. Research shows that EA induces PU and PE biases because it determines whether users' perceptions of AI roles will represent core ethical practices in healthcare (Pesapane et al., 2018). Specifically, EA is defined as an individual's ability to appreciate and maintain the ethical aspects of AI use, such as patient privacy, bias, or unfair data treatment. In the medical field, where patient satisfaction is at the core of the business, ethical sensitivity is essential to ensuring that AI technologies do not violate patient privacy, that their personal information is secure, and that systems are free of bias. Because the limitations of any particular technology's use in society are discussed within the framework of ethical considerations, EA is a critical subfield of AI (Shaw et al., 2024).

Regulatory Compliance (RC): defined as the extent to which AI technologies meet existing healthcare regulations and standards (Price & Cohen, 2019). Other reasons why compliance is important in healthcare include protecting and upholding patient rights, promoting safety, and maintaining the integrity of the healthcare sector. Certified AI products and services can provide healthcare organizations with legal support and embed the importance of patient care in their duty statements (Kim et al., 2024).

RC contributes to improved performance by mitigating many of the legal and operational factors associated with AI technologies. According to Aun, when AI tools comply with regulatory guidelines, perceived risks are reduced; thus, healthcare providers are more willing to adopt them (Zhou & Gattinger, 2024).

Therefore, RC enhances the level of trust in AI systems, which is likely to increase when established standards are met. This assurance is crucial for healthcare providers, as they know they are using tools that meet specific regulations, reinforcing the importance of improving the quality of services provided to patients (WHO, 2023).

The role of remote control in technology adoption is demonstrated in the literature. For example, Taylor et al. (2010) noted that compliance enhances the trust and acceptance of healthcare facility staff. Offered similar insights, noting that regulations make the use of AI systems safer and more effective, making them attractive for use in healthcare settings.

Institutional Pressures (IP): Healthcare professionals cannot meet the pressures of institutional norms and policies. Norms and standards that support the use of AI in healthcare can increase its adoption because the practice makes people feel it is valuable and indispensable. Conversely, a lack of institutional support reduces its adoption due to perceived risks or regulatory support (Sitthipon et al., 2022). As a result of the external pressures that healthcare organizations within the region receive to modernize their services and align them with the requirements of the healthcare industry, the use of AI may be a motivator as organizations aim to meet these external expectations and maintain viability (Santamato et al., 2024).

The rationality of intellectual property can impact overall performance by facilitating decisions regarding AI adoption. If AI adoption is driven by external forces, it becomes mandatory, making decisions about it much easier for users in healthcare organizations (Okwor et al., 2024).

In this way, they reinforce the competitiveness and compliance argument that AI tools support to enhance the contribution of intellectual property to overall performance. Thus, if organizations realize that external stakeholders expect AI programs, they will also realize that AI tools are essential to maintaining the organization's competitiveness and compliance with external regulations (Davenport & Glaser, 2022).

There has been theoretical concern about the role of institutional forces in the adoption of a particular technology. According to DiMaggio and Powell (1983), institutional pressures were a major cause of organizational change. Furthermore, Xue (2014) also explored the influence of external pressures, identifying healthcare organizations as pressured to adopt new technologies, especially if such adoption is supposed to help conform to industry standards.

1.14 Hypotheses Development

The adoption and use of AI in healthcare are multifaceted and influenced by individual, organizational, and external factors. Therefore, this research aims to formulate hypotheses about these factors, which motivate the intention to adopt AI in healthcare facilities in the West Bank (Secinaro et al., 2021). The TAM, used to measure individuals' acceptance of technology, forms the basis of this study; however, the model has been enriched to accommodate factors that may influence AI adoption in healthcare facilities (Kim, 2024).

Data readiness, or data preparedness that includes data quality, availability, and accessibility, is essential for AI systems, especially in solutions built in data-intensive fields such as healthcare (Ghaleb et al., 2023). With well-organized, error-free data available in large quantities, AI systems can make accurate predictions, diagnose disease, and recommend treatments that may best suit a patient's needs (Santamato et al., 2024). In this context, the reliability of information managed by AI systems is expected to enhance perceived utility. For example, if a cardiology center has a sound electronic health record, AI tools can improve their performance and analyze a patient's health history to diagnose health trends and alert the physician to health conditions necessary for decision-making (Bothaet al., 2024). This hypothesis is based on the theoretical framework of the TAM model, where the model assumes that the usefulness of technology is closely related to the actual data used by the technology (Kim, 2024). This study hypothesizes the following:

H1: Data Readiness (DR) Positively Influences Perceived Usefulness (PU)

Sometimes, the extent to which users interact with AI technologies may be determined by technical or operational limitations (Karalis, 2024). In healthcare, data is valuable for its high quality; it optimally feeds AI models, reduces errors, and enhances model interpretability. Data readiness eliminates some of the challenges, as practitioners receive a continuous stream of data used for diagnosis without interruption or distortion (Devi & Bansal, 2024). This seamless interaction with data thus reduces the perceived effort of using the system, supported by TAM theory, where ease of use is critical to user satisfaction (Nguyen et al., 2020). A literature review suggests that data infrastructure uptake improves the ease of implementing healthcare technologies (Gerlich, 2023).

H2: Data Readiness (DR) Positively Influences Perceived Ease of Use (PE)

Therefore, the perceived benefit of AI technology depends on FR (Ramezani et al., 2023). In healthcare, FR enables organizations to acquire advanced AI solutions, provide competencies, and train users, which enhances implementation (Santamato et al., 2024).

H3: Financial Readiness (FR) Positively Influences Perceived Usefulness (PU)

Financially prepared organizations are more capable of financing AI implementation and reducing operational barriers (Anh et al., 2024). Many organizations have stable financial resources to invest in changes that enhance user usability and familiarize their employees with inventions that are widely used (Luo et al., 2024). This readiness may reduce the challenges of adopting and operating this technology, given the readiness of users. One healthcare researcher analyzed the fact that organizations with greater FR claimed that their ability to finance the implementation of user-centric AI reduces learning curves and operational barriers (Malik & Annuar, 2021)

H4: Financial Readiness (FR) Positively Influences Perceived Ease of Use (PE)

Another obvious reason is the need for senior management support for the development of certain technologies (Santamato et al., 2024). First, if leadership supports the concept of AI and its integration into the organization, it creates awareness of the critical technological solution, promotes employee engagement in the processes associated with its implementation, and ensures access to the necessary tools (Secinaro et al., 2021). This could mean that management support in healthcare supports funding for new and promising AI solutions, creates a culture that encourages advancements in the field, and ensures that AI advancements are relevant and applicable to achieving the healthcare organization's goals (Salam &Abhinesh, 2024). This expectation stems from administrators' support for the robot, which leads employees to view AI as a valuable resource that addresses core clinical or operational challenges. Administrators' adoption of AI demonstrates that the field supports the robot and its use and stems from the change management (TAM) assumption that organizational adoption increases perceived benefit (Malik & Annuar, 2021).

H5: Top Management Support (TMS) Positively Influences Perceived Usefulness (PU)

Therefore, senior managers should ensure that AI adoption is facilitated by encouraging the use of the technology, providing clear policies on its use, training on its optimal use, and providing support services to organizations adopting it (Santamato et al., 2024). Managers who advocate for AI integration share resources and build employee confidence in the program. In healthcare, management encouragement entails providing guidance for AI use, reducing uncertainty, and offering technical assistance, all of which are part of the PE (Salam & Abhinesh, 2024). Therefore, leadership plays a crucial role in determining how easily end users access AI (Malik & Annuar, 2021).

H6: Top Management Support (TMS) Positively Influences Perceived Ease of Use (PE)

Ethical considerations are critical in AI adoption decisions, particularly in sectors that uphold core values of privacy, fairness, and transparency (Kwak et al., 2022). In the healthcare field, imposing greater constraints on how AI tools are formulated and delivered based on principles of fairness and privacy can increase perceived benefit (Gerlich, 2023). By taking these ethical considerations into account, users are more likely to see value in and trust AI systems compared to those without ethical values, such as patient safety and data integrity (Machado et al., 2023). The TAM closely reflects this hypothesis, where ethical standards complement perceptions of technology's benefit and thus help increase its value based on trust (Kim, 2024).

H7: Ethical Anxiety (EA) Positively Influences Perceived Usefulness (PU)

Ethical concerns can also impact usability, as systems developed according to ethical standards ensure that most parameters are easy to understand (Gerlich, 2023). When developing healthcare technologies, ethical considerations also mean that AI systems should focus on being as easy to understand and use as possible, avoiding limiting user freedom as much as possible to facilitate control (Kwak et al., 2022). Ethically designed interfaces evolve from clear and intuitive design, limited data collection, and easy-to-use opt-in/opt-out features, which increase the popularity of memes (Resnik & Hosseini, 2024). Based on this hypothesis, we hypothesize that ethics has played a role in AI design, enhancing usability through increased control and transparency.

H8: Ethical Anxiety (EA) Positively Influences Perceived Ease of Use (PE)

AI tools in healthcare must adhere to standards and laws that the healthcare sector adheres to worldwide, for example, the Health Insurance Portability and Accountability Act in the United States, which sets standards for patient data privacy and security (WHO, 2023). Regulatory certification assures healthcare professionals and software users that the AI systems used are safe, ethical, and reliable. This increases perceived uptake because these systems comply with ethical and legal requirements, which is critical in a sensitive field like healthcare (Zhou & Gattinger, 2024). The usefulness of the TAM framework expands if AI tools help facilities maintain compliance, as it enhances utility from both an operational and ethical perspective (Taylor et al., 2010). Compliance also means the systems can be used in clinical practice, which also helps improve AI uptake (Kim et al., 2024).

H9: Regulatory Compliance (RC) Positively Influences Perceived Usefulness (PU)

Regulatory compliance helps AI systems be user-friendly, as it facilitates the definition of clear interaction parameters (Kim et al., 2024). This is particularly prevalent in cases where regulatory issues require user interfaces to be comfortable with display design and control procedures (Zhou & Gattinger, 2024). Therefore, good regulatory compliance provides security and enhances the ease of use of AI technology, making it more widely used (WHO, 2023).

H10: Regulatory Compliance (RC) Positively Influences Perceived Ease of Use (PE)

External pressures are a way to use AI systems more effectively (Botha, Segbedzi et al., 2024).Effective competition, the need for increased efficiency in healthcare delivery, and compliance with healthcare industry standards are the major drivers of AI adoption (Williamson & Prybutok, 2024). Thus, institutional pressures increase the perceived importance of AI in maintaining competitiveness and compliance with industry requirements (Luo et al., 2024).

H11: Institutional Pressure (IP) Positively Influences Perceived Usefulness (PU)

Regulatory pressures indirectly impact ease of use, forcing healthcare users to seek more user-friendly tools (Nguyen et al., 2020). Healthcare organizations often opt for standardized systems that are easy to test, as external pressures to enforce the use of standardized systems arise from the funding forces behind these systems (Park & Kim, 2023). This choice allows users to adapt to the technology, and given its ubiquity, there is more knowledge about it within the sector (Gerlich, 2023). This can also mean that institutional pressure can demystify AI adoption and align it with users' capabilities and understanding (Luo et al., 2024).

H12: Institutional Pressure (IP) Positively Influences Perceived Ease of Use (PE)

According to the TAM model, PE directly influences PU, as a user-friendly system makes it easier to understand the usefulness of a system. If users can quickly navigate an AI system and work, it becomes easier to assess the system's performance in their workflow (Gerlich, 2023). This is important because, in administrative and clinical practice, AI's ease of use, in the form of easy-to-understand tools, is useful in assisting clinical decisions related to patient care or in continuously improving practices related to healthcare worker performance (Jeong et al., 2025). Thus, a user-friendly AI system appears more useful because it is integrated into the daily routine to assist clinicians in their tasks (Lopes et al., 2024).

H13: Perceived Ease of Use (PE) Positively Influences Perceived Usefulness (PU)

PU is primarily defined in the TAM model as a variable closely related to technology adoption when users believe the technology will improve their work (Zhu & Sun, 2021). In healthcare, if AI tools are shown to have intrinsic value in improving patient outcomes, increasing efficiency, or improving healthcare decisions, healthcare workers will feel the need to integrate these tools into their work (Botha, Segbedzi, et al., 2024). This hypothesis reflects the core tenet of the TAM model: when users perceive AI as a useful technology, they are more likely to adopt it. A literature review reveals that subjective perceptions of effectiveness are positively associated with outcomes in healthcare, as appropriate AI solutions facilitate decision-making in patient care (Witkowski et al., 2024).

H14: Perceived Usefulness (PU) Positively Influences Intention to Adopt (IA)

The usability of GSS is one of the most important industry factors in determining users' level of intention toward a particular technology (Zhu & Sun, 2021). Although most healthcare professionals report ease of use of AI systems, they will not adopt them if the implementation is complex. When it comes to healthcare, time and money are paramount, and this type of product should be as easy to use as possible (Jeong et al., 2025). Tools that do not require extensive training are more likely to be adopted faster, and we see in TAM that ease of use increases adoption intention (Gerlich, 2023). This also demonstrates that easy-to-use HC technologies are more likely to be adopted because they help reduce the load on the user's working memory (Venkatesh et al., 2003).

H15: Perceived Ease of Use (PE) Positively Influences Intention to Adopt (IA)

Thus, this hypothesis proposes that DR impacts PU by first influencing PE. In healthcare, DR explicitly refers to the status and availability of data and the format in which data is organized and made available to support AI systems (Hiniduma et al., 2024). Therefore, high data readiness can enhance the intelligence and usability of AI systems, thereby increasing the PE (Antes et al., 2021). Healthcare professionals' perceived AI usability leads to higher PU because they perceive the system to be easier to implement for clinical or operational decision-making (Bothaet al., 2024). Research suggests that the impact of data quality on value delivery leads to better usability of data-enabled technology solutions, especially in the healthcare context (Dwivedi et al., 2019). This indirect relationship also means that an environment with high data readiness increases ease of use, which improves the PU of AI tools.

H16: Data Readiness (DR) Positively Influences Perceived Usefulness (PU) Through Perceived Ease of Use (PE)

This hypothesis is that FR influences PU through PE. Money enables healthcare organizations to acquire better-designed AI applications and training modules, which significantly facilitates technology adoption (Anh et al., 2024). When AI is easy to use, healthcare professionals perceive it as more valuable, increasing PU (Luo et al., 2024). It is well established that when end-user organizations have sufficient financial capacity, they can support the provision of technology training, which reduces perceived technology complexity and enhances PU, thereby improving relationship quality. In the healthcare context, adequate funding enables the availability of AI applications within the system, enhancing both perceived ease and usefulness (Malik & Annuar, 2021).

H17: Financial Readiness (FR) Positively Influences Perceived Usefulness (PU) Through Perceived Ease of Use (PE)

TMS influences PE, which in turn increases PU. If top management embraces AI technology, they are more likely to support and facilitate its use (Santamato et al., 2024). The positive attitude toward AI that employees receive creates a perception of ease of use and acceptance, which leads them to view it as task-beneficial (Secinaro et al., 2021). Research shows that support from management is critical in reducing user resistance and increasing the likelihood of a positive experience with a new technology (Salam & Abhinesh, 2024). Similarly, in the healthcare industry, when leadership promotes AI with the message that it should be easy to use, it also enhances the technology's perceived importance.

H18: Top Management Support (TMS) Positively Influences Perceived Usefulness (PU) Through Perceived Ease of Use (PE)

This study hypothesizes that AI positively impacts overall performance through its interaction with overall performance. Therefore, healthcare professionals trust AI systems to adhere to ethical standards, including data confidentiality and non-discriminatory decision-making. The technology is perceived as less complex to interact with (Kwak et al., 2022). This sense of comfort leads users to appreciate the importance of the system, particularly in sensitive areas such as patient interactions (Shaw et al., 2024). Studies have shown that ethical awareness can reduce concerns about technology, as people feel safe and confident about it, improve its ease of use, and perceive its usefulness (Karimian et al., 2022). Thus, EA intervenes and moderates the influence of factors that influence the PU of AI in healthcare.

H19: Ethical Anxiety (EA) Positively Influences Perceived Usefulness (PU) Through Perceived Ease of Use (PE)

RC is the mediator between PE and PU in this hypothesis because RC helps improve the usability of AI systems, helping to increase the systems' PU (Kim et al., 2024). If healthcare AI systems are compliant with the necessary regulatory standards, users will be assured that their data, as well as patient data, will be secure from unauthorized access and that the developed AI systems will be ethical (Zhou & Gattinger, 2024). Additionally, it makes users feel that AI tools are safe and easy to use and indirectly increases the value of PU by making the technology more credible. Making these types of AI systems more compliant can motivate healthcare providers to adopt these tools, which improve patient satisfaction and clinical outcomes with models (WHO, 2023). This paper logically asserts that elevating IT to a regulatory-compliant level significantly increases its adoption rates; people feel more comfortable using compliant technology (Dwivedi et al., 2019). According to this test, the fact that regulatory compliance creates trust is an intangible factor that positively influences the PU of AI systems.

H20: Regulatory Compliance (RC) Positively Influences Perceived Usefulness (PU) Through Perceived Ease of Use (PE)

Pressure from institutions, in terms of requirements from other institutions or individuals, for example, from different companies or regulatory authorities, exerts pressure on PU through PE (Gerlich, 2023). Healthcare providers tend to adopt AI tools due to external pressure from regulatory and accreditation bodies once these tools have proven to facilitate work by meeting specific criteria (Güven et al., 2024). Due to institutional pressure, it is expected that when AI tools are perceived as easy to use, their PU increases because they can help the user achieve professional and organizational goals (Barchielli et al., 2021). Theoretical studies confirm that institutional arrangements compel organizations to acquire technologies because their ease of use reduces perceptions of their usefulness, as hypothesized by DiMaggio and Powell (1983). In the context of healthcare, these pressures ensure that organizations implement AI solutions that are useful and usable.

H21: Institutional Pressure (IP) Positively Influences Perceived Usefulness (PU) Through Perceived Ease of Use (PE)

In this hypothesis, PE has an influential relationship with AI through the mediator of PU. It has been established that when healthcare professionals perceive integrated AI tools as easy to use, they also perceive them as more practical, which enhances their intention to adopt the specific tools mentioned (Nguyen et al., 2020). This mediating path captures one of the central assumptions of the TAM model: ease of use leads to PU, and adoption flows from this PU (Jeong et al., 2025). One study shows that when using technology, PU, along with perceived ease, influences the intention to use it. Given the adoption of AI in clinical practice, healthcare-focused AI applications are more likely to be adopted if they are perceived as easy-to-use tools that aid healthcare practices (Davis, 1989). PE thus serves as an enabling platform through which the perceived value of AI is enhanced, leading to its adoption. Therefore, enhancing leadership engagement and user experience may increase perceptions of benefit by improving AI adoption processes (Gerlich, 2023).

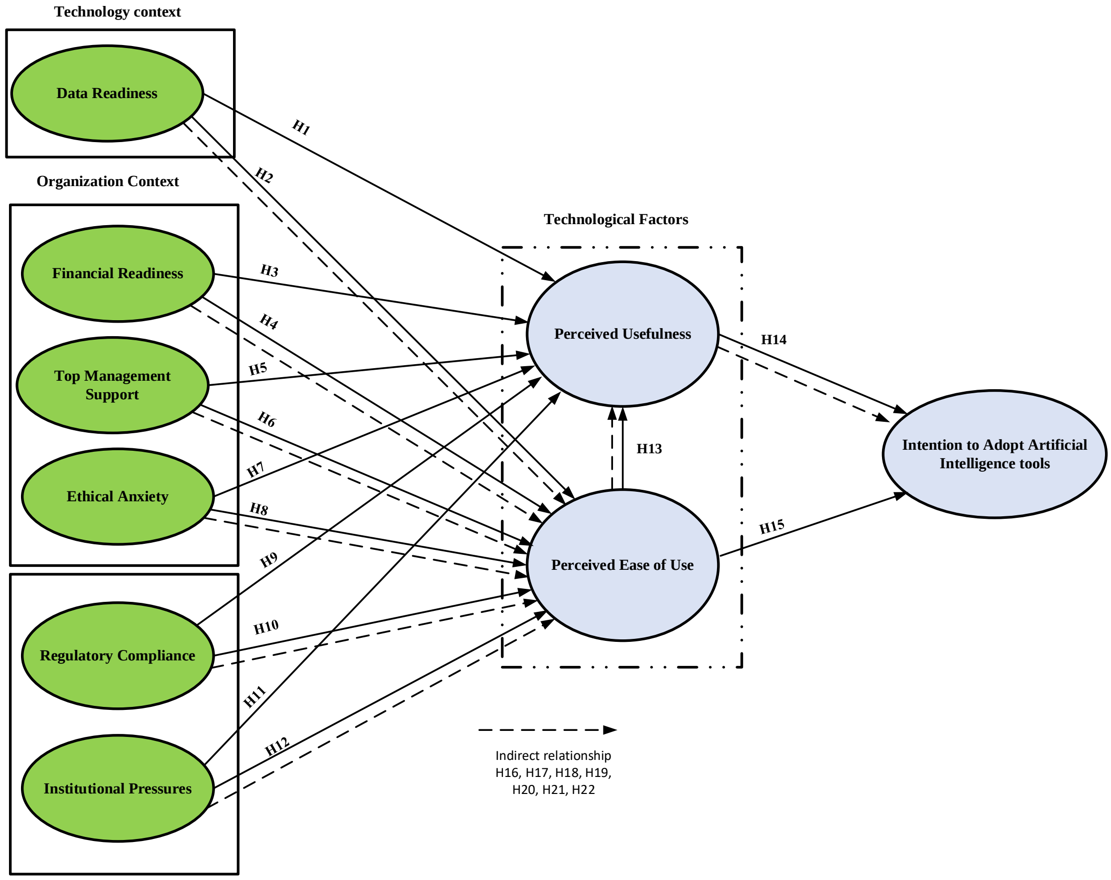
H22: Perceived Ease of Use (PE) Positively Influences Intention to Adopt (IA) Through Perceived Usefulness (PU)

1.15 Conceptual Model

Figure 1 illustrates the conceptual model that outlines the hypotheses formulated in this study. These factors include technological factors such as PE and PU, and external factors—DR, FR, RC, AI, TMS, and IP—to explain AI adoption among healthcare providers. Each variable is presented with its hypotheses, indicating direct or mediated relationships with AI use within healthcare organizations. The model described above serves as a platform for these ideas and hypotheses, upon which the empirical analysis is built.

Figure 1

Research Conceptual Model



Chapter Two
Research Methodology

2.1 Chapter Overview

Research methodology is the systematic process by which data is collected, analyzed, and interpreted. The study employs a mixed approach that combines quantitative and qualitative methodologies to gain a comprehensive understanding of emerging trends.

This chapter explains the background of the research design, followed by how the study population was designed, sampling methods, data collection tools, and analytical techniques. It then describes in detail the validity and reliability of the tests conducted.

2.2 Research Design

A mixed methods strategy was used, combining both quantitative and qualitative approaches. This strategy allows the researcher to leverage the advantages of both approaches to provide a more comprehensive understanding of the research topic. In addition to providing quantifiable patterns and trends, quantitative data facilitates broader extrapolation of findings (Creswell and Clark, 2017). However, qualitative data enables a more rigorous examination of participants' perspectives, experiences, and contextual details than can be achieved using numerical data alone (Creswell, 2014). Combining the two tools allows for a deeper understanding of the phenomenon under study, as well as improving the validity and reliability of the findings. Consequently, a mixed method design proved to be the most effective in achieving the study's objectives.

- Qualitative Design: The study methodology used a thematic analysis of semi-structured interviews with managers, engineers, and healthcare workers to identify factors influencing AI adoption.
- Quantitative Design: A structured questionnaire was used to collect numerical data to measure the extent of association between variables. Hypotheses were evaluated using structural equation modeling (SEM).

The mixed method design is characterized by the breadth and depth of addressing the research objectives and triangulating the study results to achieve higher validity (Creswell & Plano Clark, 2018).

2.3 Research Population and Sampling

2.3.1 Target Population

The target group included workers in the Palestinian healthcare sector, namely:

- Computer Engineering Department Managers.
- Computer information systems managers.
- Software development specialists.
- Healthcare professionals (doctors of various specialties, nurses, laboratory and radiology technicians) who are familiar with artificial intelligence tools.

2.3.2 Sampling Technique

The study sample was collected from the Palestinian healthcare sector, as four main sectors supervise the provision of health services in Palestine (the government health sector, the Ministry of Health, military medical services, the United Nations Relief and Works Agency for Refugees, non-governmental organizations, and the participating private sector). Human resources play a major role in the healthcare sector in Palestine, as the number of doctors registered in the union in 2021 reached 8,100 in the West Bank, while the number of nurses reached 11,494 (PCBS, 2022).

The study included all healthcare sector groups, and in total, 186 participants responded to the survey (141 doctors, 25 Health managers, 20 Medical engineers). 12 interviews were conducted with several specialists in the field of computer engineering and software development.Participants were selected based on their potential exposure to or familiarity with AI applications in healthcare. Inclusion criteria required participants to have at least basic familiarity with digital health tools and to be involved in clinical or administrative decision-making.

While this number was reasonable given time and budget constraints, it was deemed sufficient according to guidelines. Quantitative surveys in exploratory research typically include between 100 and 150 participants to enable relevant statistical analysis (Memon et al., 2020).Twelve in-depth interviews were conducted with experts in software development and computerengineering for the qualitative phase. Because qualitative research prioritizes data saturation over numerical size, interviews were conducted until no new themes emerged, ensuring the validity and comprehensiveness of the findings (Guest et al., 2005)

2.4 Data Collection Methods

In this regard, primary and secondary data sources were collected to gain a better insight.

2.4.1 Primary Data

- Semi-Structured Interviews:

Twelve experts participated in a study to identify key themes driving AI adoption.

- Questionnaires:

A compilation of quantitative data was created and distributed to healthcare professionals.

2.4.2 Secondary Data

Secondary data were obtained from reliable sources such as:

- World Health Organization (WHO) reports.
- Palestinian Central Bureau of Statistics (PCBS) records.
- Health Information Center reports.

These sources provided background context and supplementary data to support the preliminary findings.

2.5 Semi-Structured Interviews

2.5.1 Rationale

Data were collected through semi-structured interviews with participants to obtain standardized responses and then compare the data. However, this method was particularly suitable for identifying the factors influencing the adoption of AI in healthcare (Morrison, 2021).

2.5.2 Interview Structure

The interviews were carefully controlled, using a set of pre-defined questions (see Appendix E). This approach allowed the researcher to focus on specific areas of interest while maintaining consistency across all interviews. Participants included managers and engineers responsible for implementing AI tools in the healthcare sector. Their insights were critical to understanding the sector's readiness and challenges.

2.6 Surveys

Questionnaires are used to collect data from a broader population. They are a cost-effective way to gather information on social science and healthcare issues in a limited period.

2.6.1 Questionnaire Design

It is a good practice to provide measurement variables used in the survey and the related theories, and the references used in developing such variables.

The survey instrument consists of two sections:

- **Section 1 (12 items):** Demographic and organizational details were captured, including gender, experience with AI tools, workforce size, and years of experience.
- **Section 2 (33 items):** Measured factors that influence AI adoption, such as:

- Data readiness.
- Financial readiness.
- Topmanagement support.
- Regulatory compliance.
- PU and ease of use.
- Institutional pressures.
- Ethical anxiety.

2.6.2 Deployment

The questionnaire was translated into Arabic to suit the local population and distributed to hospitals and primary healthcare centers. A cover letter explaining the purpose of the study and instructions for completing it was attached.

2.7 Qualitative Data Collection Methods

Qualitative Data Collection methods were conducted with 12 healthcare experts to assess the validity and reliability of the questionnaire. A pilot study was conducted through interviews with 12 healthcare experts to assess the validity and reliability of the questionnaire (Julious, 2005). Their feedback focused on customizing and clarifying the questions, particularly regarding the financial and social factors influencing the adoption of AI tools in healthcare. Their feedback was used to improve the tool and ensure the clarity and accuracy of the questions.

2.8 Validity and Reliability

2.8.1 Validity

Expert reviews and pilot testing were conducted through interview questions to assess the clarity, relevance, and consistency of the questionnaire questions, thus establishing credibility and trustworthiness – the fundamental principles of qualitative research validity:

- **Content Validity:** Evaluated by subject-matter experts.
- **Convergent Validity:** Ensured through the intercorrelation of items within the same construct.

2.8.2 Reliability

Reliability measures the consistency of the instrument. Cronbach's Alpha was calculated for each section of the questionnaire, with values above 0.7 indicating high reliability *(*Izah et al., 2023)

2.9 Data Analysis Methods

2.9.1 Qualitative Analysis

Thematic analysis was used to analyze interview data. This involved:

- Familiarizing with data.
- Coding data to identify key themes.
- Clustering similar codes.
- Defining and refining themes.

- Reporting findings.

2.9.2 Quantitative Analysis

Structural Equation Modeling (SEM) using SmartPLS version 4and the SPSS program wasemployed for data analysis, and the steps included:

- Data management and cleaning.
- Descriptive statistics to explore variable distributions.
- Hypothesis testing to assess relationships between variables.
- Modeling to identify significant predictors of AI adoption.

2.10 Ethical Considerations

Ethical approval was obtained from the relevant authorities. Participants were assured confidentiality, and informed consent was sought before data collection.

This chapter outlined the methodology used in the study, including the research design, data collection methods, and analytical techniques. A mixed-methods approach comprehensively understood AI adoption in the Palestinian healthcare sector. The chapter also emphasized the importance of validity, reliability, and ethical considerations, ensuring the rigor and integrity of the research process.

Chapter Three
Data Analysis and Results

3.1 Chapter Overview

This chapter presents the data analysis outputs from the mixed-method approach. Thematic analysis was used to analyze the results through a qualitative approach (interviews). The chapter presents the main findings after the initial analysis of questionnaire responses and data screening, which presents the results of an analytical study using structural equation modeling (PLS-SEM). Presenting the main conclusions from the evaluation of the measurement model and the structural model also contributes to the quality of the research model. In addition to construct, convergent, and discriminant validity, the reliability analysis of the structural model also considers effect size and predictive significance.

3.2 Qualitative Analysis

The integration of AI into healthcare holds tremendous potential to improve patient outcomes, enhance diagnosis and treatment processes, and optimize resource allocation. In Palestine, where healthcare infrastructure faces unique challenges, the adoption of AI technologies presents both opportunities and threats. This comprehensive qualitative analysis examines the adoption of AI in the Palestinian healthcare sector, examining current applications, motivations, challenges, societal factors, infrastructure readiness, risks, benefits, training needs, government policies, financial considerations, ethical concerns, and institutional pressures. Twelve semi-structured interviews were conducted with healthcare professionals working in six different categories of organizations, including primary and secondary care facilities (e.g., government, commercial, non-profit, and military). The interviews involved two heads of computer engineering departments, two heads of information technology, four computer engineers, two IT staff, and two software developers (see Table 1).

Table 1
Profile of the Interviewees

No	Sector	Organization	Job position
1	Private	Hospital A	• Computer department manager • IT department employee
2	Private	Hospital B	• IT department manager • Computer engineer employee with more than years of experience
3	Private	Hospital C	• Computer engineer employee with more than years of experience • Software developer employee with more than years of experience
4	Private	Hospital D	• Computer department manager • An IT department employee with more than years of experience
5	Private	Hospital E	• computer engineer employee with more than years of experience • Software developer employee with more than years of experience
6	Private	Hospital F	• IT department manager • computer engineer employee with more than years of experience

NVivo 14 was used to systematically analyze the interview transcripts. We imported all transcripts into the NVivo project, enabling us to work with the data in an organized and structured manner. Using NVivo features, we identified key themes and categories related to AI adoption in the Palestinian healthcare sector. This qualitative analysis was conducted through a comprehensive analysis and in-depth understanding of interviews with employees of computer engineering departments operating in the Palestinian healthcare sector. The analysis summarizes the insights, challenges, and motivations for AI adoption in the Palestinian healthcare sector.

We assigned codes such as "AI Applications," "Motivations and Challenges," "Ethical Concerns," and others to relevant sections of the interviews. In the coding table below (Table 2), we organized the data into columns for themes, subthemes (if applicable), quotes, and codes. This allowed us to quickly visualize and analyze the data, identifying patterns, trends, and common themes across the interviews.

Table 2
Qualitative Analysis Coding Table

Codes	Quotation	Sub-theme	Theme
APP_Q1_R1	"Application of AI in Palestinian Healthcare is rudimentary in use."	Usage	Applications of AI in healthcare
APP_Q1_R2	"Rudimentary applications in use within... imaging machine software"	Usage	
APP_Q1_R3	"Current medical research is focusing on artificial intelligence..."	Usage	
APP_Q1_R4	"Artificial intelligence techniques are used in manufacturing and discovering medicines..."	Usage	
DRV_Q2_R5	"The lack of sufficient health institutions..."	Motivations	Drivers and Challenges
DRV_Q2_R6	"The prevailing culture in Palestinian society..."	Motivations	
CUL_Q3_R7	"The feeling of technological backwardness..."	Influence	Cultural/Societal
CUL_Q3_R8	"The lack of complete community knowledge..."	Influence	
INFRA_Q4_R9	"It is considered in good condition, but it needs to be developed..."	Readiness	IT Infrastructure
INFRA_Q4_R10	"There is partial integration within some groups..."	Integration	
RISKS_Q5_R11	"Patients' lack of confidence in artificial intelligence..."	Risks	Risks & Benefits
BENEFITS_Q5_R12	"AI can analyze big medical data to identify factors..."	Benefits	
TRAINING_Q7_R11	"Easy to use but requires some training."	Training	Training & Ease of Use
TRAINING_Q7_R12	"Needs training as AI applications are new in Palestine."	Training	
GOV_Q10_R10	"Government systems can impose it on society..."	Role	Governmental Regulations
GOV_Q10_R12	"Government policies and regulations play a major role..."	Support	
FIN_Q11_R10	"The lack of financial resources allocated..."	Impact	Financial Readiness
FIN_Q11_R12	"A negative role due to the weak budget..."	Role	
ETHICS_Q12_R11	"Ethical concerns about data leakage..."	Privacy	Ethical Concerns
ETHICS_Q12_R12	"Ethical concerns about data leakage and privacy can be controlled..."	Control	
INST_Q13_R11	"Global technological developments and the increasing spread..."	Internal	Competitive Pressures
INST_Q13_R12	"Global technological developments and the increasing spread..."	External	
OTHERS_Q14_R12	"Israeli occupation"	External Factor	

3.2.1 Applications of AI in Palestinian Healthcare

The interviews highlight future applications of AI in the Palestinian healthcare sector. Even with rudimentary applications, such as those integrated into the radiology software (APP_Q1_R2), the general use of AI remains limited. However, there is optimism about its potential for future applications, particularly in medical research and drug discovery.

3.2.1.1 Usage in Healthcare

According to the codes (APP_Q1_R1, APP_Q1_R2), AI is used in the sector's internal business systems and specific software applications, even in its early forms. These applications primarily assist in medical imaging and data analysis. (APP_Q1_R3, APP_Q1_R4) It is emphasized that while current applications are limited, there is ongoing research focused on leveraging AI to achieve broader healthcare goals.

3.2.1.2 Medical Research and Drug Discovery

According to APP_Q1_R3, AI is recognized for its role in revolutionizing medical research and drug discovery processes. By analyzing comprehensive medical data, AI algorithms can discover patterns, correlations, and insights that may help researchers.

3.2.1.3 Challenges and Opportunities

Most of the interviews conducted agreed that several challenges hinder the rapid adoption of AI tools in the Palestinian healthcare sector. These include technological challenges, such as weak infrastructure and poor data readiness (INFRA_Q4_R9, INFRA_Q4_R10), as well as cultural factors, as noted in codes (CUL_Q3_R7, CUL_Q3_R8). Codes (FIN_Q11_R10, FIN_Q11_R12) also indicated, to some extent, that financial constraints are significant barriers to adoption.

3.2.1.4 Prospects

However, there is great potential for the adoption of AI systems in Palestinian healthcare, given the current constraints. AI tools are likely to be adopted across the healthcare sector as technology advances and users become more aware of their perceived benefits.However, realizing AI's power to improve healthcare outcomes requires overcoming current obstacles and ensuring its ethical and responsible use.

3.2.2 Drivers and Challenges

3.2.2.1 Motivations for Adoption

Finally, the interviews reveal some of the motivations for adopting AI applications in the Palestinian healthcare sector. AI also contributes to healthcare through the opportunities it offers to assist in early disease diagnosis and predict health risks, supporting the ultimate goal of improving patient outcomes and the quality of healthcare provided, as highlighted in (DRV_Q2_R5).

3.2.2.2 Challenges in Adoption

However, various challenges and even motivations for adoption hinder the comprehensive integration of AI within the Palestinian healthcare sector. According to (DRV_Q2_R6), a prevailing cultural skepticism toward technology is prevalent among these respondents (the Chair). According to statistics issued by the Palestinian Central Bureau of Statistics, the number of registered physicians in the West Bank reached 8,001 in 2021. The number of nurses reached 11,494 in the West Bank. The total administrative staff reached 22,478 employees in the West Bank. (Health, 2023)

The Palestinian community's lack of trust in e-therapy programs and data collection systems is a significant barrier to adoption. Furthermore, in healthcare, there are issues related to human factors and the fact that patients desire comfort and emotional support from healthcare providers, which current AI does not provide. Additionally, the adoption of AI applications has also been hindered by limitations related to technical infrastructure, such as network connectivity and data storage. These challenges are addressed through concerted efforts to build trust in the technology, strengthen technical infrastructure, and provide adequate technical infrastructure, training, and support for healthcare providers.

3.2.3 Cultural and Societal Factors

3.2.3.1 Influence of Cultural and Societal Factors

As mentioned in (CUL_Q3_R7), Palestinian cultural values and societal norms significantly influence technology adoption in healthcare. As highlighted in (CUL_Q3_R8), historical and political contexts often influence perceptions of AI in healthcare due to a sense of technological backwardness. According to (CUL_Q3_R8), people's views on AI in healthcare are shaped by their perception of technological backwardness linked to historical and political contexts. This has a significant impact on healthcare technology adoption attitudes. According to (CUL_Q3_R8), the historical and political reasons behind the perception of technological backwardness influence perceptions of AI in healthcare. Cultural norms influence healthcare technology adoption. Historical and political contexts create a sense of technological backwardness that influences perceptions of AI in healthcare (CUL_Q3_R8). The growth of the entire AI heuristics community generates ambiguity and mistrust among healthcare practitioners and patients, hindering the adoption and maintainability of AI applications in healthcare.

3.2.3.2 Impact on Adoption

The problem behind these challenges lies in the fact that they are deeply rooted in the cultural and social context of the Palestinian healthcare sector. Healthcare workers and patients are skeptical and distrustful of technology and are reluctant to adopt it into their practices. Furthermore, a sense of technological backwardness can lead to a reluctance to accept new technologies without confidence in their efficacy and safety. Therefore, raising awareness, educating stakeholders about the benefits of AI in healthcare, and building confidence in the reliability and effectiveness of AI-enabled solutions are essential to overcome these barriers. Furthermore, cultural perspectives on technology adoption must be formulated to allow AI applications to align with Palestinian social norms and preferences.

3.2.4 IT Infrastructure Readiness

3.2.4.1 Current State of IT Infrastructure

AI applications can only be integrated and functional thanks to the IT infrastructure in Palestinian healthcare institutions. As stated in the interview (INFRA_Q4_R9), the current state of IT infrastructure is either strong, good, or limited. Interview participants agreed on the need to develop the IT infrastructure to better support the adoption of artificial intelligence.

One participant (INFRA_Q4_R9) stated, "The infrastructure is in good condition, and it can be developed and linked to business systems with unified databases." This indicates the potential for infrastructure but also points to what needs to be improved to adapt to changes in healthcare service delivery.

3.2.5 Risks and Benefits of AI Adoption

3.2.5.1 Risks Associated with AI Adoption

Despite the risks that require careful consideration, the Palestinian healthcare system is utilizing AI. Respondents cited many potential benefits of AI technologies, but also highlighted the risks of implementing them. These risks range from poor outcomes to patient trust and data privacy. The interviewee expressed concern that patients may not trust AI systems. However, they also stated that if patients do not trust AI, it could have an emotional impact on their treatment and prevent it from achieving its goal. From this concern, we can see why it is essential to gain patients' trust in AI technologies before accepting and using them. The primary reason for the Palestinian healthcare sector's limited use of AI is the risk of data leaks and privacy breaches. However, the lack of robust privacy and security measures associated with AI-powered solutions can raise ethical and legal questions regarding patient data security. According to respondents, the risks can be mitigated, and strict regulations and cybersecurity programs can protect patient privacy.

3.2.5.2 Benefits of AI Adoption

At the same time, people are apprehensive about the use of AI in Palestinian healthcare, as its advancement could significantly improve patient care and the way it is delivered. Beyond more accurate diagnoses and efficient resource management, survey participants began listing several potential benefits of using AI. (AI BENEFITS_Q5_R12) Potential benefits of using AI to analyze medical data include identifying the causes of disease and its spread.

The study stated that "AI can read massive medical datasets to extract disease-causing factors and predict how they spread, allowing for preventative measures and more effective resource allocation." In this, we demonstrate the role of AI in empowering people to make decisions based on the data they have and in discovering the best strategy for using resources to make healthcare services more efficient. Healthcare providers can make better decisions using the insights and predictive analytics unlocked by AI. Finally, AI technologies can also accelerate clinical workflow, reduce diagnostic errors, and improve treatment outcomes.

3.2.6 Training and Ease of Use

3.2.6.1 Training Needs for AI Adoption

For AI to be adopted in Palestinian healthcare, healthcare workers must have the necessary skills and knowledge to work with AI-based technologies. Participants emphasized the importance of comprehensive training programs, including training healthcare staff on the use of AI applications and equipping them with core competencies. (TRAINING_Q7_R11) explained that AI applications are very easy to use, but require some training to be fully utilized. The participant said, "It's a simple AI application to use, but any system requires low-cost training for administrative staff, training for programming teams, and data-intensive development as much as possible." The bottom line is that training initiatives should be tailored to the needs of various healthcare roles, including administrative and technical staff responsible for data management and analysis.

3.2.6.2 Ease of Use and User Experience

However, the success of AI application adoption is linked to ease of use and integration with clinical workflows. Survey participants emphasized the importance of ease of use through user-friendly interfaces and intuitive design features in the context of expanding AI adoption within healthcare provider organizations.

Respondents felt that while many perceived AI systems as complex, healthcare professionals could easily use AI-based tools in their daily practice once properly trained (TRAINING_Q7_R12): "When it first started, it was complex to use and required training, as AI applications will be new to Palestine, but they are easy to implement." Therefore, even if there is a small learning curve to adapt to AI, healthcare workers can be trained to adapt to it through appropriate supportive interventions and training.

3.2.7 Government Policies and Financial Considerations

3.2.7.1 Government Policies Facilitating AI Adoption

Government policies and regulations shape the landscape of AI in the Palestinian healthcare sector. Although the interviewees lacked specific rules for the use of AI in medicine, they felt there was scope for state intervention to ensure the continued use of AI in medicine and its integration into the healthcare sector.

(GOV_Q10_R10) demonstrates that the government system can contribute to driving the development and innovation of the healthcare sector. According to the interviewee, "The government system can impose it on society and create a conducive environment for adopting AI applications." This underscores the importance of government support in providing a solid foundation for the growth of an integrated ecosystem that supports AI innovation and adoption.

3.2.7.2 Financial Constraints Hindering AI Adoption

Similarly, challenges also precede the potential benefits of adopting AI and financial considerations for healthcare institutions in Palestine. Healthcare institutions face limited budgets and numerous difficulties in financing investments in AI infrastructure, training programs, and technical upgrades, limiting the adoption of AI technologies.

External support is important for the Palestinian healthcare sector. FIN_Q11_R12 shows that the Palestinian healthcare sector is overly dependent on external support and is therefore overly sensitive to changes in donor funding or international aid, for example. The "negative role of weak budgets, lack of funding, and the need for dedicated budgets for AI applications" also demonstrates healthcare institutions' reliance on external funding and how difficult it has been to secure a sustainable financial basis for AI projects.

3.2.8 Ethical Anxiety and Institutional Pressures

3.2.8.1 Ethical Considerations in AI Adoption

Access to data, the right to protect it, and the right not to share it are among the determinants of adopting artificial intelligence tools in healthcare. According to an analysis of the opinions of the survey participants, it is necessary first to establish laws and ensure strict protection and controls for the security of information, and to ensure that it is not shared or used for any other unethical purposes. (ETHICS_Q12_R12). This reinforces the importance of maintaining the integrity of patient information to mitigate the problems that AI may cause.

3.2.8.2 Institutional Pressures Driving AI Adoption

In addition to ethical considerations, institutional pressures play a significant role in promoting the adoption of AI in Palestinian healthcare. During interviews, participants indicated that internal and external pressures, including global technological developments and government initiatives, are forcing healthcare organizations to adopt AI technologies and modernize their practices. Global technological advancements and the increasing use of AI applications worldwide are putting pressure on the Palestinian healthcare sector to keep pace with technological developments and leverage AI-based innovations to improve patient care. As (INST_Q13_R11) explained: "Global technological developments and the increasing prevalence of AI applications worldwide are increasing pressure on the Palestinian healthcare sector to adopt modern technologies and keep pace with developments."

3.3 Quantitative Analysis

3.3.1 Response rates

After distributing the questionnaires and analyzing the responses, the final number of eligible participants was 186 out of a target of 210. The sample size was determined using Craigie and Morgan's (1970) sample size table, which considers the minimum recommended sample sizes based on a known population. Participants are a common and acceptable practice in studies aimed at assessing the attitudes and knowledge of healthcare workers towards new technologies such as artificial intelligence (Adithyan et al. , 2024). With a response rate of 88.57%. As shown in Table 3, the number of male participants reached 126 (68%) and 60 (32%) female participants in this study, and the age group 18-25 years constituted (6%), while the age groups 26-35 years, 36-45 years, and 46-55 years constituted percentages (38%, 30%, 23%), where the numbers reached (70, 57, 43). The age groups that constituted the percentages (38%, 30%, 23%). The numbers (70, 57, 43) were between 26 and 35 years old, 36 and 45 years old, and 46 and 55 years old, with the age group 56 years and older accounting for 6% of the numbers (5). According to the professional classification, there were more than 76% of doctors (n = 141) and about 13% of health managers (n = 25),while their percentage of medical engineers was 11% (n = 20). Most of the study participants (78%) (n = 145) work in large organizations, while 22% (n = 41) work in medium-sized organizations.

About 6% (n = 11) of participants had less than a year of experience, while 38% (n = 70) had one to five years, 24% (n = 46) had six to ten years, and 32% (n = 59) had eleven to fifteen years. In terms of education, 33% (n = 62) had graduated from university, 35% (n = 64) had a master's degree, and 32% (n = 60) had a doctorate. Eighty-six (n = 141) reported using AI tools in their work, while 14% (n = 25) did not. The most commonly used tool was Google Health's DeepMind, which accounted for 49% (n = 90). The percentage of those who had no experience or previous interaction with AI tools was (13%) (n=25), while the percentage of those with little to moderate experience was (59%) (n=110) and (22%) (n=40), a similar percentage to those with extensive experience, who made up (6%) (n=11). Most participants agreed that AI tools can improve the efficiency and quality of health services.

Table 3
Summary of Respondents' Profiles

Items	Options	N	(%)
Gender	Male	126	68%
	Female	60	32%
	Total	186	100%
Age	18-25 years old	11	6%
	26-35 years old	70	38%
	36-45 years old	57	30%
	46-55 years old	43	23%
	56 years or older	5	3%
	Total	186	100%
Use artificial intelligence tools	Yes	161	86%
	No	25	14%
	Total	186	100%
Level of experience with AI tools	No previous experience	25	13%
	Little experience	110	59%
	Average experience	40	22%
	Wonderful experience	11	6%
	Total	186	100%
Education	Secondary	0	0
	Diploma	0	0
	University	62	33%
	Master's degree	64	35%
	Ph. D	60	32%
	Total	186	100%
Scientific specialization or profession	Doctor/	141	76%
	Health manager	25	13%
	Medical engineer	20	11%
	Researcher in the field of health	0	0
	Total	186	100%
Work experience in the health sector	Less than a year	11	6%
	1-5 years	70	38%
	6-10 years	46	24%
	11-15 years	59	32%
	More than 15 years	0	0
	Total	186	100%
Size of the health institution	Small (less than 50 employees)	0	0
	Medium (50-500 employees)	41	22%
	Large (more than 500 employees)	145	78%
	Total	186	100%
The organization you work for has adopted or used AI tools	Yes	60	32%
	No	78	42%
	Not sure	48	26%
	Total	186	100%

3.3.2 Questionnaire Analysis

This research analysis was conducted using SmartPLS4, a statistical technique for analyzing large data sets and multiple variables using a small sample size. Smart PLS includes several graphical and statistical problems, such as structural equation modeling (SEM) and variance-based structural equation modeling (VBSEM). These methods allow us to analyze a data set, interpret relationships between variables, identify significant relationships, and develop strategies for making more informed decisions.

In our research, the analysis was conducted via the Smart PLS platform using a two-step approach: building and evaluating a measurement model, and building and evaluating a structural model.

3.3.2.1 Assessment of Measurement Model (Outer Model)

The essential first step in assessing the reliability and validity of the constructs in our study is to evaluate the reflective measurement model. Reliability is the consistency of what a measure purports to measure, and validity is the extent to which a measure accurately measures the intended constructs under different conditions. When using PLS-SEM for our analysis, the measurement model (the measurement items and their relationship to the corresponding latent variables) must be evaluated (Hair, 2011). Evaluating the measurement model involves tests of convergent validity and discriminant validity.

3.3.2.1.1 Convergent Validity

The degree of interrelationship between the scales of the same construct (i.e., convergent validity) assesses the similarity of the loadings between items. Demonstrating convergent validity must rely on certain prerequisites, such as Cronbach's alpha coefficient, composite reliability (CR), and average variance extracted (AVE). Table 4 below summarizes the results of the analysis.

Table 4
Construct Reliability and Validity

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
DR	0.793	0.840	0.905	0.826
FR	0.799	0.806	0.908	0.832
TMS	0.864	0.864	0.936	0.880
EA	0.736	0.784	0.881	0.788
RC	0.829	0.834	0.897	0.745
IP	0.750	0.767	0.855	0.664
PE	0.684	0.688	0.825	0.611
PU	0.835	0.835	0.924	0.859
IA	0.729	0.823	0.843	0.649

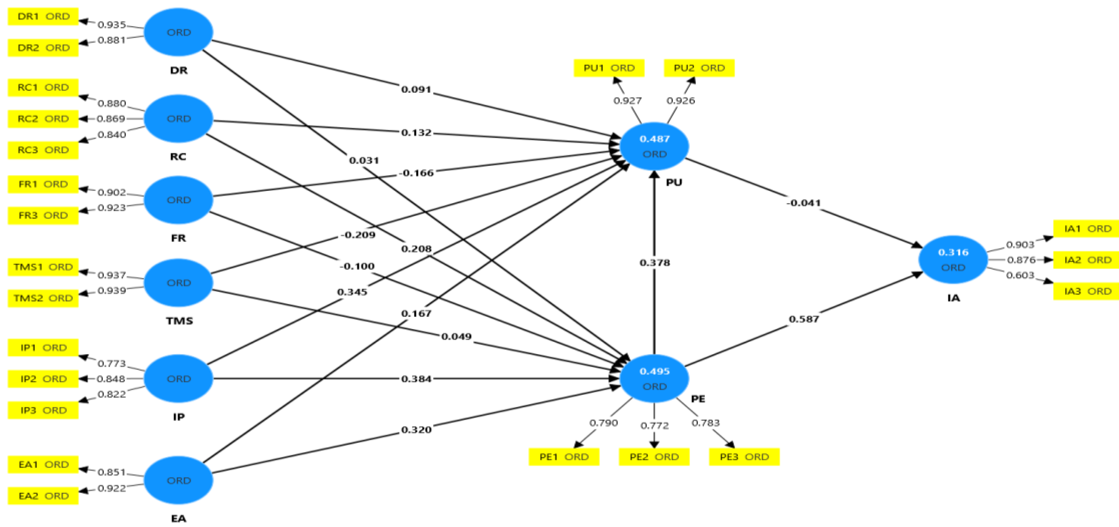
Cronbach's alpha is a measure of internal consistency, indicating the degree to which specific items are interrelated. This analysis shows that Cronbach's alpha for most determinants exceeds the 0.7 standard, indicating reliable measurement. The PU and TMS values were 0.835 and 0.864, respectively, demonstrating ideal internal consistency. For PE, Cronbach's alpha was 0.684, slightly below the optimal threshold. However, it is close enough to be considered acceptable (Julious, 2005), with a slight refinement of the items in this determinant improving its performance.

The composite reliability criterion also confirms strong internal consistency by assessing the overall reliability of the construct. High-reliability values reflect the robustness of the item in consistently measuring the constructs it was intended to measure.

The measurement model's validity is secondly verified using the average variance extracted (AVE) by determining the amount of variance due to measurement error versus the variance captured by each construct. All constructs meet the required average variance extracted threshold of 0.5, meaning that their associated constructs explain most of the variance in the indicators. Figure 2 demonstrates the measurement model for this study.

Figure 2

Measurement Model



3.3.2.1.2 Discriminant Validity

Discriminant validity of a model refers to ensuring that its constructs differ and measure independent concepts without any overlap. A strong discriminant validity criterion is the hetero topic-to-mono topic ratio (HTMT), as shown in Table 5. The lower the better; it is usually less than or equal to 0.85, but 0.90 is fine (Izah, Sylva, & Hait, 2023). The following section explains the hetero topic-to-mono topic ratio values for the above constructs.

Table 5

HTMT values

	DR	EA	FR	IA	IP	PE	PU	RC	TMS
DR									
EA	0.328								
FR	0.844	0.255							
IA	0.788	0.533	0.762						
IP	0.782	0.449	0.809	0.858					
PE	0.595	0.711	0.482	0.738	0.799				
PU	0.421	0.570	0.234	0.375	0.619	0.820			
RC	0.873	0.415	0.645	0.691	0.672	0.664	0.492		
TMS	0.830	0.280	0.882	0.827	0.850	0.569	0.294	0.714	

The results indicate that all values are less than the conservative minimum of 0.90, and if all HTMT values are less than 0.90, this indicates that discriminant validity has been demonstrated.

The Fornell-Larcker criterion is a commonly used method for detecting discriminant validity in structural equation modeling (Henseler, 2015), as shown in Table 6.For example, this criterion states that the square root of the AVE for each construct should exceed the correlations between the construct and all other constructs. This ensures greater covariance between the construct and its indicators than between the construct and other constructs.

Table 6
Fornell and Larcker Criterion

	DR	EA	FR	IA	IP	PE	PU	RC	TMS
DR	0.909								
EA	0.240	0.888							
FR	0.665	0.188	0.912						
IA	0.572	0.406	0.549	0.805					
IP	0.602	0.324	0.618	0.638	0.815				
PE	0.455	0.510	0.364	0.562	0.588	0.782			
PU	0.353	0.461	0.194	0.323	0.502	0.621	0.927		
RC	0.716	0.317	0.528	0.533	0.529	0.512	0.411	0.863	
TMS	0.679	0.207	0.732	0.631	0.677	0.450	0.250	0.610	0.938

Analysis using Fornell and Larcker criteria demonstrates that all constructs in the model have acceptable discriminant validity. Although there are higher correlations within some constructs (FR and TMS, respectively), none of them fall below the required threshold. Therefore, the scales are unique, making unique contributions to the structural model. These results strengthen the robustness of the measurement model for further analysis.

3.3.2.1.3 Analysis of Collinearity Statistics Using the Variance Inflation Factor

The variance inflation factor (VIF) measures the degree of multicollinearity between the indicators in an exogenous model. One form of multicollinearity is the correlation between the independent variables, and in many cases, the correlation between them may be significant, leading to unstable regression coefficients. Acceptable ranges for VIF values are values below 3 (considered low), values between 3 and 5 (medium), and values above 5 (high), which require corrective action(Liao, 2012), as shown in Table 7.

Table 7
VIF Outer Model

	VIF
DR1	1.761
DR2	1.761
EA1	1.514
EA2	1.514
FR1	1.793
FR3	1.793
IA1	1.848
IA2	1.850
IA3	1.207
IP1	1.491
IP2	1.514
IP3	1.493
PE1	1.279
PE2	1.398
PE3	1.339
PU1	2.059
PU2	2.059
RC1	2.001
RC2	2.102
RC3	1.710
TMS1	2.372
TMS2	2.372

The VIF values of the indicators indicate that there is no multicollinearity problem within any construct.

3.3.2.2 Assessment of Structural Model (Inner Model)

3.3.2.2.1 Model Fit Assessment

Model fit is assessed by examining several indices to ensure that the structural model describes the data well. The Standardized Root Mean Square Residual (SRMR) as shown in Table 8, dull, dog, Chi-Square, and the Normed Fit Index (NFI) of the saturated and estimated models are reviewed as indices.

Table 8
Model Fit

	Saturated model	Estimated model
SRMR	0.082	0.121
d_ULS	1.706	3.726
d_G	0.748	0.845
Chi-square	840.274	901.066
NFI	0.657	0.632

- **Standardized Root Mean Square Residual (SRMR)**

The SRMR is the average amount of variance in the observed and predicted correlations. The SRMR for the saturated model is 0.082, which is below 0.10, which is generally considered adequate (Pavlov et al., 2020). The SRMR of the estimated model is (0.121) higher than the minimum.

- **Normed Fit Index (NFI)**

The model fit indices indicate that the saturated model matches the observed data more closely than the estimated model, particularly concerning SRMR, d_ULS, and chi-square values. However, both models exhibit suboptimal NFI values, suggesting room for improvement in the overall model fit. Improving structural relationships or revisiting specific paths in the model could improve the fit and enhance the model's consistency with the observed data.

3.3.2.2.2 R-Square (R^2)

R^2 values (Appendix A) indicate the proportion of variance in the dependent variables that the independent variables can explain (Shi et al., 2018), while adjusted R^2 values take into account the number of predictors and sample size to provide a more accurate measure.

For the measure, the R^2 value is 0.316, with an adjusted R^2 of 0.309. This means that the predictors explain approximately 31.6% of the variance in IA, demonstrating moderate (Shi et al., 2018) explanatory power. The small difference between the R^2 and adjusted R^2 indicates a well-fitting model with stable predictors for this construct.

For the measure, the R^2 value is 0.495, and the adjusted R^2 is 0.478. The independent variables explain 50% of the variance in PE, demonstrating strong explanatory power. The slight decrease in the adjusted R^2 coefficient reflects the complexity of the model but still supports its robustness. For PU, the R^2 is 0.487, and the adjusted R^2 is 0.466. Approximately 48.7% of the variance in PU is explained, demonstrating strong explanatory power. The slight decrease in the adjusted R^2 coefficient indicates that model complexity only affects explanatory power.

3.3.2.2.3 f-Square Analysis

The f-square values (Table 9) measure the size of the effect of each independent variable on the dependent variables, with the limits of 0.02, 0.15, and 0.35 representing small, medium, and large effects, respectively (Shi et al., 2018).

Table 9
f-squared

	f-square
DR -> PU	0.006
DR -> PE	0.001
FR -> PU	0.021
FR -> PE	0.008
TMS -> PU	0.029
TMS -> PE	0.002
EA -> PU	0.040
EA -> PE	0.174
RC -> PU	0.014
RC -> PE	0.038
IP -> PU	0.094
IP -> PE	0.135
PE -> PU	0.141
PU -> IA	0.001
PE -> IA	0.310

Overall, R^2 values highlight strong explanatory power for PE and PU, with moderate explanatory power for adoption intention. F-square analysis also identifies environmental awareness, Institutional Pressures, and PE as the most influential factors. These results suggest areas for strategic focus, focusing on constructs with medium to large effects to enhance adoption outcomes.

3.3.2.2.4 Analysis of PLSPredictResults

- **Q^2predict**

Q^2predict values are the out-of-sample prediction accuracy of the model, with values above zero indicating that the model was predictive.

The Q^2predict value for the IA factor is 0.364, indicating moderate predictability. Therefore, the model can predict IA in future samples with reasonable reliability, enabling the model to be used to understand adoption behavior.

The highest Q^2predict value, 0.444, was for the PE factor, demonstrating a high level of predictive validity. This reflects the model's ability to predict users' perceptions of ease of use.

The Q^2predict value of 0.361 indicates moderate predictive validity for the PU factor. The model predicts users' opinions about the usefulness of a system or innovation.

- **RMSE and MAE**

The mean squared error (RMSE) and weighted mean error (MAE) are measures of the model's prediction error. Better prediction performance is achieved with lower values for these measures.

The RMSE is 0.819 and 0.609 for IA. These values indicate moderate prediction accuracy for adoption intention, but prediction errors could still be further improved.The results indicate that PE is the construct for which the model gives the most accurate predictions.

The RMSE is 0.814 and the MAE is 0.649 for PU. These values indicate moderate prediction accuracy for adoption intention and slightly lower accuracy than PE.

Finally, the PLS prediction results demonstrate that the PLS prediction model has high predictive robustness, particularly for the PLS prediction of PE,"which has the highest Q^2 value and lowest error measure. Along with AI and PU, which have good predictive significance, there is room for improvement to reduce prediction errors in these constructs. Overall, the model's robustness ensures that it helps us generate actionable insights into user perception and intent.

3.4 Analysis of Hypothesis Testing

- **Direct Effects (Path Coefficients)**

The direct effects reveal the strength and significance of the relationships between these elements, as shown in Table 10.DR does not significantly affect PUor PE, with coefficients of (**H1**: $\beta = 0.091$, $p = 0.335$) and (**H2**: $\beta = 0.031$, $p = 0.764$), respectively. This suggests that DR is not a determining factor in shaping perceptions.On the other hand, FR negatively affects PE (**H3**: $\beta = -0.166$, $p = 0.034$) but does not show a significant effect on PE (**H4**: $\beta = -0.100$, $p = 0.234$).TMS negatively influences PU (**H5**: $\beta = -0.209$, $p = 0.041$), but it does not significantly influence PE (**H6**: $\beta = 0.049$, $p = 0.626$). EA shows a strong and significant effect on both PU (**H7**: $\beta = 0.167$, $p = 0.022$)

and PE (**H8**: β = 0.320, $p < 0.001$), highlighting its role in enhancing user perceptions.RC shows no significant effect on PU (**H9**: β = 0.132, p = 0.226), but positively influences PE (**H10**: β = 0.208, p = 0.029). IP significantly affects PU (**H11**: β = 0.345, $p < 0.001$) and PE (**H12**: β= 0.384, $p < 0.001$), indicating that high competence enhances perceived ease and usefulness. PE affects PU (**H13**: β = 0.378, $p < 0.001$), confirming its pivotal role. However, PUdoes not significantly affect IA (**H14**: β = -0.041, p = 0.680). Finally, PE has a strong positive effect on intent to adopt AI (**H15**: β = 0.587, $p < 0.001$).

- **Mediation Effects**

Mediation analysis identifies indirect relationships through mediating variables. DR shows no indirect effect on PU through PE (**H16**: β= 0.012, p = 0.763). FR does not indirectly affect PU through PE (**H17**: β=-0.038, p = 0.244). In addition, TMS shows no mediation effect through PE on PU (**H18**: β = 0.019, p = 0.637), while EA shows partial mediation through PE on PU (**H19**: β= 0.121, p = 0.001).Interestingly, RC shows full mediation through PE on PU (**H20**: β = 0.079, p = 0.046), with PE fully explaining the relationship, while IP shows partial mediation (**H21**: β= 0.145, p = 0.002), indicating that PE partially mediates the effect of IP on PU. Finally, the relationship between PE and IA through PU also lacks mediation (**H22**: β = -0.015, p = 0.695) -see table 11 Appendix F- .

Table 10
Path Coefficients – Direct Effects

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
H1	0.091	0.090	0.094	0.965	0.335
H2	0.031	0.036	0.103	0.300	0.764
H3	-0.166	-0.163	0.078	2.122	0.034
H4	-0.100	-0.099	0.084	1.191	0.234
H5	-0.209	-0.212	0.102	2.044	0.041
H6	0.049	0.044	0.101	0.488	0.626
H7	0.167	0.169	0.073	2.295	0.022
H8	0.320	0.322	0.061	5.245	0.000
H9	0.132	0.127	0.109	1.210	0.226
H10	0.208	0.205	0.096	2.180	0.029
H11	0.345	0.350	0.087	3.945	0.000
H12	0.384	0.386	0.100	3.820	0.000
H13	0.378	0.376	0.074	5.119	0.000
H14	-0.041	-0.052	0.099	0.413	0.680
H15	0.587	0.589	0.085	6.945	0.000

In conclusion, the hypothesis testing highlights the key factors influencing users' perceptions and adoption intentions. EA and IP emerge as critical factors, significantly impacting PE and PU. Enterprise infrastructure has been shown to have a direct and strong influence on AI, making it a vital component in shaping user adoption behavior.

The mediation analysis highlights the importance of enterprise infrastructure in partially explaining the effects of EA and IP on PU. Furthermore, the observed full mediation between PE through PE andPU highlights the unique role of PE in this relationship. These findings provide a roadmap for organizations to focus on improving user efficiency, learning achievement, and PE to achieve adoption outcomes.

Chapter Four
Discussion and Conclusion

4.1 Discussion of Qualitative Analysis

This study identified that although AI-designed applications are easy to use, training can help us understand AI adoption and help develop human competency. Qualitative data demonstrated that operational knowledge can be overcome with training. This finding is important because training interventions should include diverse roles within healthcare systems.

Through qualitative analysis, which helped explain the reasons for AI adoption and its impact on the healthcare sector, multiple factors that facilitate AI adoption were highlighted (ease of use, government policies, financial constraints, ethical concerns, and institutional pressures).

In addition, human resource development is essential to overcoming infrastructure barriers. Participants noted that healthcare users perceive AI systems as complex, yet healthcare workers can quickly develop their skills if provided with the necessary support and resources. In the case of Palestine, financial constraints and government policies play a crucial role in creating an environment that encourages innovation and technological advancement. For example, limited donor funding for healthcare is a major obstacle to the purchase of AI technologies, preventing investment in training and infrastructure development, and impacting human resource development. This requires healthcare organizations to incorporate the full range of data protection measures, not just technical but also organizational.

Furthermore, qualitative data analysis revealed that institutional pressures significantly motivate the adoption of AI and that rapid technological advancements and the global spread of AI provide an external incentive for Palestinian healthcare organizations to develop it. Therefore, organizations are driven to use AI to provide better patient services and better hospital management.

Policymakers can benefit from the results of the qualitative analysis, but they are troubling and have profound implications for the Palestinian healthcare sector. These results help us reach:

- **Training Programs:** These programs are designed to meet the needs of the healthcare system, identify priorities to avoid shortages, and help leverage the adoption of AI tools.
- **Regulatory Frameworks:** Having clear guidelines on the use of ethical AI can mean stakeholder confidence in the company, which can also protect patients' rights.
- **Financial Strategies:** Funding for AI initiatives can be secured by encouraging partnerships with international donors and private sector actors.
- **User-Centric Design:** Towards the most useful AI applications, we strive to ensure that AI applications are intuitive and easy to integrate into clinical workflows.

Finally, in the resource-limited Palestinian context, qualitative analysis is appropriate for understanding the challenges that may face the adoption of AI in healthcare. To enable transformation in healthcare delivery, barriers to AI adoption were highlighted. Through interviews with healthcare professionals and practitioners, this study identified several themes, including limited information about AI, uncertainty about legal frameworks, financial instability, and institutional inertia.

For example, many participants highlighted the lack of institutional guidelines for integrating AI and indicated that ethical uncertainty remains a major barrier to AI-based healthcare systems. By analyzing the challenges facing the modernization of the Palestinian healthcare sector, qualitative analysis guides the promotion of AI adoption in a comprehensive, ethical, and impactful manner.

4.2 Hypothesis Testing Discussion

4.2.1 Direct relationships

The use of any technology is a key factor in determining its widespread acceptance, as confirmed by the relationship between perceived performance and Drothers' hypothesis.

H1: The impact of DR on PU: The results of this study indicate that data readiness is technically necessary, but it does not appear to directly impact its usefulness to users without the support of information channels. However, this underscores the need for organizations to go beyond simply preparing data and to make the system's usefulness or success understandable and clear to users. Tailored training programs that demonstrate practical applications of AI systems in the real world and better communication strategies to make the benefits of using high-quality data tangible can go some way to bridging this gap. Organizations must take a closer look at how to better manage user expectations, recognizing that additional data increases system performance and helps meet their needs. These efforts may not be realized in terms of the technology's usefulness, which could inhibit its adoption and user satisfaction within the organization. According to Kim (2024), for example, the TAM model sees the PU of change as closely related to the quality of inputs and data readiness in the case of a learning management system. However, the results of this study reveal that the TAM model may not fully capture the richness of user perception. The weak association between data readiness and PU suggests that other factors may have an influence not included in this model, such as culture.

H2: The impact of DR on PE: Data readiness contributes to successful and effective interaction with AI systems, as does data quality, accessibility, and integration. According to the study results, DR does not significantly affect PE. This indicates that, despite high levels of data readiness, users still face difficulties in using AI systems; system design and user experience are more important factors influencing perceived usability than data readiness alone (Venkatesh & Davis, 2000). Integrating data across robust platforms is crucial, as the design ensures that systems built on this data are usable, reliable, and aligned with the real-world needs of healthcare users in Palestine, which helps adopt a holistic perspective (Davenport & Kalakota, 2019). This unexpected finding may be explained by the low level of expertise with AI tools, as emphasized by many interviewees who expressed difficulty interacting with existing digital platforms, and the lack of digital expertise among many Palestinian healthcare workers. The successful adoption of AI depends not only on the availability of data but also on how this data is intuitively and ethically transformed into actionable actions. In a Palestinian context like this, the usability of AI systems becomes far more important than simply having a robust data architecture. The results of this study suggest that emergency response does not significantly impact PE in the Palestinian healthcare context.

H3: The impact of FR on PU: According to this hypothesis, the financial capacity of healthcare organizations influences the PU of AI systems. Ramezani et al. (2023) highlight that organizations with good FR can afford to purchase advanced AI tools, ongoing maintenance, and technical support, which ultimately enhances the efficiency and productivity of AI systems. However, the results of this study contradict the hypothesis. A negative and significant relationship was found between FR and PU. Thus, external resource users may perceive the system as inherently less useful.

A negative relationship of this kind can be explained by the fact that reliance on external support can indicate shortcomings or limitations in the system, reducing its PU. This study suggests that organizations should push toward self-sufficient systems that require little orno external intervention. This means ensuring that AI is robust, appropriately designed, and has a well-integrated support mechanism to be useful to people. However, the results of this study do not support these findings and instead demonstrate that over-reliance on external support can be counterproductive. The explanation for this discrepancy is that the healthcare systems observed in this case vary in context. Large, financially stable organizations might expect immediate FR to translate into more productive AI systems, but more stressed and resource-constrained organizations (i.e., those in the Palestinian healthcare sector) may face different challenges. If Palestinian healthcare organizations develop the capacity to build AI systems themselves and even foster a culture of self-sufficiency among themselves, such systems could become inherently effective and beneficial. Additionally, focusing on long-term, sustainable resource commitments to building internal expertise could lead to more successful AI implementation and increase the perceived utility of these technologies in Palestinian healthcare.

H4: The impact of FR on PE: The impact of FR on PE is greater in organizations that have the financial resources to provide AI systems with the resources necessary to achieve PE (including user training and technical support) (Anh et al., 2024). These organizations can implement AI solutions that address the learning curves and operational barriers faced by users (Luo et al., 2024). This study also suggests that organizations with a strong financial profile can allocate resources to developing AI-human interaction technologies, enhancing the usability of AI systems while reducing barriers to adoption and operation. However, this study found otherwise, finding that the relationship between financial readiness (FR) (used as an indicator of financial readiness) and PE was negative and statistically insignificant, with a path coefficient of -0.100, a t-value of 1.191, and a P-value of 0.234.

Therefore, external resources (such as training or technical support) do not influence users' acceptability of systems and their beliefs about the ease of use of the system. This unexpected finding may be explained by the fact that users may weigh other factors (such as the system interface and specific task capabilities) more heavily than the intrinsic usability of AI systems. Therefore, external support may be perceived as secondary or insufficient to influence usability. Similarly, FR plays a role in facilitating the usability of AI systems in the Palestinian healthcare sector. However, the contextual constraints that healthcare organizations in Palestine may face are likely to differ significantly from those in better-off and more financially sound regional contexts. Many healthcare organizations in Palestine operate on small budgets, which hinders their ability to invest in the training, support, and infrastructure needed to facilitate the use of AI systems for staff. The results of this study demonstrate that even when training, support, and resources are available, users may not find the system easy to use if other critical factors, such as the design of the AI system itself, are at play. In addition to improving system design, Palestinian healthcare organizations must establish sustainable internal capabilities to support AI systems, including in-house technical teams and user training programs. By reducing dependence on external support, the system becomes more self-sufficient, contributing to the resolution of resource and usability issues. Through this work, we highlight how improving usability in the Palestinian context requires focusing on the intrinsic characteristics of an AI system rather than simply the presence of external support.

H5: The impact of TMS on PU: Leadership support in the healthcare context is particularly important as it includes funding AI solutions, creating an environment for innovation, and ensuring that AI technologies are aligned with organizational goals (Secinaro et al., 2021; Salam &Abhinesh, 2024; Malik & Annuar, 2021) state that top management endorsement of AI systems, leading to AI being viewed as an essential tool that solves central clinical and operational challenges, gives the AI system a sense of usefulness among employees. However, the results of the current study revealed unexpected research findings. The analysis shows that TMS negatively impacts PU with the path coefficient. Rather than being expected, it is the case that too much involvement from top management will lead to user perceptions of overreach or distrust, thus reducing the PU of the system. This finding suggests that leadership support is essential, but it can become a barrier beyond a certain level, especially if it leads to micromanagement or infringement on user autonomy. If management interferes too much, users may believe they are not trusted to make good decisions about the technology and thus feel its usefulness is reduced. The results of this study differ from previous research, which emphasizes the beneficial effect of TMS on the PU of technology (Santamato et al., 2024; Secinaro et al., 2021; Salam &Abhinesh, 2024), among others, suggest that leadership involvement within the healthcare setting nurtures an environment that supports technology adoption. Similarly, senior management is instrumental in determining the perceived benefits of AI technologies (Malik and Annuar, 2021). The results of these studies confirm that management is actively working to enhance employees' ideas and perceptions of the benefits of AI technologies in healthcare. Therefore, healthcare organizations in Palestine must strike the right balance between an appropriate strategic direction and regulating healthcare worker ownership to achieve optimal results.

H6: The impact of TMS on PE: TMS is essential in technology development in organizations (Santamato et al., 2024), as it informs employees of the importance of technology, generates interest in it, and provides them with the necessary resources. Theresults of the current study revealed that the LMS did not affect the performance coefficient (PE), with the path coefficient, t-value, and p-value being -0.049, 0.488, and 0.626, respectively. This finding contrasts with previous studies (Ragu-Nathan et al., 2004; Wu et al., 2008). These findings suggest that although TMS may facilitate the adoption of AI technologies, it may not directly influence users' perceptions of ease of use. Factors such as system design, user experience, and user training may have a greater impact on these perceptions.

H7: The impact of EA on PU: In sectors that are more sensitive to integrity and ethical values, such as healthcare, users tend to perceive the value of AI systems more when ethical principles are built into the design and use of the system. Technology can enhance trust by creating that ensures it is fair and private (Kwak et al., 2022). This, in turn, improves the ethical awareness perception of the usefulness of AI because users are willing to accept systems that they believe follow these ethical rules (Gerlich, 2023; Machado et al., 2023). Contrary to the study, EA significantly affects PU witha path coefficient of 0.167, a T-value of 2.295, and a P-value of 0.022. Finally, this means that while the PE by users enhances the PU of an AI system, the two are related; that is, using an easy system comes without effort, and therefore, the PU of the system is excellent, unlike a rigid system that users find difficult, and consequently. While ethical considerations are important, the PU of AI in healthcare may be determined by its ease of use. These findings have implications for the context of the Palestinian healthcare sector. Despite being a developing country, Palestine faces numerous challenges in its health system, all of which are linked to limited resources, structural constraints, and the ethical and practical need to adopt a technological system. Indeed, EA is essential for gaining trust in and adopting AI systems in a context where patient privacy and fairness are paramount, but similarly, Jeong et al. (2025) found that users may evaluate the usefulness of AI tools based on ease of use. The findings suggest that for AI to be adopted in Palestinian healthcare settings, an ethical design approach is not sufficient; user training and support systems that facilitate the use of AI technologies will also be required. They can invest in comprehensive user training programs, simplify user interfaces, and provide ongoing technical support to help healthcare professionals feel confident and comfortable using AI tools. Palestinian health organizations can improve the perceived benefit and adoption rate of AI by taking into account ethical considerations and usability concerns.

H8: The impact of EA on PE: The results of this study show a significant positive relationship between EA and PE with a path coefficient of 0.320, a t-value of 5.245, and a p-value of 0.000. The study provides evidence that users who perceive AI systems as requiring less effort also tend to perceive them as easy to use. The results emphasize the need to consider ethical considerations and user data in healthcare-based AI systems. This enables healthcare providers to use AI technology naturally and easily, increasing confidence in the use of AI technologies in healthcare. For Palestinians, this increases reliance on AI and its successful integration into the healthcare sector.

H9: The impact of RC on PU: Taylor et al. (2010) suggested that RC reinforces the TAM by showing that compliance adds to operational efficiency and ethical and legal assurance, which are critical in the healthcare industry. Furthermore, the results show that RC did not significantly affect PU, yielding a path coefficient of 0.132 and a P-value of 0.226. Based on these results, if resource allocation conveys reliability or commitment, it does not necessarily lead to higher perceptions of usefulness. Users do not somehow associate RC with the tangible benefits or outcomes of the system. Compliance should mean an operational benefit visible to users (Taylor et al., 2010). Kim et al. (2024) explain that integrating AI tools into clinical practice is enabled by regulations (here, compliance), but in and of itself, this may not mean much to users unless it brings clear and actionable benefits. Overall, RC is essential for building trust and credibility in healthcare AI systems, but it contributes little to achieving the expected benefits due to the lack of clear evidence of their practical feasibility. The Palestinian healthcare sector can engage leaders in educating users, developing unified regulations for compliant AI systems, and achieving tangible results to enhance benefit perception and accelerate the adoption of compliant AI systems. Local challenges can be addressed, focusing on the operational benefits of compliance to ensure the reliability and value of AI tools, thereby improving patient outcomes.

H10: The impact of RC on PE: The study's findings indicate that RC has a significant positive effect on the PE of AI tools in the healthcare sector, which is a stand-in for regulatory compliance, and has a substantial positive association. According to the proposed link, resource allocation demonstrates an organization's commitment to ensuring ease of use, which enhances user trust and reduces perceptions of complexity. These findings are consistent with prevailing beliefs compared with previous research.

H11: The impact of IP on PU: Healthcare organizations typically need to foster innovation and maintain intellectual property rights to enhance their competitive advantage and mitigate any pressure from competitors or government agencies. (Witkowski et al., 2024; Luo et al., 2024). The results show that IP has a significant positive effect on PU, as evidenced by the path coefficient (0.345), t-value (3.945), and p-value (0.000). The result reflects the time resolution linking users' propensity to innovate and their opinion of the usefulness of AI systems.When a healthcare organization finds itself underperforming compared to competitors, the perceived benefit of adopting AI tools in healthcare increases exponentially (Witkowski et al., 2024; Luo et al., 2024).

H12: The impact of IP on PE: The findings reveal that IP influences PE, as shown by the path coefficient (0.384), t-value (3.82), and p-value (0.000). To create good opportunities for innovation in artificial intelligence technologies, rational institutional pressures must be imposed (Bennich, 2022; Ketikidis et al., 2012). These findings highlight the importance of IP in driving organizational change across different sectors, suggesting that carefully designed institutional pressures can encourage the adoption of new practices without creating resistance.

H13: The impact of PE on PU: Understanding how AI systems gain user acceptance is essential and related to this relationship. Thus, easy-to-use, low-effort AI tools in healthcare will directly increase PU if they do not require much effort from the user (Jeong et al., 2025) in clinical or administrative practice. This, in turn, facilitates higher perceived value because the technology is easy and useful in enhancing patient care or operational efficiency, according to physicians or healthcare workers (Lopes et al., 2024). The results in this study indicate that PE significantly influences PU, with a path coefficient of 0.378, a t-value of 5.119, and a p-value of 0.000. It is also consistent with the TAM framework, where a bidirectional relationship exists between usability and usefulness. Users perceived systems as more useful when they believed they were easier to use. These findings support the theory by showing that simplifying the user experience can influence a technology's perceived ease and usefulness. Ease of use is one of the strongest predictors of the PU of a particular technology (or, more broadly, a product), especially in healthcare, where user time and efficiency are important. Gerlich (2023) shows that in the clinical setting, easy-to-use AI tools improve providers' speed and decision-support capabilities, contributing to the PU of the technology. The findings suggest that Palestinian healthcare organizations should focus on developing simple, user-friendly AI systems that fit the routine tasks of healthcare providers. These systems reduce the cognitive burden and technical barriers to AI adoption and are therefore considered beneficial, encouraging their wider adoption (Jeong et al., 2025).

Encouraging wider adoption of AI technologies is the fact that ease of use can mitigate challenges faced by healthcare workers in Palestine, such as a lack of training or unfamiliarity with advanced technologies.

H14: The impact of PU on IA: The hypothesis is that when users believe that a technology is useful, they are more likely to intend to adopt it than otherwise. According to the TAM framework, technology adoption is driven by PU, a relationship that serves as the cornerstone of this framework. This is supported by Zhu and Sun (2021) in that the more useful they find a technology, the more likely users are to adopt it in their daily work. AI tools that can be perceived as helping patient outcomes (Bothaet al., 2024), healthcare professionals' efficiency, and decision-making assistance are more likely to be integrated into healthcare professionals' daily jobs. Witkowski et al. (2024) reported that healthcare workers who strongly believe in using AI to improve patient care are more likely to accept the technology, especially if they feel confident enough to use it.

H15: The impact of PE on IA: Healthcare professionals consider the potential of AI systems to be great in terms of ease of use and the reduced time and cognitive effort required to complete the task. Jeong et al. (2025) expressed that time and financial constraints are critical in healthcare, and an easy-to-use tool would be a natural choice. Stakeholders in the Palestinian healthcare system should provide a simple and accessible AI system, specifically designed to meet the needs and constraints of healthcare professionals.

This study demonstrated that in a resource-limited environment such as Palestine, adopting AI technologies in healthcare is challenging, as institutional pressures pose a significant challenge. Other factors, such as ease of use, external pressures, and regulatory requirements, are more important drivers of adoption (Park & Kim, 2023). Reality, policymakers and healthcare leaders must consider these factors and develop strategies that help improve the practical usefulness and usability of AI systems.

While institutional pressures undoubtedly play a major role in the adoption of AI in Palestinian healthcare, the tangible benefit of AI systems in the Palestinian healthcare landscape will best be shaped by healthcare professionals' willingness to innovate and experiment with these systems. Therefore, senior management in Palestinian healthcare organizations should focus on regulatory compliance, which creates an environment conducive to innovation; this environment should pave the way for exploring the true potential of AI systems.

If AI systems are structured in a way that makes them more ethical, they are perceived as more user-friendly, and ethical concerns arising from the user-maintained goal of ease of use of AI technologies (e.g., through transparency in data collection practices, ensuring clear and intuitive interfaces, etc.) could be another direction for exploration. Gerlich (2023) found that ethical design in healthcare technology enhances trust and ease of use. Ethical AI design standards reduce complexity, allowing for easier interaction with AI systems and increasing users' sense of control over the system. User-friendly ethical AI systems will provide users with features such as a simple and intuitive interface, easy opt-in and opt-out, clear information about data privacy, and other features that make the system easy to use (Resnik & Hosseini, 2024).

4.2.2 Indirect Relationships (Mediation)

H16: PE mediates the relationship between DR and PU: The results of this study showed a weak and statistically insignificant correlation between data quality, analysis accuracy, and system usability. The statistical hypothesis was rejected with a p-value of 0.763. The study findings suggest that while data quality is a fundamental requirement for artificial intelligence systems, it does not necessarily guarantee ease of use or improved performance. One possible reason for the lack of statistically significant results is that healthcare professionals did not perceive data quality as a limiting factor for system usability or value, but rather as a basic prerequisite. In other words, poor data quality will impact the ability of AI to be used well, but it will not degrade user perceptions unless these quality issues manifest themselves in a degraded user experience in the form of accuracy issues faced by the user or other key factors. This suggests a dissonance between data infrastructure and user experience, where clinical use of a data product may trump the technical aspects of data readiness in favor of ease of use and system performance (Gebler et al., 2025).

Furthermore, the results refute the notion that DR indirectly affects PU through PE. However, some studies have indicated that a well-prepared data environment improves system usability (Bothaet al., 2024), but the results of this study show that the perception of such a relationship may not always be significant. Unlike DR was found to be associated with the PE of healthcare technology, the rejection of this hypothesis in this study implies that other factors, including system design, ease of user interaction, or external factors (such as organizational support), may override user perceptions. The study's findings have important policy implications for the Palestinian healthcare sector. The resources and structure of data management systems are often limited in this industry. Although data availability and quality have improved for healthcare professionals in Palestine, they may not perceive these improvements as increasing the usability of AI systems or leading to the technology's utility. Some healthcare professionals may view data readiness as a baseline expectation; they will assume their AI system will work if the data is present, whether for data quality or regulatory suitability. Furthermore, in Palestine, where AI and data technologies are still in their infancy, the actual utility of systems and their apparent ease of use may depend more on their simplicity and ability to integrate with existing workflows thanon their data. The findings suggest that developers and healthcare managers in Palestine should focus not only on improving data infrastructure but also on designing user-friendly interfaces and easy integration with healthcare processes. Even good data may not be enough to drive physicians' adoption of AI if AI systems are not easily integrated into physician's routines.

H17: PE mediates the relationship between FR and PU: Healthcare organizations' perceptions of the usefulness and ease of use of AI systems are greatly influenced by the financial resources available to them.FR helps organizations purchase well-designed AI systems and provides training to enhance system usability, thereby increasing ease of use and PU through the underlying theory. Anh et al. (2024) suggest that increased financial resources enable organizations to purchase more effective and user-friendly technologies and provide necessary training to healthcare professionals. Luo et al. (2024) argue that such investments make AI systems appear easier to use and more useful to healthcare workers. To this end, Malik and Annuar (2021) explicitly state that better technology implementation results from adequate financial resources, which makes implementation more useful and user-friendly. However, the study results do not support this theoretical hypothesis. We did not find the hypothesized positive relationship between FR and PU through PE, with a p-value of 0.244, well above the normal threshold for statistical significance. This suggests that FR does not predict the ease of use or PU of AI systems by healthcare professionals, contrary to what previous studies have suggested. FR may explain delays in technology acquisition, but not the difficulty of use or PU. While healthcare professionals may view financial investment as a prerequisite for technology purchase, they may not consider it a key factor that can improve AI usability or make its use beneficial to healthcare professionals. However, it is doubtful that other factors, such as the quality of training, system design, and operational performance, strongly influence these perceptions. The findings of this study suggest that the FR argument for purchasing, however essential, does not lead to ease of use or PU unless the purchase is followed by thoughtful implementation and effective user support. The role that FR plays in the adoption of AI technologies in the Palestinian healthcare context is of critical importance. The availability of funds to purchase and deploy advanced AI systems remains a significant challenge for Palestinian healthcare organizations. However, the results of the current study indicate that having the financial means to purchase technology does not necessarily mean that users have positive perceptions of the ease of use or usefulness of the system.

H18: PE mediates the relationship between TMS and PU: Learning management systems (TMS) positively impact job performance through professional performance. Santamato et al. (2024) reported that if senior management commits to supporting AI, this can be used to create a culture of acceptance among employees and increase their awareness of the technology's potential. Combined with a positive organizational attitude, this support can reduce resistance to new technologies and make them seem more appropriate and beneficial. Management support reduces user resistance, thus helping healthcare professionals leverage AI systems, as stated bySecinaro et al. (2021). According to Salam and Abhinesh (2024), TMS for new technologies is a positive experience for employees, as they view it as a tool that improves their work processes. Hypothesis testing results show a non-statistically significant relationship between TMS and PU through PE (P = 0.637). The result contradicts the theoretical assumption that TMS significantly enhances users’ ease of use and usefulness ratings. One explanation is that TMS, which may be critical in the early stages of AI adoption (e.g., acquiring resources or generating early interest in the technology), does not necessarily translate into positive user experiences with the system. Healthcare professionals may value the system's design, performance, and ease of use more than senior management support in shaping their ongoing perceptions of ease of use and usefulness.

Previous research offers conflicting views regarding the influence of management support on technology adoption. According to Santamato et al. (2024), the ease of use of AI tools and how useful they appear to be depend mainly on CEO approval. Researchers argue that leadership committed to new technologies creates a positive organizational context for introducing them, making them easier to use and more valuable to users. Secinaro et al. (2021) argue that managerial support is key in managing resistance to new technologies to ensure successful adoption. Salam and Abhinesh (2024) argue that managerial support prevents users from fearing new technologies, positively accepts new technologies, and enhances their PU. However, the results of the current study contradict this claim, as TMS did not have the expected impact on PE and usefulness. We speculate that this discrepancy is explained by top management approval facilitating initial adoption. In the Palestinian context of resource-constrained healthcare organizations, securing funding and resources for AI systems at the top management level may ultimately be beneficial to increasing the number of available AI systems, but it remains to be seen whether this will improve user experience or perception. In Palestine, regarding the ease of use and PU of AI systems for healthcare professionals, considerations will revolve around practicality, with preference given to systems that fit into existing workflows, provide high-quality training, and feature a user-friendly interface design. TMS is essential for initial approval and resources, but the long-term success of AI technology in Palestinian healthcare organizations will depend more on the functionality and user-oriented design of the developed systems. The findings also suggest that healthcare organizations in Palestine should focus on gaining senior management support and creating a supportive environment for users through targeted training, appropriate system customization, and ongoing support. If AI systems are to be implemented in healthcare practices in Palestine, a more holistic approach to AI adoption that takes into account user experience is recommended, as the findings indicate no significant relationship between senior management support and PE or usefulness.

H19: PE mediates the relationship between EA and PU: Environmental analysis positively impacts job performance through professional performance. The hypothesis is that awareness of ethical standards, such as data confidentiality, limited access, and bias prevention, reduces the perceived complexity of technology in the context of professional ethical standards. A significant positive relationship exists between environmental analysis and job performance through professional performance, with a p-value of 0.001. Ethical considerations are important for healthcare professionals in shaping their perceptions of the ease of use and usefulness of AI systems.

This indicates that while EA remains crucial in developing user perceptions, other contributing variables (system design, training, and performance) are also present. Healthcare providers are increasingly concerned about the sensitivity of healthcare data and the need to ensure non-discrimination, which may influence decision-makers' attitudes. Ethical considerations of AI systems can be a significant barrier to the adoption of technologies in healthcare. The Palestinian healthcare sector faces several limitations that can impact people's perceptions of AI systems. However, this finding suggests that Palestinian healthcare organizations should focus on ethical considerations that encourage the adoption of AI technologies, as PE will enhance their perceived utility and their successful and sustainable integration into healthcare practices.

H20: PE mediates the relationship between RC and PU: When AI systems in the healthcare sector comply with regulatory standards, they enhance user safety by ensuring the integrity of their data and that of their patients. This sense of security reduces perceived complexity, making AI systems easier to use and enhancing the expected benefits for users (Kim et al., 2024). Meeting these regulatory requirements makes AI systems more trustworthy and ethical, meaning healthcare providers are more willing to use these technologies (Zhou & Gattinger, 2024). The World Health Organization (WHO, 2023) states that AI systems that comply with regulatory standards are more likely to lead to better clinical outcomes and improved patient satisfaction. The results of this study confirm this theoretical hypothesis. RC positively influences PU based on PE ($P = 0.046 < 0.05$). These results show a significant and positive effect of RC on the PU of AI systems, mediating the effect of PE on AI system usefulness.

Adopting AI tools in the healthcare sector requires developing the necessary legal framework and implementing regulations that are consistent with ethical and societal values. Therefore, RC is critical in shaping the PE and usefulness of AI systems in healthcare globally and in the Palestinian healthcare sector. As AI systems in healthcare continue to emerge, regulations that ensure compliance with regulatory standards are essential to drive adoption and increase user awareness of these technologies.

H21: PE mediates the relationship between IP and PU: The effect of IP on PU through PE: According to Gerlich (2023), IP, regulations, or pressures from peer institutions, for example, pull organizations toward the adoption of new technologies. Güven et al. (2024) argue that healthcare providers under such pressures may adopt AI tools that are perceived to meet these regulatory requirements, thereby giving the tools added value and greater ease of use. Additionally, Barchielli et al. (2021) argue that IP from these dynamics can drive the adoption of AI technologies, partly because healthcare providers feel that they cannot achieve specific professional and organizational goals without them. DiMaggio and Powell (1983). This study presents a theoretical framework for how institutional arrangements compel organizations to adopt technologies that meet external standards, increasing the likelihood that these technologies will be perceived as useful and easy to use. Hypothesis tests support the theoretical framework with a statistically significant positive relationship between intellectual property (IP) and optimal utilization (PU) through functional performance (PE), with a p-value of 0.002, which is less than the 0.05 significance level.

Institutional pressure partially mediates healthcare professionals’ perceptions of ease of use; however, such perceptions are also influenced by factors other than system design and experience, such as the actual system design and user experience. In this context, IP shows a partial mediation effect, which is consistent with the idea that IP may drive the adoption of AI systems by shaping perceptions of ease of use and usefulness. However, IP does not explain all users’ attitudes toward technology. However, institutional pressure enhances users' confidence in implementing AI tools, particularly when the tool is perceived as supporting the users' professional or organizational goals. Given the regulatory challenges and shifting goals of healthcare practices in the region, institutional pressure may play a particularly key role in facilitating AI adoption in the Palestinian healthcare sector. International regulatory bodies and professional organizations will pressure Palestinian healthcare providers when selecting and implementing AI tools by incorporating a set of criteria, such as data security, quality of patient care, or even privacy. For example, if there is sufficient external pressure to use these tools, it may act as a motivator that fosters a sense of obligation on the part of healthcare professionals to use the tools in ways beneficial to their professional and organizational goals. However, this study demonstrates that while institutional forces are likely to push firms toward the initial adoption of AI systems, they do not help maintain positive corporate perceptions of this technology. In the Palestinian healthcare sector, where resources may be limited and healthcare infrastructure is still developing, the usability and PU of AI tools will depend on the quality of the tools themselves, the availability of adequate training, and the extent to which AI is integrated into the healthcare workflow. While institutional pressures may push healthcare providers to adopt AI tools, their long-term success will depend on whether they are appropriately designed to specifically address the needs of Palestinian healthcare professionals and their patients. In conclusion, institutional pressures are an indispensable factor in driving hospitals to adopt AI systems; however, their impact on hospitals' perceptions of the ease or usefulness of AI systems is only part of the bigger picture. The long-term success of AI adoption in Palestinian healthcare organizations depends on institutional pressures for adoption, successful system design, user support, and training initiatives tailored to the needs and constraints of the Palestinian healthcare context.

H22: PU mediates the relationship between PE and IP: The TAM assumes that PE leads to increased users' understanding of the benefits and intentions to adopt AI (Davis, 1989).This theoretical model is supported by Nguyen et al. (2020) and Jeong et al. (2025). Furthermore, Gerlich (2023) argues that improving user experience can enhance the perception of additional benefits and influence the decision to adopt AI.However, the results of this hypothesis reveal that there is no significance associated with the relationship between PE and IA through PU, as the p-value is 0.695. This result contrastswith what would be expected from the aforementioned studies. The lack of significance in this study may indicate that other correlates have a greater influence on the adoption decision, perhaps the impact of AI on healthcare outcomes, the suitability of the technology to specific healthcare tasks or practices, or factors beyond the control of the study participants, such as regulations or organizational support. It also suggests that after healthcare professionals perceive the usefulness of AI systems, other push factors (such as trust, integration support, or even external incentives) may become more important in determining adoption intention than ease of use. Previous studieshave shown the significance of PE as a factor in PU and subsequent adoption (Davis, 1989; Nguyen et al., 2020; Jeong et al., 2025). According to Gerlich (2023), leadership involvement and user experience can positively influence perceptions of technology usefulness and adoption. The current study did not demonstrate significant mediation of such an effect through ease of use; however, it was noted that in real-life settings (such as healthcare), the decision to adopt AI technologies may not depend solely on ease of use. However, key factors of importance could be trust in the technology, perceived effectiveness, and whether the technology meets the needs of healthcare professionals, all of which would be more strongly related to adoption intentions. This contrasts with previous research that has focused on ease of use as a key factor in adoption. The results of this hypothesis may be significant for the adoption of AI technologies in the Palestinian healthcare sector. Healthcare professionals desire to work with systems they find easy to use, but this study points to the fact that the PU of systems, and thus AI tools, is not solely based on their ease of use. Resource constraints and what may be a separate set of limitations in training and infrastructure compared to other regions, such as Palestine, for example, may make the perceived impact of AI on improving healthcare outcomes a more important driver of adoption in such a setting. Similarly, AI's ease of use may also be less important than other factors in motivating healthcare professionals to adopt the technology, given the technology's importance to specific healthcare practices (improving patient care, streamlining administrative processes, or enhancing decision-making).

The findings suggest that when implementing new ICTs in the Palestinian public healthcare sector, factors such as cost, ease of use, the feasibility of integrating them into existing organizational culture, their actual benefit in improving healthcare delivery and integrating them into existing workflows, their social impact and impact on the workforce, and the training and support provided to users should be considered. Trust in the technology and leadership engagement may be critical for adoption. Given the challenging social, political, and economic conditions in Palestine, healthcare professionals may be more interested in exploring how AI can directly contribute to improving patient care and meeting their professional needs, rather than the technical ease of use.

Thus, the TAM model emphasizes ease of use as a factor influencing adoption. However, the study results suggest that other factors, such as the perceived importance of AI and its impact on healthcare professionals' work, may have a greater impact on their adoption intention. These alternative adoption factors could be explored through future research and additional studies into how PU and adoption intention influence adoption.

The result highlights that innovation-driven behaviors enhance the PU of AI technologies. However, the difference between the hypothesized effect of institutional pressures and the observed effect of propensity to innovate suggests that external pressures can stimulate the adoption of AI technologies, but their usefulness depends on users' innovative behavior. For those who are open to experimentation and push the boundaries of what AI tools can do, their value will become more apparent and beneficial. This finding underscoresthe importance of fostering a culture that encourages innovation within Palestinian healthcare institutions. Thus, while institutional pressures undoubtedly play a key role in AI adoption in Palestinian healthcare, the PU of AI systems in the Palestinian healthcare landscape is best shaped by healthcare professionals' willingness to innovate and experiment with these systems. Therefore, senior management in Palestinian healthcare institutions should focus on regulatory compliance, which creates an environment conducive to innovation; this environment should pave the way for exploring the true potential of AI systems.

4.3 Study Recommendations

This study demonstrates several beneficial implications for policymakers, healthcare professionals, and healthcare system developers:

- Emphasize practical benefits over ease of use: Results suggest that PE may not affect the IA via PU. For this reason, AI system developers and government policymakers in Palestine should focus on demonstrating the tangible benefits of AI technologies. For example, this report highlights how these tools can be directly used to improve healthcare outcomes, reduce workloads, and enhance patient care, rather than simply demonstrating their ease of use.

- Foster trust and ethical assurance: Adopting strategies should center on trust in AI systems and assurance of ethical compliance. To gain trust and increase perceived benefit, healthcare professionals want AI tools to adhere to ethical standards when collecting and using data and making decisions. Ethical concerns should be addressed using transparent mechanisms.
- Provide context-specific training and support: Appropriate training programs must be developed for the Palestinian healthcare community. Training should focus on how to effectively handle and utilize AI systems to achieve healthcare professionals' goals.
- Leveraging Leadership Engagement and Institutional Support Decision-makers and healthcare professionals must have the ability to provide the necessary resources to adopt artificial intelligence in healthcare and develop appropriate plans to address any potential challenges without affecting the healthcare sector's ability to provide services with the highest possible quality.
- Focus on System Performance and Relevance:A healthcare system must be appropriate to meet all the needs of its workforce to achieve the best outcomes for all users.
- Support Infrastructure Development:Decision-makers in Palestine should invest in developing the IT infrastructure in the Palestinian healthcare sector to achieve the greatest benefits from adopting AI tools.
- Further Future Research: In addition, it is recommended to conduct research to investigate additional factors that may influence AI adoption in the Palestinian healthcare sector, including trust in technology, perceived importance, and institutional readiness for AI. This will help design strategies specifically tailored to AI adoption in communities with limited capacity.
- To be compatible with the workflow in Palestinian hospitals, AI tools were designed with simple interfaces, specifically for healthcare professionals with limited digital experience. They also directly and positively impact perceived utility (PU) (H13), including PE.
- Healthcare organizations should fund ongoing hands-on training programs, as findings show that perceived usefulness or ease of use cannot be predicted by FR or resource availability alone (H2, H4, H17). To help staff use effective tools.

By implementing these recommendations, the Palestinian healthcare sector can reduce barriers to adopting AI tools, promote their use in appropriate and effective ways, and leverage them to improve healthcare delivery.

4.4 Study Limitations and Future Directions

4.4.1 Study Limitations

This study has various limitations as follows: firstly, the study specifically addresses the Palestinian healthcare sector, whose social, economic, political, and technological conditions are unique. These factors may be limited to other regions or healthcare systems with different circumstances. Secondly, the study focuses on PE, PU, and IA as mediating factors. They ruled out other potential factors such as trust, organizational culture, or the quality of AI system implementation, but these could have played a major role in adoption.Secondly, the study collects data from a single point in time, which hinders inferences of causality and assessments of long-term adoption trends. A longitudinal approach may provide a more comprehensive perspective on how perceptions evolve overall. Thirdly, the research was conducted in an area characterized by a lack of resources and technical infrastructure. These limitations likely influenced participants' perceptions of ease of use and usefulness, and thus the estimated impact of these factors was biased toward lowering in environments with greater resources. Finally, the Western Bank’s health facilities solely depend on foreign grants, and these funds are mostly used to meet urgent health needs, with virtually no provision for investing in long-term technological developments like artificial intelligence (Baidoun et al., 2018). For this reason, most of the rural-based hospitals and clinics in the region cannot adopt AI-based healthcare technology solutions, which are available only in urban areas (Abu Zayyad, 2021).

4.4.2 Future Directions

– Exploration of alternative adoption factors: Other reasons influencing the adoption of AI should also be studied in future research, including trust in technology, system interoperability, and user training, along with external incentives (Venkatesh, Thong, & Xu, 2012). It would offer a better holistic view of barriers and enablers to adopt AI.

- Longitudinal Studies: Longitudinal studies might also track how key perceptions about how AI systems are perceived change as healthcare professionals get used to the technology. Adoption and usage sustainability insights could be provided using this approach.
- Comparative Analysis Across Regions: Future research can incorporate comparative studies across the different regions at various levels of technological advancement and with varying resources available for health care to enhance generalizability. Identifying the universal and context-specific factors influencing AI adoption would be possible with such studies.
- Incorporation of objective data: Objective data, including patient outcomes, usage logs, or organizational performance metrics, should be included as part of the data collected to complement survey responses. It would be better to depict how AI can change how healthcare is practiced.
- Focus on ethical and cultural Factors: Future research should focus on how the considerations of ethics and culture affect perceptions and acceptance of AI tools in broad healthcare settings where EA is crucial.
- Technology-specific studies: By analyzing types of AI applications (e.g., diagnostic tools, predictive analytics, robotic assistants, etc.), one may gain more nuanced insights into factors determining adoption for a particular technology and the diverse challenges each tool poses.

Addressing these limitations and following the proposed future directions will enable researchers to provide more actionable insights to promote the successful integration and adoption of AI technologies in healthcare systems worldwide, including resource-deprived regions such as Palestine.

4.5 Conclusion

This study examined the factors influencing the adoption of artificial intelligence in healthcare, with a focus on the Palestinian context. Taking TAM as a theoretical basis, the research examined the influence of PE, PU, IA, and external variables, FR, TMS, IP, and EA. Although the availability of resources is important and managerial advocacy is a driving force, they are not always sufficient to increase perceived utility, build trust, or improve user perceptions or adoption intentions.

This study indicated that AI adoption in healthcare is more complex, as end-user experience, system functionality, training quality, and external incentives may far exceed initial perceptions of ease of use. The results of some hypotheses were insignificant, suggesting the need for a more nuanced approach to understanding adoption dynamics that prioritizes user-centered design, trust in AI systems, and compatibility with users' professional workflows.

The unique challenges of limited resources, technological infrastructure, and social and political constraints in the Palestinian healthcare sector complicate the adoption process. However, the study highlights the potential of AI to transform healthcare delivery in such resource-limited settings, provided that ethical standards, institutional requirements, and user support mechanisms are strictly observed.

This research contributes to the growing literature on AI adoption by emphasizing the critical role of EA and institutional pressures, while challenging conventional assumptions about the linear relationship between ease of use, PU, and adoption intentions. The findings have practical implications for healthcare policymakers, technology developers, and institutional leaders, emphasizing the need for a collaborative, context-sensitive approach to integrating AI.

Finally, the study acknowledges its limitations, including its cross-sectional design, reliance on subjective measures, and focus on a specific geographic region, and provides a roadmap for future research. By addressing these limitations and expanding the scope of the research, future studies can build on this work to provide a more comprehensive understanding of AI adoption in healthcare, drive innovation, and improve patient outcomes in diverse settings.

List of Abbreviations

Abbreviation	Term
TAM	Technology Acceptance Model
IA	Intention to Adopt
DR	Data Readiness
EA	Ethical Anxiety
FR	Financial Readiness
IP	Institutional Pressure
RC	Regulatory Compliance
PU	Perceived Usefulness
PE	Perceived Ease of Use
IoT	Internet of Things
PLS-SEM	Partial Least Squares Structural Equation Modeling

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Appendices

Appendix A

R-squared

	R-square	R-square adjusted
IA	0.316	0.309
PE	0.495	0.478
PU	0.487	0.466

Appendix B

f -square

	f-square
DR -> PE	0.001
DR -> PU	0.006
EA -> PE	0.174
EA -> PU	0.040
FR -> PE	0.008
FR -> PU	0.021
IP -> PE	0.135
IP -> PU	0.094
PE -> IA	0.310
PE -> PU	0.141

Appendix C

Research Constructs & Indicators

Irem	Statement	1	2	3	4	5
Data Readiness						
DR1	There is access to data sources relevant to my tasks and goals.					
DR2	I believe the quality of the data used in analysis and decision-making by AI is excellent.					
DR3	I believe the volume of data I regularly use is sufficient for data analysis.					
Regulatory Compliance						
RC1	The current regulatory standards and guidelines in the Palestinian healthcare sector are sufficient to evaluate AI in healthcare.					
RC2	Automation helps improve the accuracy and consistency of regulatory compliance by reducing human error.					
RC3	My medical institution encourages the creation of national bodies to oversee AI, public policy algorithms, and regulatory responses like licensing and R&D.					
Financial Readiness						
FR1	My medical institution allocates a sufficient budget to cover the high initial costs of using AI.					
FR2	My medical institution has a sufficient budget to cover operational costs.					
FR3	Obtaining financial support from local banks or financial institutions to adopt AI technologies would be easy.					
Top Management Support						
TMS1	Top management in my medical institution supports the adoption of AI technologies.					
TMS2	Top management encourages doctors and staff to apply the latest AI technologies daily.					
TMS3	Our medical institution rewards employees with skills and knowledge related to AI-based systems.					
Institutional Pressure						
IP1	My medical institution believes that adopting AI impacts market competitiveness.					
IP2	AI applications globally pressure the Palestinian healthcare sector to adopt modern technologies.					
IP3	Some local and regional medical institutions have already used AI for treatment and patient services.					
Perceived Usefulness						
PU1	AI helps predict risks and improve healthcare delivery, such as patient management.					
PU2	AI significantly improves diagnosis based on the patient's condition and predictive capabilities.					
PU3	AI automates medical tasks with greater speed, accuracy, and lower cost.					

Perceived Ease of Use						
PE1	I can easily learn to use AI tools without extensive training.					
PE2	I can get quick answers to inquiries using AI tools.					
PE3	I believe AI tools are flexible in interaction.					
IT Infrastructure						
IT1	There is a designated person or group to help resolve system difficulties.					
IT2	I have support for hardware and network conditions used with AI tools.					
IT3	I have all the required resources to develop a database used for treating patients.					
Ethical Anxiety						
EA1	I am concerned that generative AI products will collect too much personal information.					
EA2	I hesitate to use the system for fear of making mistakes I cannot correct.					
EA3	I don't know exactly how AI tools make decisions, which makes me anxious.					
Intentions to Adopt AI Tools						
I1	I intend to use AI tools to improve the quality of medical services.					
I2	I am willing to use AI tools to reduce the institution's operational costs.					
I3	I intend to use AI tools to protect the environment and public health.					

Appendix D

Semi-Structured Interview Questions

1- What are the applications of artificial intelligence used in the Palestinian healthcare sector, and are there any studies or pilot projects ongoing or planned?

2- What are the main drivers and challenges in adopting artificial intelligence applications in the Palestinian healthcare sector.

3- Are there specific cultural or societal factors affecting the adoption of artificial intelligence in the Palestinian healthcare sector?

4- Can you describe the current state of your IT infrastructure in terms of data readiness and its ability to easily use and share data in your health organization?

5- What are the perceived risks of adopting artificial intelligence tools in the Palestinian healthcare sector?

6- What is the perceived benefit of adopting artificial intelligence tools in the Palestinian healthcare sector?

7- How do you see the ease of using artificial intelligence systems and the extent of their impact on the daily work of doctors and administrators? Is there a need for training before use?

8- Are there systems that define and regulate the work of artificial intelligence applications in health care in Palestine, and what is the extent of your health institution's regulatory compliance with these systems?

9- Are there internal or external pressures that accelerate the adoption and use of artificial intelligence in the Palestinian health sector? What is the nature of these pressures?

10- What role do government policies and regulations play in facilitating or hindering the adoption of artificial intelligence applications in the healthcare sector in Palestine?

11- How do financial considerations such as budget constraints affect the adoption of AI applications in the Palestinian healthcare sector?

12- Are there ethical concerns in adopting artificial intelligence applications in the Palestinian healthcare sector, and how can they be addressed in the Palestinian context?

13- Please rank these factors from strongest (1) to weakest (10) in terms of their impact on the adoption of artificial intelligence tools in health care in Palestine

-Social and cultural factors

-Financial factors

-Infrastructure and data readiness

-Regulatory compliance

-Government support

-Institutional pressure

-Perceived risks

-Perceived usefulness

-Ease of use

-Experience

14- Are there any other factors affecting the adoption of artificial intelligence tools in the healthcare sector in Palestine? mention it.

An-Najah National
University
Faculty of Medicine &
Health Sciences
Institutional Review Board

جامعة النجاح الوطنية
كلية الطب وعلوم الصحة
لجنة اخلاقي البحث العلمي

Ref:Mas. Feb. 2024/23

IRB Approval Letter

Title of Research:

Factors influencing the adoption of artificial intelligence tools in Palestinian Healthcare sector: An empirical study

Submitted by:
Nour Eddine Adeeb Muhammad Abdullah

Supervisor:
Mohammed Othman

Approved:
26th Feb.. 2024

Your Study Title "**Factors influencing the adoption of artificial intelligence tools in Palestinian Healthcare sector: An empirical study**" *r*eviewed by An-Najah National University IRB committee and was approved on 26th Feb. 2024.

Hasan Fitian, MD

IRB Committee Chairman

IRB
Institutional Review Board

Nablus - P.O Box :7 or 707 | Tel (970) (09) 2342902/4/7/8/14 | Faximile (970) (09) 2342910| E-mail : IRB@najah.edu

Appendix E

Questionnaire

An-Najah National University

College of Graduate Studies

Master of Engineering Management Program

Factors affecting the adoption of artificial intelligence tools in the Palestinian health care sector: an experimental study

Dear reader :

This questionnaire is part of scientific research, in fulfillment of the requirements for obtaining a master's degree in engineering management. Your participation in this survey will help identify the influencing factors, as well as barriers, and the future of adopting artificial intelligence tools in the Palestinian healthcare sector.

This assessment will take you ten minutes to complete accurately, noting that all information will be confidential and will only be used for scientific research purposes.

Thank you very much for taking the time to fill out this questionnaire

Researcher: Nour al-Din Adeeb Muhammad Abdullah

Master of Engineering Management

Email: nor_azam93@hotmail.com

Mob: 0599106191

Section One: Personal and General Information

Please mark (√) on the appropriate option

1- Do you use artificial intelligence tools to do your work

○Yes ○No

2- If the answer to the previous question is yes, what is the artificial intelligence tool used (more than one option can be chosen):

- (IBM Watson Health)Merative L.P.,

Google Health's DeepMind -

Tempus -

PathAI -

Aidoc -

- Zebra Medical Vision

Butterfly Network -

Prognosis -

- Atomwise

Pathfinder Software by Tempu -

Other tools, mention them………………………………………………. -

3 -What level of experience or previous work do you have with AI tools?

o No previous experience

o Little experience

o Average experience

o Great experience

4- Gender:

o male

o female

5 - Age :

o Under 18 years old

o 18-25 years old

o 26-35 years old

o 36-45 years old

o 46-55 years old

o 56 years or older

6 - Academic achievement :

o Secondary

o Diploma

o University

o Master's degree

oPh.D

7 - Scientific specialization or profession :

o Doctor/female doctor

o Nurse

o Health manager

o Medical engineer

o Researcher in the field of health

o Other, mention the specialty or profession ……………………………………

8 - Extent of work experience in the health sector :

o Less than a year

o 1-5 years

o 6-10 years

o 11-15 years

o More than 15 years

9 - The size of the health institution in which you work :

o Small (less than 50 employees)

o Medium (50-500 employees)

o Large (more than 500 employees)

10 - Has the organization you work for adopted or used AI tools in the health sector?

o Yes

o No

o Not sure

11 - Do you think that artificial intelligence tools can improve the efficiency and quality of health services?

o Yes

o No

o Not sure

12 - Do you face any challenges or concerns regarding adopting or using AI tools in healthcare?

o Yes (please explain the most prominent challenges………………………………….

o No

Section Two: Factors affecting the intention to adopt artificial intelligence tools :

Please mark (√) in the appropriate column.

No.	**Sentence**	**Strongly agree**	**Agree**	**Neutral**	**Disagree**	**Strongly Disagree**
Data Readiness						
13.	There is access to data sources relevant to my tasks and goals.					
14.	I believe that the quality of the data used in analysis and decision-making by AI is excellent.					
15.	I believe the volume of data I work with regularly is sufficient for data analysis.					
Regulatory Compliance						
16.	The current regulatory standards and guidelines in the Palestinian healthcare sector are sufficient to evaluate AI in healthcare.					
17.	Automation helps improve the accuracy and consistency of regulatory compliance by reducing human error.					
18.	My medical institution encourages the creation of national bodies to oversee AI, public policy algorithms, and regulatory responses like licensing and R&D.					
Financial Readiness						
19.	My medical institution allocates a sufficient budget to cover the high initial costs of using AI.					
20.	My medical institution has a sufficient budget to cover operational costs.					
21.	It would be easy to obtain financial support from local banks or financial institutions to adopt AI technologies.					
Top Management Support						
22.	Top management in my medical institution supports the adoption of AI technologies.					
23.	Top management encourages doctors and staff to apply the latest AI technologies in daily work.					
24.	Our medical institution					

	provides rewards for employees with skills and knowledge related to AI-based systems.					
Institutional Pressure						
25.	My medical institution believes that adopting AI impacts market competitiveness.					
26.	AI applications globally increase pressure on the Palestinian healthcare sector to adopt modern technologies.					
27.	Some local and regional medical institutions have already used AI for treatment and patient services.					
Perceived Usefulness						
28.	AI in healthcare helps predict risks and improve healthcare delivery, such as patient management.					
29.	AI significantly improves diagnosis based on the patient's condition and predictive capabilities.					
30.	AI automates medical tasks with greater speed, accuracy, and lower cost.					
Perceived Ease of Use						
31.	I can easily learn to use AI tools without extensive training.					
32.	I can get quick answers to inquiries using AI tools.					
33.	I believe AI tools are flexible in interaction.					
IT Infrastructure						
34.	There is a designated person or group to help resolve system difficulties.					
35.	I have support for hardware and network conditions used with AI tools.					
36.	I have all the required resources to develop a database used for treating patients.					
EthicalAnxiety						
37.	I am concerned that generative AI products will collect too much personal information.					
38.	I hesitate to use the system for fear of making mistakes I cannot correct.					
39.	I don't know exactly how AI tools make decisions, which					

	makes me anxious.					
Intentions to Adopt Artificial Intelligence						
40.	I intend to use AI tools to improve the quality of medical services.					
41.	I am willing to use AI tools to reduce the institution's operational costs.					
42.	I intend to use AI tools to protect the environment and public health.					

Thank you for taking the time to participate in the survey

جامعة النجاح الوطنية

كلية الدراسات العليا

برنامج ماجستير الإدارة الهندسية

العوامل المؤثرة في تبني أدوات الذكاء الاصطناعي في قطاع الرعاية الصحية الفلسطيني: دراسة تجريبية

عزيزي القارئ/القارئة:

تحية طيبة ":

هذا الاستبيان هو جزء من بحث علمي، وذلك استكمالاً لمتطلبات الحصول على درجة الماجستير في تخصص الإدارة الهندسية. سوف تساعد مشاركتك في هذا الاستبيان على تحديد العوامل المؤثرة وكذلك العوائق ومستقبل تبني أدوات الذكاء الاصطناعي في قطاع الرعاية الصحية الفلسطيني.

هذا التقييم سوف يستغرق منك عشرة دقائق لإتمامه بدقة علما بأن كافة المعلومات سوف تكون سرية ولن يتم استخدامها إلا لأغراض البحث العلمي.

شكراً جزيلاً على تخصيص جزء من وقتك لتعبئة هذا الاستبيان

الباحث: نورالدين أديب محمد عبدالله

ماجستير الإدارة الهندسية

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القسم الأول: المعلومات الشخصية والعامة

نرجو وضع علامة (√)على الخيار المناسب

1. هل تستخدم أدوات الذكاء الاصطناعي في تأدية عملك؟

- نعم
- لا

2. إذا كانت إجابة السؤال السابق بنعم, فما أداة الذكاء الاصطناعي المستخدمة (يمكن اختيار أكثر من خيار):

- (IBM Watson Health)Merative L.P.,
- Google Health's DeepMind
- Tempus
- PathAI
- Aidoc
- Zebra Medical Vision
- Butterfly Network
- Prognos
- Atomwise
- Pathfinder Software by Tempu
- أدوات أخرى , اذكرها..

3. ما هو مستوى التجربة أو التفاعل السابق لديك مع أدوات الذكاء الاصطناعي؟

- لا يوجد تجربة سابقة
- تجربة قليلة
- تجربة متوسطة
- تجربة كبيرة

4. **الجنس:**

- ذكر
- أنثى

5. **العمر:**

- أقل من 18 سنة
- 18−25 سنة
- 26−35 سنة
- 36−45 سنة
- 46−55 سنة
- 56 سنة أو أكثر

6. **التحصيل العلمي:**

- ثانوي
- دبلوم
- جامعي
- ماجستير
- دكتوراه

7. **التخصص العلمي أو المهنة:**

- طبيب/طبيبة
- ممرض/ممرضة
- مدير صحي
- مهندس طبي

- باحث في مجال الصحة
- غير ذلك , اذكر التخصص أو المهنة: ....

8. مدى خبرة العمل في القطاع الصحي:

- أقل من سنة
- 1−5 سنوات
- 6−10 سنوات
- 11−15 سنة
- أكثر من 15 سنة

9. حجم المؤسسة الصحية التي تعمل فيها:

- صغيرة (أقل من 50 موظف)
- متوسطة (50−500 موظف)
- كبيرة (أكثر من 500 موظف)

10. هل قامت المؤسسة التي تعمل فيها بتبني أو استخدام أدوات الذكاء الاصطناعي في القطاع الصحي؟

- نعم
- لا
- غير متأكد

11. هل تعتقد أن أدوات الذكاء الاصطناعي يمكن أن تحسن كفاءة وجودة الخدمات الصحية؟

- نعم
- لا
- غير متأكد

12. هل تواجه أية تحديات أو مخاوف فيما يتعلق بتبني أو استخدام أدوات الذكاء الاصطناعي في مجال الرعاية الصحية؟

- نعم (يرجى توضيحابرز التحديات..)
- لا

<u>القسم الثاني: العوامل المؤثرة على نية تبني أدوات الذكاء الاصطناعي:</u>

نرجو وضع علامة (√)على العمود المناسب

الرقم	الجملة	أوافق بشدة	أوافق	محايد	لا أوافق	لا أوافق بشدة
جهوزية البياناتData Readiness						
.13	يوجد إمكانية للوصول إلى مصادر البيانات ذات الصلة بمهامي و أهدافي.					
.14	أعتقد أن جودة البيانات المستخدمة في التحليل واتخاذ القرار بواسطة الذكاء الاصطناعي ممتازة.					
.15	أعتقد أن حجم البيانات التي أعمل معها بانتظام كاف لتحليل البيانات.					
الامتثال التنظيمي RegulatoryCompliance						
.16	تعتبر المعايير التنظيمية والمبادئ التوجيهية الحالية في قطاع الرعاية الصحية الفلسطيني كافية لتقييم الذكاء الاصطناع في الرعاية الصحية					
.17	يساعد التشغيل الآلي على تحسين دقة الامتثال التنظيمي واتساقه من خلال تقليل مخاطر الخطأ البشري.					
.18	تشجع مؤسستي الطبية على إنشاء هيئات وطنية للرقابة على الذكاء الاصطناعي وخوارزميات السياسة العامة التقليدية والأستجابات التنظيمية مثل الترخيص ومراقبة البحث والتطوير.					
الاستعداد المالي Financial Readiness						
.19	تخصص مؤسستي الطبية ميزانية كافية لتغطية التكاليف التأسيسية المرتفعة لاستخدام الذكاء الاصطناعي في العمل .					
.20	يوجد لدى مؤسستي الطبية ميزانية كافية لتغطية تكاليف التشغيل.					
.21	سيكون من السهل الحصول على الدعم المالي من البنوك المحلية و/ أو المؤسسات المالية الأخرى لتبني تقنيات الذكاء الاصطناعي .					

دعم الإدارة العليا Top Management Support						
.22	تقوم الإدارة العليا في مؤسستي الطبية بدعم تبني تقنيات الذكاء الاصطناعي.					
.23	تشجع الإدارة العليا الأطباء و العاملين على تطبيق أحدث تقنيات الذكاء الاصطناعي في العمل اليومي .					
.24	توفر مؤسستنا الطبية مكافآت للموظفين الذين لديهم المهارات والمعرفة المتعلقة بالأنظمة القائمة على الذكاء الاصطناعي.					
الضغط المؤسسي Institutional Pressure						
.25	تعتقد مؤسستي الطبية أن تبني الذكاء الاصطناعي يؤثر على القدرة التنافسية في السوق.					
.26	تساهم تطبيقات الذكاء الاصطناعي في العالم في زيادة الضغط على القطاع الصحي الفلسطيني لتبني التقنيات الحديثة ومواكبة التطورات.					
.27	قامت بعض المؤسسات الطبية المحلية و الإقليمية بالفعل باستخدام الذكاء الاصطناعي لأغراض العلاج و خدمة المرضى					
الفائدة المدركة Perceived Usefulness						
.28	يساعد استخدام الذكاء الاصطناعي في الرعاية الصحية بالتنبؤ بالمخاطر وتقديم التوصيات حيث يمكن تحسين تقديم الرعاية الصحية مثل إدارة المرضى.					
.29	يساعد استخدام الذكاء الاصطناعي في الرعاية الصحيةعلى تحسين التشخيص القائم على الحالة الصحية للمريض والقدرة التنبؤية بشكل كبير .					
.30	يساعد استخدام الذكاء الاصطناعي في الرعاية الصحية على تنفيذ المهام الطبية بطريقة آلية وبسرعة ودقة أعلى وتكلفة اقل .					
سهولة الاستخدام Perceived Ease of Use						
.31	يمكنني بسهولة تعلم استخدام أدوات الذكاء الاصطناعي دون الحاجة إلى تدريب مكثف.					
.32	يمكنني الحصول على إجابة سريعة لاستفساري باستخدام أدوات الذكاء الاصطناعي.					
.33	اعتقد أن أدوات الذكاء الاصطناعي مرنة أثناء التفاعل معها .					
البنية التحتية لتقنية المعلومات IT Infrastructure						
.34	يتوفر شخص (أو مجموعة) محدد للمساعدة في حل صعوبات النظام المحوسب.					
.35	لدي دعم للأجهزة وظروف الشبكة المستخدمة في أدوات الذكاء الاصطناعي.					
.36	يوجد لدي جميع الموارد المطلوبة لتطوير قاعة بيانات تستخدم لعلاج المرضى					

القلق الأخلاقي Ethical Anxiety						
.37	أشعر بالقلق من أن منتجات الذكاء الاصطناعي التوليدية ستجمع الكثير من معلوماتي الشخصية .					
.38	أتردد في استخدام النظام خوفا من ارتكاب أخطاء لا استطيع تصحيحها .					
.39	لا أعرف بالضبط كيف تتخذ أدوات الذكاء الاصطناعي القرارات، مما يجعلني أشعر بالقلق .					
نوايا تبني أدوات الذكاء الاصطناعي Intentions to Adopt Artificial Intelligence Tools						
.40	لدي نية لاستخدام أدوات الذكاء الاصطناعي لتحسين جودة الخدمات الطبية.					
.41	أنا على استعداد أدوات الذكاء الاصطناعي لتقليل التكاليف التشغيلية للمؤسسة.					
.42	لدي نية لاستخدام أدوات الذكاء الاصطناعي حفاظا على البيئة و الصحة العامة.					

نشكرك على وقتك في المشاركة في الاستبيان

Appendix F

Tables

Table 11

Path Coefficients – Indirect Effects

	Original sample (O)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Mediation?
H16	0.012	0.039	0.302	0.763	Not supported
H17	-0.038	0.032	1.165	0.244	Not supported
H18	0.019	0.040	0.472	0.637	Not supported
H19	0.121	0.035	3.447	0.001	Partial
H20	0.079	0.039	1.997	0.046	Complete
H21	0.145	0.046	3.157	0.002	Partial
H22	-0.015	0.039	0.392	0.695	Not supported

جامعة النجاح الوطنية

كلية الدراسات العليا

العوامل المؤثرة على تبني أدوات الذكاء الاصطناعي في قطاع الرعاية الصحية الفلسطيني: دراسة تجريبية

اعداد

نور الدين أديب محمد عزام

إشراف

د. محمدعثمان

قدمت هذه الرسالة استكمالا لمتطلبات الحصول على درجه الماجستير في الادارة الهندسية، من كلية الدراسات العليا، في جامعة النجاح الوطنية، نابلس– فلسطين

2025

العوامل المؤثرة على تبني أدوات الذكاء الاصطناعي في قطاع الرعاية الصحية الفلسطيني: دراسة تجريبية

إعداد
نور الدين أديب محمد عزام
إشراف
الدكتور محمد عثمان

الملخص

في الآونة الأخيرة، شهد استخدام الذكاء الاصطناعي في الرعاية الصحية نموًا كبيرًا. تهدف هذه الدراسة إلى تحديد العوامل والعقبات الرئيسية التي تؤثر على استخدام تقنيات الذكاء الاصطناعي في قطاع الرعاية الصحية الفلسطيني. وتهدف إلى تقديم رؤى قيّمة حول مستوى الثقة والعقبات الأخلاقية التي يواجهها أخصائيو الرعاية الصحية في استخدام أنظمة وأدوات الذكاء الاصطناعي في قطاع الرعاية الصحية. تم استخدام نهج بحثي مختلط لهذا البحث: مقابلات شبه منظمة واستبيانات. تم اعتماد أسلوب أخذ العينات العشوائية للمشاركين من مختلف أماكن الرعاية الصحية، مثل المستشفيات والعيادات ومؤسسات البحث. تم جمع البيانات من 186 مشاركًا يعملون في قطاع الرعاية الصحية. تم تطوير استبيان المسح بناءً على النظريات الراسخة والمقاييس المعتمدة. تم تطوير استبيان منظم لتقييم مستوى الثقة بين أخصائيي الرعاية الصحية في استخدام أنظمة وأدوات الذكاء الاصطناعي. تم استخدام طريقة النمذجة بالمعادلات الهيكلية القائمة على المربعات الصغرى الجزئية (PLS–SEM) لاختبار الفرضيات. أظهرت النتائج أن اعتماد الذكاء الاصطناعي كان مدفوعًا بعدة متغيرات، بما في ذلك الضغط المؤسسي والامتثال القانوني والقلق الأخلاقي، ظهرت اختلافات ملحوظة في التأثيرات الوسيطة لهذه العوامل كمؤشرات مفيدة لفهم ديناميكيات تبني الذكاء الاصطناعي. على سبيل المثال، زيادة الفائدة المتصورة من خلال سهولة الاستخدام المتصورة، ولكن ليس من خلال الاستعداد المالي أو دعم الإدارة العليا. لذلك، على الرغم من أهمية توافر الموارد إلا أنها قد لا تكون كافية لزيادة الفائدة المتصورة أو بناء الثقة أو

تحسين تصورات المستخدم أو نوايا التبني. كما أشارت الدراسة إلى أن التصورات المبكرة لسهولة الاستخدام يمكن أن تفوقها إلى حد كبير تجربة المستخدم النهائي وأداء النظام وجودة التدريب والحوافز الخارجية، مما يعقّد تبني الذكاء الاصطناعي في الرعاية الصحية. تبرز هذه الدراسة لأنها تعمل على قطاع الرعاية الصحية الفلسطيني، والذي لم يحظ باهتمام كبير من الدراسات حول تبني الذكاء الاصطناعي. تقدم هذه الدراسة فحصًا مباشرًا للعوامل المحددة التي تؤثر على قبول الذكاء الاصطناعي في نظام رعاية صحية نامٍ ومحدود الموارد، على الرغم من أن الأبحاث السابقة قد درست نشر الذكاء الاصطناعي في الرعاية الصحية عالميًا. ستعزز النتائج الوعي الذاتي وتخفف من التحيزات وتحسن عملية صنع القرار الأخلاقي فيما يتعلق بتطبيق الذكاء الاصطناعي في قطاع الرعاية الصحية. توفر هذه الدراسة معلومات مفيدة للقادة والأطباء ومطوري التكنولوجيا الذين يرغبون في تعزيز تكامل الذكاء الاصطناعي في بيئات مماثلة من خلال تحديد العقبات والدوافع الفريدة في السياق الفلسطيني.

الكلمات المفتاحية: الذكاء الاصطناعي، نية التبني، قطاع الرعاية الصحية، قبول التكنولوجيا.