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MANAGEMENT INFORMATION SYSTEMS

MASTER´S FINAL WORK

DISSERTATION

HOW AI HAS BEEN IMPACTING THE HEALTHCARE SECTOR

MARIA CAROLINA GONÇALVES FERREIRA

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SUPERVISION:
PROFESSOR ANTÓNIO PALMA DOS REIS

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Para o meu querido pai,

Que estará sempre comigo

I know somewhere there´s
something amazing

Chris Martin, Coldplay

Glossary

AI - Artificial Intelligence

CDSS - Clinical decision support systems

CNNs - Convolutional Neural Networks

CT - Computerized tomography

EHR - Electronic Health Records

IoT - Internet of things

MFW - Master’s Final Work

ML - Machine Learning

MRI - Magnetic Resonance Imaging

NHS - National Health Service

NLP - Natural Language Processing

SPSS - Statistical Package for Social Science

WHO - World Health Organization

Abstract

Artificial Intelligence is an expanding technology across all sectors of society. In the healthcare sector, it has been presented as an innovative solution to face the main challenges affecting health systems on a global scale.

In this way, to understand its impact in the healthcare field, it is necessary to identify not only the areas that could benefit from the use of this technology but also to understand how healthcare professionals perceive the importance of integrating AI into their professional practice.

To this end, a primary investigation was carried out, which identified through the literature review that, at the moment, the main areas where these tools are applied are diagnoses and administration. However, based on the authors consulted, were also studied the advantages and challenges arising from the adoption of AI. The questionnaire was exclusively developed for professionals and students in the healthcare field, in order to investigate their perceptions regarding the advantages, disadvantages, and challenges associated with the implementation of AI tools.

Specifically, it assessed how the variables Training and Confidence contribute to improve the professionals' perceptions about diagnostic accuracy and administrative efficiency, while also exploring how the last one may be responsible for reducing workload and enhancing overall patient satisfaction. This study gathered a sample of 111 responses and was conducted using a quantitative approach, using the statistical software SPSS (Statistical Package for Social Science).

The key findings of this study indicate that the adoption of this technology is associated not only with greater diagnostic accuracy but also with greater administrative efficiency, which consequently leads to overall patient satisfaction and may contribute to the reduction of professional's workload. However, barriers such as data security, ethical concerns, and professionals' resistance, normally associated with lack of training, remain significant challenges to the full adoption of this technology.

KEYWORDS: Artificial Intelligence; Healthcare; Diagnoses Accuracy; Administrative Efficiency; Training; Confidence; Workload; Patients Experience

Resumo

A Inteligência Artificial é uma tecnologia em expansão em todos os setores da sociedade. No setor da saúde tem sido apresentada como uma solução inovadora para fazer frente aos principais desafios que afetam os sistemas de saúde a nível global.

Deste modo, para compreender os seus impactos na área da saúde, é necessário perceber não só quais as áreas que poderão beneficiar com a utilização desta tecnologia, mas também perceber de que forma os profissionais de saúde percecionam a importância de integrar IA na sua prática profissional.

Neste sentido, foi realizada uma investigação primária, que identificou através da revisão da literatura, que neste momento, as áreas predominantes onde estas ferramentas estão presentes são nas áreas do diagnóstico e da administração. Contudo, e tendo por base os autores consultados, foram ainda estudadas as vantagens e desafios decorrentes da adoção de IA. O questionário desenvolvido, exclusivamente para profissionais e estudantes da área da saúde, teve como objetivo investigar as perceções dos mesmos sobre as vantagens, desvantagens e desafios associados à implementação de ferramentas de IA.

Concretamente, aferiu-se de que forma as variáveis Treino e Confiança contribuem para melhorar perceção sobre precisão de diagnóstico e eficiência administrativa, e ao mesmo tempo perceber como esta última, poderá ser responsável pela redução da carga de trabalho e satisfação geral do paciente. O estudo contou com uma amostra de 111 respostas e foi realizado numa abordagem quantitativa, utilizando o software estatístico SPSS (*Statistical Package for Social Science*).

A análise dos resultados, indica que a adoção desta tecnologia está associada não só a uma maior precisão diagnóstica, mas também a uma maior eficiência administrativa, o que consequentemente gera uma satisfação geral nos utentes e poderá contribuir para a redução da carga de trabalho dos profissionais. No entanto, barreiras como a segurança dos dados, preocupações éticas e resistência dos profissionais, que estão normalmente associadas à falta de formação, continuam a ser desafios significativos que condicionam a adoção plena desta tecnologia.

KEYWORDS: Inteligência Artificial; Setor da Saúde; Precisão dos Diagnósticos; Eficiência Administrativa; Treino; Confiança; Carga de Trabalho; Experiência do Utente

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1.Introduction

1.1 Context

The world as we know it is changing at a mind-blowing pace, driven by tremendous investment in new technologies over recent years. According to the International Data Corporation (2023), companies worldwide invested 166 billion dollars in artificial intelligence solutions.

Although the previous investment was already considered very significant, in January 2025 a never-seen record was broken. According to CNN, the current President of the United States announced a ground-breaking investment of 500 billion dollars in AI infrastructure in the country (Duffy,2025).

This extraordinary investment in AI is redefining companies' horizons and restructuring business models. As well as reflecting a trend, it reflects an urgent need to adapt and innovate, driving a new era of opportunity and accelerated growth. The impact on various sectors has been remarkable, and healthcare is no exception. In recent years, healthcare has undergone significant changes in different areas of healthcare, with a special impact on medical diagnosis, achieving remarkable levels of accuracy and personalised treatments based on each patient's profile (Rajkomar et al.,2019).

Additionally, it is enhancing administrative efficiency, allowing hospitals to optimise data management, streamline operations, reallocate resources more effectively and provide clinical decision support by analysing medical histories and leveraging vast datasets. By doing that, it provides evidence-based recommendations that contribute to more accurate, safer, and more efficient healthcare. These advancements enhance and refine the essence of medical practice, bridging the gap between technology and human expertise and leading to improved patient outcomes, which will be reflected in an improved quality of life and average life expectancy (Reddy et al., 2019).

However, despite the benefits mentioned above about adopting AI tools, there are also several challenges that need to be explored and considered. This raises pertinent questions such as: Are we really ready for this revolution? As algorithms become increasingly important in medical decisions, complex challenges arise: Will patients' data be adequately protected? (Smeaton & Christie, 2020) How will governments in different countries manage to create laws that ensure the safe use of patients' clinical data? (Shaw et al.,2019) Will algorithmic biases compromise diagnoses, and will technological barriers perpetuate health inequalities? (Ratwani et al.,2024).

1.2 Objectives

The main objective of this dissertation was to comprehend the real impacts of Artificial Intelligence in the healthcare sector, focusing on investigating the areas of healthcare that currently utilise this technology the most, as well as presenting the benefits and challenges of its implementation, while always taking into consideration the professionals' perceptions. To achieve the objective, a methodology was developed to study the hypotheses derived from the literature review, articulating the analysis of the benefits and challenges of AI in two key areas: diagnostics and administration. The developed survey is specifically designed for healthcare professionals and students, who are the target population of this study.

1.3 Structure of the Document

After the introduction, this dissertation contains four more chapters.

Chapter two presents the literature review, which is subdivided into four subchapters that aim to explore the fundamental concepts of AI, how it began to be used, the evolution it has undergone in recent decades, as well as the main areas of activity, its benefits, and challenges.

The third chapter develops and justifies the adopted methodology, detailing the hypotheses under study. This section also includes a comprehensive explanation of the survey conducted, a summary of the ethical considerations involved, and a description of the sample collected.

Chapter four presents the results obtained from the questionnaire, along with a detailed analysis and a discussion of the results. Finally, the fifth chapter concludes the project by addressing the research questions and objectives outlined, presenting the main contributions of the study, highlighting existing limitations, and offering suggestions for future research.

2. Literature Review

2.1 Introduction to AI

Even if indirectly, the first use of the term Artificial Intelligence dates back to 1950, when Alan Turing began to explore the concept through the “Imitation Game”, in which he proposed that true intelligence could be demonstrated if a machine could impersonate a human being (Turing,1950). More than half a century later, this research continues to be the talk of researchers and marks the transition between optimistic expectations and a more pragmatic view of the challenges involved in developing machine intelligence (French, 2000).

Another important date goes back to 1956, when the researchers at the Dartmouth Summer Research Project, began studying AI as a scientific discipline. According to the authors Trigo-Guedes and Palma-dos-Reis (2019, p. 2), from this meeting it was possible to assume that any type of knowledge could be described and reduced to something so precise and accurate that it could be simulated by any machine. The research directions defined during the project have evolved into the foundational technologies that helped advance research in machine intelligence and drive innovations in modern AI, but besides that also defined key research directions that remain relevant today (McCarthy et al., 2006).

Artificial intelligence can be classified as a science that uses algorithms and complex mathematical models to create systems capable of processing a large amount of data and information. As noted by Du-Harpur et al. (2022, p.424), AI refers to the use of algorithms and statistical models that learn from labelled training data, from which they can recognize and infer patterns.

For the proper work of this technology, it must first be trained with sets of data so that the system is able to recognize patterns and consequently solve problems and make decisions based on these inputs. In simplest terms, it can be defined as a system that imitates and simulates the human mind's intelligence (Rigillo, 2023).

From the earlier years has emerged as an extremely useful and transformative tool in several sectors, facilitating decision-making and offering a competitive advantage for the companies that use it. The health sector stands to gain significantly from the use of AI, as it has vast potential for dealing with the exponential growth of clinical data, as well as addressing the complexities in providing diagnoses. It can analyze medical images to detect diseases at early stages, assist in patient outcomes and streamline administrative workflows (Rajkomar et al., 2019). These advancements not only improve efficiency but also enhance the accuracy and timeliness of care, solidifying AI´s role as an indispensable tool in modern healthcare (Rajkomar et al., 2019).

2.2 Evolution of AI on HealthCare Sector

In the health sector, the first developments incorporating AI tools took place between 1970 and 1980, with the creation of specialized systems capable of helping professionals make decisions based on specific information. One of the most important examples in this area was the integration of this technology into a system called HELP (Health Evaluation through Logical Processing) developed at the University of Utah. This pioneering system combined the storage and management of health data, allowing data to be saved on disk and new medical data to be added to the patient's file whenever necessary (Warner, 1973). In addition, HELP was able to monitor functions in real-time and collaborate to support decision-making, as it kept personal information on each patient and provided reports, scoped displays and alarm indicators for each of them. Therefore, it can be said that the development of systems like HELP seems to have paved the way for the adoption of more advanced AI technologies in healthcare, making them suitable for today´s needs.

In parallel with the system mentioned above, another important AI-based consultation system, the MYCIN, was created in 1972 at Stanford University. This system aimed to diagnose and recommend a therapy selection for patients with bacterial infections based on reported symptoms and medical test results. The system's knowledge was encoded in the form of some 350 production rules that embody the clinical decision criteria of infection disease experts (van Melle, 1978). Despite the promising advantages of this system, it is important to mention that due to ethical and legal issues surrounding the use of computers in medicine, the resistance shown by many doctors and the high cost of adopting this technology resulted that the system has not been widely adopted (Shortliffe, 1977; Copeland, 2018; Rajkomar et al., 2019).

The type of programming used in the systems mentioned above is not comparable to the programming methods used today. Traditional systems were programmed with rules and principles, while these new tools that incorporate AI use Machine Learning to program algorithms that derive from statistical rules and logical data. These algorithms learn from the patterns of health trajectories of numerous patients, which enables superhuman performance (Rajkomar et al., 2019). One of the most recent innovations is deep learning, which can be classified as a subset of ML capable of training itself to perform tasks like speech and image recognition through CNNs, capable of learning extremely complex relationships between features and labels to provide diagnoses from medical images with accuracy comparable to or greater than human capabilities (Liang et al., 2014; LeCun, 2015; Miotto et al., 2018).

2.3 Actual Applications and Benefits of AI

In recent years, the healthcare sector has experienced a remarkable development with the arrival of what many refer to as “Healthcare 5.0”. At a theoretical level, this concept mainly consists of the integrated use of emerging technologies, including Smart IoT devices, 5G communication services, AI- tools, big data analytics, cloud computing, and blockchain. The combination of these technologies allows on the centralisation of the patient as the protagonist of their treatment, i.e., the patient allows their clinical data, monitored by personal devices, to be provided to the doctors so that they can make the most of the patient's information honestly and transparently so that the treatments are as effective as possible. The approach considers the individual needs of each patient, resulting in a more personalised and humanised experience (Wu et al., 2024).

Integrating emerging technologies enables the full exploitation of the synergies resulting from their use. For example, using a smartwatch to measure patients' heartbeats uses IoT for connectivity while relying on Big Data to store and analyse the vast amount of data generated (Reddy et al., 2019). The growing prevalence of personal devices for monitoring clinical data is increasingly evident. According to the report "Smart Wearables Statistics 2025 By Devices, Technology, Usage" by Market.us Scoop, the use of smartwatches has risen significantly, from 213 million in 2022 to an estimated 454 million by the end of 2024, and it is expected to continue growing in the coming years.

The exponential use of these devices makes it possible to monitor vital signs such as heart rate, oxygen levels, blood alcohol, blood pressure, glucose and if abnormalities are detected, these devices automatically send alerts to the user so that they seek medical help as soon as possible (Reddy et al., 2019). The early identification of health problems such as cardiac arrhythmias (which can be detected by most wearables) results in more effective treatments that can save countless lives and provide a better quality of life (Wazid et al., 2022).

2.3.1 Diagnostics Accuracy

The traditional methods of diagnosis rely on the subjective interpretation of professionals, which can sometimes lead to ambiguities and uncertainties regarding the patient's actual problem and, consequently, inadequate treatment to combat the disease. For all these reasons, the integration of AI tools in the area of diagnosis promises to revolutionize and bring numerous benefits to users. According to the authors, AI-assisted diagnostic tools are already becoming a crucial aid in various healthcare specialities, such as the recognition of patterns in exams, including Magnetic Resonance Imaging (MRI), X-rays, and Computerized tomography (CT) scans (Wazid et al., 2022). In several cases, by interpreting the images resulting from scans, AI systems are already able to detect bone fractures in real-time and distinguish between malignant and benign tumours (Hosny et al., 2018; Smeaton & Christie, 2020).

Looking at the experience of Tian et al. (2023) for the Academic Journal of Science and Technology, which used data from several patients to test the performance of CNN models on various types of medical images, such as X-rays, computed tomography, magnetic resonance, and ultrasound images. Based on the results obtained, it was possible to verify that all the CNN models submitted for testing demonstrated much greater precision when compared to traditional methods. For example, when processing X-ray images, the accuracy of the CNN model was as high as 94%, compared to 88% for traditional diagnostics, indicating that AI is more accurate in identifying relevant pathological features. It can also be concluded that when excluding non-cases, CNN showed a specificity of 93%, indicating that it also has advantages in avoiding diagnostic errors. It can, therefore, be easily understood that the application of AI in the field of medical diagnosis provides a valuable reference for future technological applications (Tian et al.,.2023).

AI can reduce the variability of outcomes by providing consistent, data-driven insights, leading to more reliable diagnoses. As stated by the "World Economic Forum", when breast cancer is detected at stage one, the five-year survival rate is over 90%; although it cannot be overstated, the early detection of diseases such as heart attacks, liver cirrhosis, cancer, brain seizures, diabetes, asthma, and other conditions, allows for more targeted and effective diagnosis, treatment, and medication. Early detection improves the chances of increasing life expectancy and enables individuals to live with higher quality (Reddy et al., 2019).

2.3.2 Administrative Efficiency

AI emerges as a promising solution with the potential to revolutionize the landscape of hospital management practices such as efficiency, accuracy, and overall effectiveness (Najjar,2023). The importance of AI goes far beyond mere technological innovation; it signifies a transformation in the operational framework of healthcare institutions. One of the most impactful applications of AI is also in data management. This technology transforms how hospitals handle vast amounts of healthcare information within hospital administration by ensuring rapid access to relevant pertinent patient data. It addresses the challenge of information overload, allowing healthcare organizations to collect actionable insights from vast datasets (Bhagat & Kanyal, 2024).

AI also plays a pivotal role in streamlining operations to address challenges such as resource constraints and the increasing demand for personalized and efficient healthcare services. In this area, there is potential for AI tools to help with tasks such as: intelligent scheduling, staff allocation and execution of other routine tasks that could result in greater productivity, affording healthcare professionals more time to dedicate to direct patient care (Bhagat & Kanyal, 2024). Additionally, AI can also predict absences and automatically send reminders to patients so that they don't forget their appointments. This logistical and administrative automation helps to reduce no-show rates and improve overall efficiency in healthcare delivery (Smeaton & Christie, 2020).

Besides that, it also addresses opportunities for resource allocation by optimising it across various domains, such as staffing levels, medical supplies, and facility utilisation, by scrutinising historical data, current trends, and future projections. The power that AI has in analysing hundreds of data points contributes to the use of predictive analytics to save on costs and better utilise resources, fostering a healthcare system more responsive to the dynamic demands of patient care (Bhagat & Kanyal, 2024). The predictive nature of AI in resource allocation enables hospitals to proactively adjust their operations, minimising waste and maximising the impact of available resources (Reddy et al., 2019).

2.3.3 Patient Monitoring and Self-Management

AI tools can also be used to monitor hospitalised patients (Ellis,2024). The adoption of waveform pattern learning has contributed significantly to improving monitoring in more complex hospital environments, as it has shown efficacy in analysing electrocardiograms, electroencephalograms, electromyographs, and Doppler ultrasounds.

These advances are particularly relevant in critical hospital environments, such as intensive care units, where AI-enabled software can interpret vital signs for cardiovascular and respiratory monitoring, providing more accurate analysis and faster interventions (Reddy et al., 2019).

In addition to using AI in more critical situations, this tool can also be used for patients who have been discharged. For example, the possibility of using chatbots, virtual assistants, and intelligent wearables enabled by NLP (Natural Language Processing) means that these systems can interpret patients' questions, provide health advice, and suggest making an appointment with a professional whenever necessary. This "triage" carried out by these assistants could prevent unnecessary hospital visits, thereby avoiding overcrowding and overloading professionals (Smeaton & Christie, 2020).

The monitoring of patients with AI represents a transformative milestone in healthcare, enabling continuous and personalised monitoring. However, it is essential to ensure that these systems are aligned with the specific needs of each patient, ensuring that the benefits offered are fully achieved (Reddy et al., 2019).

2.3.4 Clinical decision support

In clinical decision support (CDSS), AI has become a crucial tool. CDSS have evolved significantly with the integration of AI techniques that can support clinicians with tasks, including prescribing medications, diagnosing conditions, and identifying patients at risk of adverse events (Smeaton & Christie, 2020). In this specific area, AI has the power to analyse millions of medical histories and leverage vast datasets. Considering this capacity to deal with data, this powerful feature offers evidence-based recommendations, contributing to more accurate, safe, and efficient care. These systems utilise clinical data and medical knowledge to assist healthcare professionals in making informed decisions, reducing errors, and improving healthcare consistency (Elhaddad & Hamam, 2024).

The integration of predictive analytics applications in healthcare is becoming increasingly common. Given this significant advancement, healthcare organizations can now analyse complex patterns in patient records, treatment histories, and demographics to identify high-risk patients and develop targeted interventions more accurately (Bhagat & Kanyal, 2024).

According to a study by Innowise, the Healthcare predictive analytics Market Size is expected to skyrocket from $ 14.51 billion in 2023 to $ 154.61 billion in 2034 as it integrates information from Electronic Health Records (EHRs), claims databases, and wearables. These advanced platforms use ML and advanced analytics to identify the likelihood of future outcomes based on historical data (Alexdev,2024).

Additionally to the mentioned above, it is important to consider a study from Indiana University, which found that the predictive capacity of machine learning algorithms; which is that the AI Framework employing sequential decision-making can recommend alternative treatment plans, infer patients' health status even when measurements are not available, and refine treatment plans as new information is received. Considering everything that was mentioned it is easy to understand that the continuous use of predictive analytics could be a significant competitive advantage for healthcare professionals, as it enables the implementation of timely interventions, thereby enhancing the quality of care and optimising resource utilisation within the healthcare system (Bhagat & Kanyal, 2024).

2.4 Challenges and Limitations of AI on Healthcare Sector

2.4.1 Data Privacy and Security

AI has brought numerous benefits to the sector, but unfortunately, its implementation also carries significant risks and limitations. The most important challenges are related to data privacy and security. Concerns that the widespread use of AI in healthcare increases the potential for cyberattacks (Smeaton & Christie,2020). The need to share large data sets with external programmers during AI development can increase the risks of a data breach, as well as the risk of a hacker defrauding the healthcare system to extract patient data (Finlayson et al.,2019).

Contributing to increasing the concerns about data privacy, the use of wearables is right now under investigation due to their primary function of continuously monitoring and collecting sensitive data, such as the user's location, physical activity level and mental health as this is such sensitive and private data, it must be protected (Mamdiwar et al.,2021). Additionally, the concerns are even deeper when authors such as Junaid et al., (2022) defend that right now there is currently no comprehensive solution to handle all the possible security and privacy issues posed by wearable sensors, thus further research and development is necessary to enhance the security and privacy elements of wearable devices.

According to the United Nations, the urge of ransomware attacks is putting the world healthcare infrastructure at critical risk, destabilizing health systems and consequently endangering patient safety. In 2023, total ransomware payments reached $1.1 billion; the problem has been increasing over the years mainly because of the discrepancy of investment in security across the different sectors; for instance, a survey of the Healthcare Information and Management Systems Society concluded that US healthcare organizations allocate an average of 7% of spending to cybersecurity, whereas the average amount spent across sectors is about 11%–12%. So, as noted by UN Director-General Tedros Adhanom Ghebreyesus, it's crucial to invest in cybersecurity to protect healthcare facilities because they are not just issues of security and confidentiality, they can be issues of life and death (Mishra,2024).

2.4.2 Diagnostic Challenges and Algorithm Bias

In addition to the challenges of data security, another significant obstacle revolves around AI diagnostic capabilities, especially when it comes to more complex patients and diseases. These concerns are related to potential risks, including misdiagnosis and perpetuation of bias in AI systems. For instance, this bias may arise without considering the differences in disease presentation between populations of different ethnicities (FitzGerald & Hurst,2017).

According to Obermeyer et al., (2019) the U.S. healthcare systems uses commercial algorithms to guide health decisions. These algorithms are programmed to consider black patients to be sicker than white patients, pointing to evidence of racial bias. This algorithm used health care costs as its target variable, underrepresenting black patients due to systemic barriers to access to care despite having a significant burden of illness (Ratwani et al.,2024). As a result, it appears that this racial bias reduces the number of black patients identified for extra care for “more than half”. The algorithm thus falsely concludes that black patients are healthier than equally sick white patients, which leads to impacting diagnosis accuracy and potentially leading to wrong care outcomes (Ratwani et al.,2024).

2.4.3 Technological and Operational Barriers

Compounding these issues is the matter of intellectual property, which presents its own unique set of challenges. Issues such as unlicensed content in training data, copyright, patent, and trademark issues with AI creations (Lorenz et al.,2023). The fact that most healthcare systems are not compatible with the latest AI solutions reveals another problem because updating these systems to accommodate AI can be costly and time-consuming, requiring significant investments in technology and training for healthcare professionals (Mulukuntla, 2022). Incorporating AI into healthcare systems requires significant technological upgrades, a solid data architecture and staff training to bridge knowledge gaps. As adapting to AI-driven methods often requires changes to established workflows and practices, it can provoke resistance from most traditional healthcare providers (Dankwa-Mullan,2024).

2.4.4 Regulatory and Ethical Concerns

The integration of AI in healthcare introduces a complex ethical and legal landscape; as countries and international bodies strive to keep up with technological advances, they face the challenge of developing regulations that guarantee patient safety and data privacy without stifling innovation (Shaw et al.,2019). The fact is that AI-driven decision-making necessitates the establishment of clear guidelines for accountability, so healthcare institutions must navigate these challenges by defining the roles and responsibilities of human operators and ensuring transparency in decision-making processes. It is also essential that communication and dissemination about the use of AI and its possible implications for patients is transparent and understandable, as they should have a clear understanding of the risks and benefits they may face (Naik et al., 2022).

In the regulation Ethics and Governance of Artificial Intelligence for Health, the WHO (World Health Organization) proposed ethical principles for the use of AI to deal with the growing concerns about the use of AI. However, the practical implementation of these principles is still in its early stages. According to WHO guidance, one major issue with regulations is that they often fail to keep pace with rapid technological advancements, resulting in an entrance into the market without adequate regulatory oversight, so establishing ethical frameworks and legal precedents that govern liability in AI-related incidents is essential for fostering trust among healthcare professionals, patients, and stakeholders (Naik et al., 2022).

2.4.5 Overreliance on AI in Clinical Practice

Lastly, there is a risk that healthcare professionals may degrade traditional clinical skills. According to the article "Navigating the Fine Line: Technology vs Human Insight in Decision Making": excessive dependence on technology could lead to a loss of ability to make diagnoses or decisions without technological assistance. According to Exam magazine, in 2024, technology outages affected 140 hospitals in the UK, resulting in nearly 20,000 cancelled hospital appointments and operations. As a consequence, National Health Service (NHS) professionals had to revert to using pen and paper to record test results due to limited access to computerized records.

Although AI algorithms have already been trained for many years, the fact is that we are still in the early stages of using AI algorithms so the possibility of errors is very high, and in complex cases or rare conditions, it can result in incorrect diagnoses and, consequently, inadequate treatment. For this reason, it is extremely crucial that healthcare professionals do not practice blind acceptance of AI recommendations without questioning or validating decisions, because it can lead to a loss of critical judgment. Plus, minimizing direct interaction between patients and doctors can emotionally affect patients, leading them to question and lose interest in finding solutions to their problems. This dependency could lead to a devaluation of traditional clinical skills and judgment, potentially eroding the quality of care (Shaw et al.,2019).

2.5 Hypotheses Elaboration

The hypotheses developed are directly related to the results observed during the analysis carried out in the literature review. According to the literature, the primary areas in which AI tools are currently used are diagnosis and administration. Taking the aforementioned areas into consideration, an investigation was conducted to understand how the concepts of training, confidence, workload, and patient experience are associated with each respective area. With this objective, the perceptions of healthcare professionals were taken into account.

2.5.1 The Importance of Training

These hypotheses (H1) and (H2) were formulated to recognise that the successful implementation of AI in the health sector depends not only on technological advancements but also on the training and skills of health professionals (Dankwa-Mullan,2024).

Studies have shown that the application of AI algorithms, especially those based on ML and DL, can analyse medical images and patient data with higher accuracy. For example, Tian et al. (2023) indicated that AI-based methods were more accurate than traditional diagnostic methods, suggesting that AI is more sensitive and, therefore, more accurate in identifying relevant pathological features.

In addition to the direct impact on clinical practice, the level of training in AI also proves to be relevant in the administrative sphere, as many AI-based systems are implemented to optimise routine processes (Najjar, 2023; Bhagat & Kanyal, 2024).

However, it is necessary to understand that the correct use of this technology in both areas requires a solid understanding among healthcare professionals. As noted by Dankwa-Mullan (2024), Mulukuntla (2022), and Chaves Cano & Pérez Gamboa (2024), the use of AI tools requires adequate training to ensure that professionals are familiar with their proper application. This training allows for bridging knowledge gaps and ensures efficient integration into workflows.

So, it is possible to understand that the lack of training can lead to inappropriate use of these tools, potentially compromising patient safety; being reasonable to assume that trained professionals are better equipped to accurately interpret the results generated by algorithms and integrate them into their decision-making processes, improving the accuracy of diagnoses and administrative processes.

In this context, the study aims to empirically evaluate whether health professionals acknowledge that training can positively impact clinical and operational areas. Consequently, two hypotheses were formulated:

H1: Health professionals consider that Training in AI has a positive influence on the Accuracy of Diagnoses.

H2: Health professionals consider that Training in AI has a positive influence on the Administrative Efficiency.

2.5.2 The Importance of professional's Confidence

Besides the necessity of adequate levels of training to use AI tools, "Confidence" in these tools is revealed to be a key variable in the adoption of this technology. Regardless of the area of application, the level of user confidence is directly related to the benefits perceived in the performance of their duties (Finlayson et al., 2019; Dankwa-Mullan,2024).

In the clinical field, AI has demonstrated promising results in improving the accuracy of diagnoses, particularly through the analysis of medical examinations, such as X-rays and CT scans (Smeaton & Christie, 2020; Tian et al., 2023). The correct use of these technologies has the potential to reduce diagnostic errors, enabling earlier detection of diseases (Hosny, 2018; Reddy, 2019).

While AI can bring advantages to the clinical field, it can also revolutionise administrative processes by optimising bureaucratic and routine tasks, such as resource allocation and data management (Najjar, 2023; Bhagat & Kanyal, 2024).

In both cases, professional's confidence is crucial for the effective use of technology and for achieving the expected results. So, on the other hand, this confidence can be compromised due to concerns about data privacy, system security, ethical risks, and potential programming errors in AI algorithms (Shaw et al., 2019; Mamdwar et al., 2021).

Based on the assumption that confidence acts as a vital facilitator for the successful adoption of AI in the health sector, the study of hypotheses H3 and H4 aims to evaluate if the level of confidence perceived by professionals can positively impact clinical and administrative areas. Consequently, two hypotheses were formulated:

H3: Professionals consider that higher Confidence in AI is associated with improved Diagnostic Accuracy.

H4: Professionals consider that higher Confidence in AI is associated with improved Administrative Efficiency

2.5.3 Workload Reduction

The use of AI in healthcare promises to revolutionise the way professionals manage healthcare institutions. This promising innovation aims to change clinical management practices forever, promoting gains in efficiency and effectiveness (Najjar, 2023). Specifically, these improvements involve optimising workflows by automating routine tasks and efficiently managing professionals' schedules based on historical data and projections (Bhagat & Kanyal, 2024).Researches indicates that AI improves administrative efficiency by relieving the operational pressures that traditionally fall on professionals and, for that reason, allows them to focus on critical functions, such as direct patient care (Topol, 2019), which may lead to a reduction in their overall workload.

As a result, the fifth hypothesis (H5) was formulated to determine whether healthcare professionals recognise that the adoption of AI in administrative efficiency helps to reduce their workload:

H5: Healthcare professionals consider that Administrative Efficiency contributes to Workload reduction.

2.5.4 Patients Experience

For the patients, at a very first glance, the administrative efficiency seems to have no effect at all. In fact, it is quite the opposite; AI tends to have an indirect but substantial impact on the quality of the user experience. The management of administrative processes, such as resource allocation, contributes to clear communication and optimization of appointments and exams scheduling. This, in turn, reduces response times and enables a quicker response to users' needs (Parry et al., 2023; Bhagat & Kanyal, 2024).

Additionally, AI's ability to automatically predict appointment absences and send personalised reminders to patients (Smeaton & Christie, 2020) contributes to minimising absences, increasing the efficiency of care provision.

Intelligent resource allocation based on predictive analytics Reddy et al. (2019), ensures that resources are better prepared to meet demand. This creates a more organised and efficient clinical environment, which professionals associate with an improved user experience.

This hypothesis aims to assess whether healthcare professionals perceive AI as a tool that improves the patient experience by reducing delays in medical care. By analysing survey responses, this research will provide empirical information on the effectiveness of AI in improving the patient's overall experience and validate the following hypothesis:

H6: Healthcare professionals consider that Administrative Efficiency positively influences the Patient Experience.

The conceptual model, created through the literature review, is a visual summary of the hypotheses mentioned above and was adapted based on the variables identified about the adoption of AI in the health sector, as shown in Figure 1.

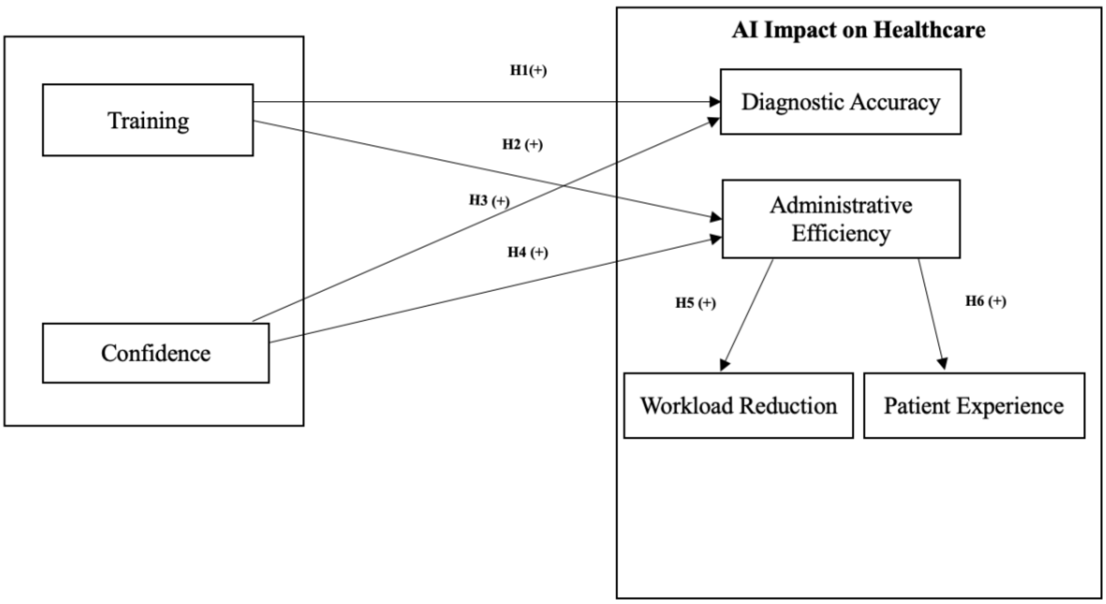

Figure 1- Conceptual Model of AI Impact on Healthcare (Hypotheses Overview)

3. Methodology

This section describes the process of the data collection model and the relevant analyses that will be carried out during the research, with the main objective of validating the hypotheses under study. To validate the hypotheses, were defined and executed three stages: developing a survey, collecting, and interpreting data, and finally, conducting a statistical analysis.

3.1 Justification for the Quantitative Methodology

For this study, a quantitative methodology was selected since this method makes it possible to objectively measure health professionals' perceptions about the adoption of AI, providing structured statistical data, facilitating the analysis and interpretation of the results, as well as supporting the validation of the hypotheses formulated (Ghanad,2023).

Considering that the hypotheses were designed to analyse the perceptions, benefits, and challenges of AI in healthcare, collecting data through the questionnaire makes it possible to: quantify the degree to which respondents agree with the accuracy of AI-assisted diagnoses and administrative efficiency. Determine percentages and patterns of use in hospitals and clinics and statistically evaluate whether training and confidence influence perceptions about this technology.

The quantitative analysis enables the use of statistical tools to identify significant trends, correlations, and patterns in the collected data (Ghanad, 2023). It is thus possible to verify whether there is a consensus among health professionals on the current usefulness of AI, measure their perception of data security, and determine whether there is a relationship between this variable and resistance to the adoption of AI.

In this way, this methodology enables an objective and representative assessment, guaranteeing rigorous statistical analysis and allowing general trends to be identified among a large number of participants.

The questionnaire developed includes various types of questions with different response scales: Likert, checkboxes, and multiple-choice options. This inclusion allows for the collection of qualitative data that complements and enriches the analysis by providing insights into the reasons behind some of the quantitative responses.
It also pretends to value the opinions of professionals and students because, in this specific case, personal and human experiences can carry significant weight.

This approach can lead to new ideas that may not have been considered in the closed questions and considering that paving the way for future research. (Creswell & Creswell, 2018, p.11).

3.2 Survey

Based on the hypotheses to be investigated, a survey was conducted following the objectives of this study. The Google Forms platform was used for this survey.

First, a pre-test was carried out on three participants to identify any problems, such as syntax errors and respondents' perceptions about each question.

After identifying the problems, the necessary corrections were made. Some questions that raised doubts were rewritten for clarity and directness, while others were eliminated altogether. With these adjustments in place, an online pilot test was conducted, surveying six individuals to ensure that the model and the selected platform functioned properly and met the required quality standards.

After implementing all the necessary changes, the questionnaire was made available to the target audience; the requests were sent to health professionals, as well as to the most varied public and private organisations, so that they could share it internally, which required intensive research on various online platforms. The requests were sent via social networks and email.

The survey is composed of 35 (thirty-five) questions, organised into seven groups, which cover different aspects of the research. To reach a wider audience, respondents can choose to complete the survey in either Portuguese or English after opening the provided link.

The first group consists of a presentation of the survey that is intended to be developed based on the topic under investigation. A brief explanation of the study's main objectives is presented, reinforcing the purpose of analysing the perceptions of professionals and students in the healthcare field. This reinforces that the study is exclusively directed at them. There are also provided instructions on how to complete the questionnaire, emphasising the anonymity of the respondents' personal data. At the end of this group, the first question regarding the preferred language of response is presented.

The second group is made up of sociodemographic questions designed to gather information such as nationality, age, gender, educational qualifications, professional area or field study. Based on their previous answer, if the participants are health professionals, they will be directed to specify the type of institution in which they work (public or private). Otherwise, they will be directed to the next question, which seeks to determine how long they have been studying in the health area.

The third and fourth groups aim to investigate professionals' and students' understanding of AI application topics in specific areas, such as diagnostic accuracy and administrative efficiency. These sections present questions with several answer options, multiple-choice questions, and statements with Likert scales ranging from 1 to 5 in order to measure its current relevance and how professionals perceive it.

The fifth group aims to explore healthcare professionals' perceptions about the benefits, challenges, and barriers. The sixth group intends to investigate how important the participants consider it to receive training to develop the necessary skills for working with AI tools.

Most of the answers to the questions presented in the different groups use a Likert scale: 1 - Strongly disagree; 2 - Disagree; 3- No opinion; 4 - Agree; 5 - Strongly agree, but in addition to this, some other questions also offer multiple-choice answers, allowing a greater diversity of opinions to be captured, improving the quality of the data collected and making the analysis richer and more comprehensive to understand the real impact of the technology under study.

Finally, the last group consists of an open and optional question to understand whether there is any additional impact of AI on the respondent's professional practice.

At the end of the questionnaire, the inquirers are thanked for their attention and willingness to participate. A message is also displayed, asking respondents to invite new participants from their network of friends and connections. This feature is intended to facilitate link sharing, consequently contributing to a significant increase in the survey's outreach. The questionnaire is presented in detail in Appendix I.

3.3 Ethical Considerations

During the preparation of the study, the importance of keeping the inquirers informed about what would happen during the survey was always taken into consideration. For this reason, in the first group of the population survey, a brief introduction to the topic was given, along with a description of the aim of the study, the methodology adopted and an explanation of how the data collected would be used so that the participants could understand the research proposals.

One of the main concerns was to ensure that the participant's data was stored and processed anonymously and thus ensure that no personal information could be identified during data collection. Additionally, they were also informed that they could leave the survey at any time without any penalty.

Taking into consideration academic integrity and impartiality, the data collected was used exclusively for scientific purposes and was not manipulated to support biased results, guaranteeing the transparency and reliability of the results.

3.4 Sample Characterisation

The target population for the survey was a very specific group within society: students and professionals from the healthcare sector. For that reason, it was necessary to use a method called "snowball sampling", which consists of a non-probabilistic technique in which invited participants select additional participants. A screening question ensured that only those with academic or professional experience in health could access the rest of the questionnaire. As a result, the final sample is composed exclusively of individuals from the healthcare field.

The sample is composed of 111 individuals, of which 84.7% are females and the rest are males (Table 1). In terms of age group, according to Table 2, those aged between 20-29 account for 26.1 % of the sample, and the second largest age group belongs to the 60-69 bracket (24.3 %).

Despite the efforts made to diversify the nationality of the participants in order to receive insights from different cultures, it can be seen from Table 3, that the total number of respondents is exclusively of Portuguese nationality.

Of the total number of people surveyed, it is possible to see (Table 4), that around 52.3% have a bachelor's degree, and the second highest group (19.8%) has a Postgraduate degree, while the master's degree accounts for 18% of the sample. When asked about the number of years they have been working or studying in the health sector, the largest percentage (33.4%) said they had been working for more than 30 years, and the second largest group (22.5%) said they had been working for between 11 and 20 years (Table 5).

When asked about their current situation (Table 6), 81.1 % are health professionals, while the rest are students in the same field. Of those who indicated that they were professionals (Table 7), 65.6% belonged to the professional career of nursing and (13.3%) in medicine, with the rest of the sample indicating that they were other types of professionals. Regarding those who indicated that they are students in the area, (38%)

indicated that they are studying nursing. In comparison, others (38%) indicate that they are studying medicine, while the rest are pursuing studies in another field (Table 8).

Finally, from Table 9, it is possible to understand that the vast majority of the sample (68.9%) work in a public institution, and taking into consideration this percentage, (38.7%) mention that they work in a hospital (Table 10). The remainder (23.3%) work in a private institution (Table 9), of which 47.6% say they work in a hospital (Table 10).

Gender	Frequency	%
Female	94	84.7%
Male	17	15.3%

Table 1- Gender

Age Group	Frequency	%
20–29	29	26.1%
30–39	20	18%
40–49	18	16.2%
50–59	15	13.5%
60–69	27	24.3%
≥70	2	1.8%

Table 2- Age Group

Nationality	Frequency	%
Portuguese	111	100%

Table 3- Nationality

Qualifications	Frequency	%
High School	10	9%
Bachelor's Degree	58	52.3%
Master	20	18%
Post Grad.	22	19.8%
PhD	1	0.9%

Table 4- Qualifications

NºYears Working/Studying on health sector	Frequency	%
<1	4	3.6%
1–5	24	21.6%
6–10	10	9%
11–20	25	22.5%
21–30	11	9.9%
>30	37	33.4%

Table 5- Nº Years Working/Studying on health sector

Situation	Frequency	%
Health Professional	90	81.1%
Student	21	18.9%

Table 6- Situation

Work area	Frequency	%
Medicine	12	13.3%
Nursing	59	65.6%
Other	19	21.1%

Table 7- Work Area

Area of Studies	Frequency	%
Medicine	8	38%
Nursing	8	38%
Other	5	24%

Table 8- Area of Studies

Type of institution	Frequency	%
Public	62	68.9%
Private	21	23.3%
Not applicable	2	2.2%
Other	5	5.6%

Table 9- Type of Institution

Public Institution	Frequency	%
ULS - Hospital	24	38.7%
ULS - Healthcare center/ Similar	20	32.3%
ULS – Public Health	16	25.8%
Other	2	3.2%

Private Institution	Frequency	%
Hospital	10	47.6%
Clinic	5	23.8%
Other	6	28.6%

Table 10- Professionals working on Public or Private Institution

4. Analysis and Discussion of the Results

In this chapter, its presented the analysis carried out to test the model using IBM's statistical software, Statistical Package for Social Science (SPSS), version 30. The first step was to clean and remove all invalid answers from the database. Subsequently, in order to carry out the statistical tests, some of the variables were transformed to allow proper analysis. After this process, it was possible to proceed with the descriptive analysis, the correlation analysis, the validation of hypotheses, as well as a complementary and comparative analysis between groups.

4.1. Descriptive Analysis of the Data

The first step of this study was to carry out a descriptive analysis of the data collected from the online questionnaire. For some of the model's concepts, it was necessary to construct composite indicators or transform the data to ensure consistent interpretation. All variables presented were created by the author based on the questionnaire responses and according to the structure defined in the theoretical model.

This analysis is presented in Table 11, which shows the number of responses, the minimum, maximum, mean, and standard deviation for each of the scales used.

Diagnoses Accuracy

This variable was calculated as the average of the items DA4, DA5 and DA6, which assess the participants perceptions of AI´s contribution to diagnostic accuracy. The resulting indicator presented an average of approximately 3.75, which, according to the Likert scale of 1 to 5, is above the midpoint of the scale (2.50), which suggests a tendency to attribute to AI a positive role in improving clinical accuracy, indicating that professionals perceive significant diagnostic benefits from adopting AI tools.

Administrative Efficiency

To measure this concept, the mean value of items AE1 and AE3 was used, both addressing the role of AI in streamlining administrative processes. The computed average was 3.92, which is above the midpoint of the Likert scale (2.50). This value suggests agreement about the contribution of AI to simplifying administrative processes, suggesting that professionals recognise gains in efficiency with the adoption of AI technologies.

Patients Experience

For this concept was measured the item AE5, where participants indicated whether AI positively impacts the patient experience. The variable under study obtained an average of 2.53, on a scale where 'Yes=3', 'I Don't know=2' and 'No=1'. The value obtained suggests that professionals tend to recognise the positive impacts of AI on the user experience, although many of them indicate that they do not know how to answer the question. This value suggests some uncertainty by professionals about user satisfaction and may indicate that there are limitations in direct contact with patients or a lack of objective evidence perceived by professionals.

Workload Reduction

This variable derived from the item AE6, which examined the extent to which professionals feel their workload is reduced due to utilisation of AI tools. Responses were transformed into a binary scale, where ‘No=2’ and ‘Yes=1’. Looking in detail at the variable under study, it is possible to understand that professionals tend not to recognise a significant relief in their workload resulting from the use of AI.

AI Training

The variable ‘Training’ was measured through the average of the questions SC1 and SC2, which aims to find out how important professionals consider it to receive training to deal with AI tools, and also to evaluate whether they have received enough. The variable in question recorded an average of 2.30, which on a scale of ‘Yes=3’, ‘Don't know=2’ and ‘No=1’ suggests that, overall, professionals consider it important to receive training to deal with AI tools. However, this average also indicates that training may not have been sufficient across all respondents.

Confidence

This concept aims to find out the level of trust that professionals have in using tools that incorporate AI in both clinical and administrative contexts. It was calculated by averaging responses to PC2 and PC5, the result of 2.09 was recorded, below the midpoint (2.50) on a Likert scale of 1 to 5. This value suggests that professionals, on average, do not trust tools that incorporate AI. This dimension explains the reluctance of some professionals to fully adopt these technologies despite recognising their potential benefits.

Table 11- Descriptive Analysis of the Data

Concept	N	Minimum	Maximum	Average	Standard Deviation	Label
Diagnostic Accuracy *(DA4, DA5, DA6)*	111	1	5	3.75	0.68	Likert
Administrative Efficiency *(AE1, AE3)*	111	2	5	3.92	0.72	Likert
Patient Experience *(AE5)*	111	1	3	2.53	0.63	Yes=3; Don't Know=2; No=1
Workload Reduction (*AE6)*	62	1	2	1.65	0.48	Yes=1; No=2
Training *(SC1, SC2)*	111	1	3	2.30	0.42	Yes=3; Don't Know=2; No=1
Confidence *(PC2, PC5)*	111	1	5	2.09	0.74	Likert

According to the question 'Do you identify any AI tools in your professional practice?', the figure 2 shows that of the total sample, the highest percentage (49.5%) admits that they identify AI tools in their professional environment, as opposed to those (35.2%) who don't recognise them yet.

Regarding the question about the frequency of use of this tool, it can be seen in figure 3 that the highest percentage (36.4%) are professionals who use this type of tool occasionally. It is also possible to see that there is the same percentage (10.9%) of professionals who say they have never used it and who use it daily.

According with figure 4, when the professionals were asked about their familiarisation with AI tools, 45% of respondents admitted that they didn't know how to answer. Even so, the second largest proportion of the sample (18.9%) said they were familiar with the tool, but (12.6%) answered that they were not familiar at all.

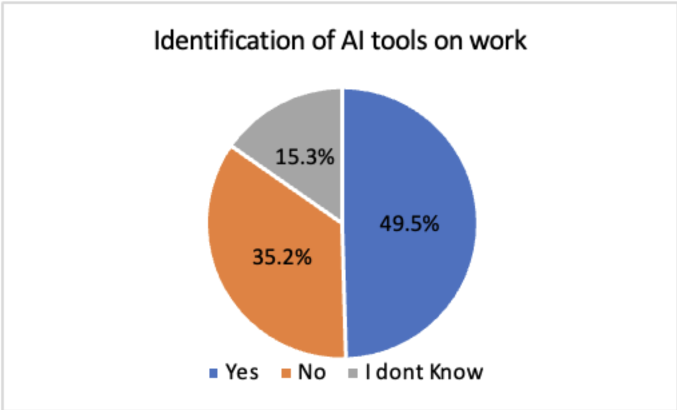

Figure 2- Identification of AI tools on professional practice

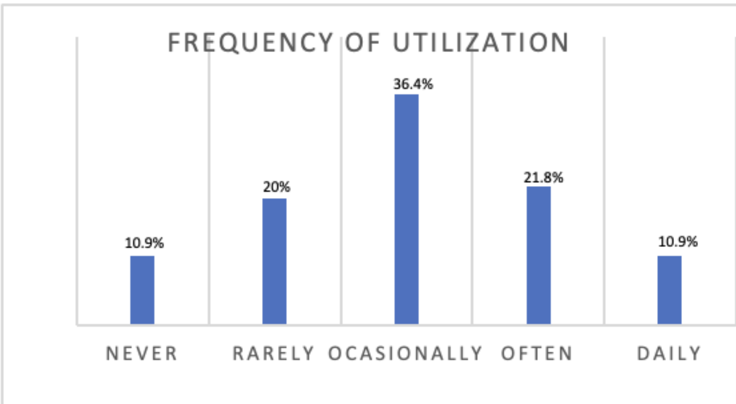

Figure 3- Frequency of utilisation of AI tools

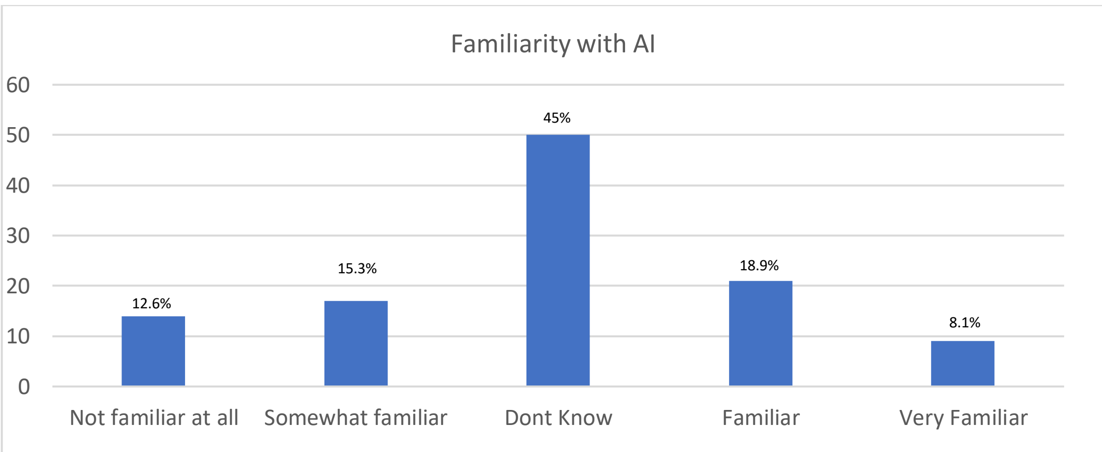

Figure 4- Familiarity with AI

4.2 Correlation Analysis

Correlations were analysed using Spearman's Correlation Coefficient, which measures the strength of the relationship between variables (Hauke & Kossowski, 2011).

The correlation, identified by the letter ‘rs’, can vary between the numerical values -1 and 1. The closer the value obtained is to these extremes, regardless of whether the value is positive or negative, demonstrates that the existing correlation is considered very strong, and the negative sign of the correlation indicates that the variables vary in the opposite direction, demonstrating that when one variable increases, the other decreases (Hauke & Kossowski, 2011).

Below, the table 12 shows the results of the Spearman Coefficient Analysis for the variables studied.

Table 12- Analysis of Spearman's Correlation Coefficients

Correlations

	1	2	3	4	5	6
1. Diagnostic Accuracy	1					
2. Administrative Efficiency	.377**	1				
3. Patient Experience	.275**	.342**	1			
4. Workload Reduction	.090	.110	.223	1		
5. Training	.235*	.189*	.215	-0.011	1	
6. Confidence	.359**	.196*	.142	.002	.0063	1

**. The correlation is significant at the 0.01 level (2 endpoints).

*. The correlation is significant at the 0.05 level (2 endpoints).

Looking at the results from the table above, the Administrative Efficiency variable shows a positive and significant correlation with Diagnostic Accuracy (0.377), which indicates that as the perception of administrative efficiency increases, the perception of diagnostic accuracy also increases.

The Patient Experience variable shows a positive and significant correlation with Diagnostic Accuracy (0.275); this may indicate that patient satisfaction tends to increase when diagnostic accuracy increases. The same is verified when this variable is crossed with administrative efficiency (0.342), which is in line with (Reddy, 2019; Smeaton & Christie, 2020; Bhagat & Kanyal, 2024), who argue that user satisfaction tends to increase when are met requirements such as: speed in booking appointments, ease of communication between clinic and user, speed in diagnosis and effective treatment.

According to the training variable, which the authors (Shaw et al.,2019; Mulukuntla,2022; Dankwa-Mullan,2024;Chaves Cano & Pérez Gamboa, 2024) defend is necessary to deal appropriately with tools that incorporate AI, it can be seen that this shows a positive and significant correlation for both Diagnostic Accuracy (0.235) and Administrative Efficiency (0.189), indicating that the efficiency and accuracy of clinical processes tend to increase depending on the level of training received by professionals. This indicates that the idea defended by the authors aligns with the results obtained.

Looking at the correlation value of the Workload variable with Administrative Efficiency, it can be seen that it is positive (0.110) but not significant, so it can be understood that although professionals do not recognise a significant decrease in workload, they tend to agree that in the future it could contribute to reducing it. These results are in line with (Topol,2019), although not significantly.

The Confidence is positively and significantly associated with diagnostic accuracy (0.359) and administrative efficiency (0.196). This result may indicate that higher levels of trust in dealing with AI tools can contribute to both greater diagnostic accuracy and administrative efficiency, thus corroborating the authors (Mamdiwar et al., 2021; Mulukuntla, 2022) who believe that trust is a crucial factor for the effective use of this technology.

4.3. Validation of the Research Hypotheses

To validate hypotheses H1, H2, H3, and H4, was used the statistical linear regression model. The use of this method allowed to determine the relevance of the variables in the model, making it most suitable for testing the veracity of the hypotheses (Moreira et al., 2020).

However, to validate hypotheses H5 and H6, it was necessary to use the logistic regression model since the dichotomous nature of the dependent variables requires a model that estimates the probability of a certain outcome occurring as a function of the explanatory variables (Moreira et al., 2020).
The statistical adequacy of each of the hypotheses is fundamental to reinforce the robustness of the results obtained.

To test hypotheses H1 and H3, 'Diagnostic Accuracy' was defined as the dependent variable and the variables 'Training' and 'Confidence' as the independent variables. Table 13 shows that the Training (β=0.178) and Confidence (β=0.356) variables have positive and significant β values ($p<0.05$). Therefore, it can be confirmed that these hypotheses are valid, meaning that higher levels of training and confidence contribute positively to the perception of the accuracy of AI-assisted diagnoses.

Table 13- Linear Regression Analysis (Training and Confidence)

Model	B (Non-Standardized)	Error	B (Standardized)	t	Sig.
1 (Constant)	4.137	1.211	-	3.415	<0.001
Training	0.611	0.303	0.178	2.017	0.046
Confidence	0.517	0.128	0.356	4.036	<0.001

a. Dependent Variable: **Diagnostic Accuracy**

An equivalent method was used to test hypotheses H2 and H4, where 'Administrative Efficiency' was defined as the dependent variable and the variables 'Training' and 'Confidence' as independent variables. Table 14 reveals that only hypothesis H4 was validated, with a positive and significant (β=0.193) ($p<0.05$). Hypothesis H2 was rejected as it showed a ($p>0.05$).

Table 14- Linear Regression Analysis (Training and Confidence)

Model	B (Non-Standardized)	Error	B (Standardized)	t	Sig.
1 (Constant)	3.822	.854	-	4.477	<0.001
Training	.325	.214	.143	1.523	.131
Confidence	.186	.090	.193	2.058	.042

a. Dependent Variable: **Administrative Efficiency**

After converting the dependent variables into a binary format for analytical purposes where (Yes = 1 and No/Don't know = 0), it was possible to carry out a binary logistic regression to analyse the impact of Administrative Efficiency, as an independent variable, on reducing Workload (H5) and on improving Patient Experience (H6), both as dependent variables.

For H5, in Appendix II (Table 20) it is possible to see that the model is statistically significant, and therefore, useful for estimating the dependent variable ($\chi2 = 7.294$, $p < 0.05$). The model has a Nagelkerke R2 of 0.101, revealing that around 10.1% of the variability of the dependent variable is explained by the perception of administrative efficiency. Analysing Table 15, it can be concluded that administrative efficiency is statistically relevant ($\beta = 0.654$; $p < 0.05$) for validating the hypothesis under study.

While for H6, looking at Appendix II (Table 21), it can be seen that the model is valid and statistically significant for estimating the user experience variable ($\chi 2 = 20.082$, $p < 0.001$), and it can also be seen that R2 Nagelkerke indicates that the model explains approximately 22.4 per cent of the variation in the dependent variable. Therefore, looking at Table 16, it can be concluded that administrative efficiency proves to be statistically significant ($\beta = 0.918$; $p < 0.001$) for validating the hypothesis under study.

The model indicates that professionals who perceive greater administrative efficiency tend to associate it both with a reduction in workload (H5) and with an improvement in the user experience (H6).

To summarise, 5 of the 6 hypotheses formulated were validated. Professionals recognise benefits in terms of diagnostic accuracy when they perceive Confidence and adequate Training to deal with AI tools. When it comes to administrative efficiency, it can be seen that this tends to increase with the Confidence perceived by professionals and is also associated with a reduction in workload and an improvement in the user experience.

Table 15- Analysis of Logistical Regression Model (Workload Reduction)

Variables in equation

Etapa 1[a]	B	S.E.	Wald	df	Sig.	Exp(B)
Admin Efficiency	.654	.258	6.417	1	.011	1.923
Constant	-5.363	1.633	10.781	1	.001	.005

a. Insert variables on the 1 step: Admin. Efficiency

Table 16- Analysis of Logistical Regression Model (Patient Experience)

Variables in equation

Etapa 1[a]	B	S.E.	Wald	df	Sig.	Exp(B)
Admin Efficiency	.918	.233	15.530	1	<.001	2.504
Constant	-4.877	1.349	13.080	1	<.001	.008

a. Insert variables on the 1 step: Admin. Efficiency

4.4. Complementary Analysis

To provide a complementary analysis to the hypotheses developed and considering the other questions in the questionnaire, we attempted to explore the personal opinions of each respondent in greater detail by using graphs.

Considering the question 'Which are the AI-administrative tools that you use in your institution?', it can be seen from figure 5, that the largest percentage of the professionals surveyed (42.3%) don't know how to answer, while (23.4%) admit that they don't use any kind of tool that incorporates AI. However, of those who do use this type of tool, it can be seen that the most commonly used are data management tools, scheduling and managing patient appointments and chatbots to communicate with them.

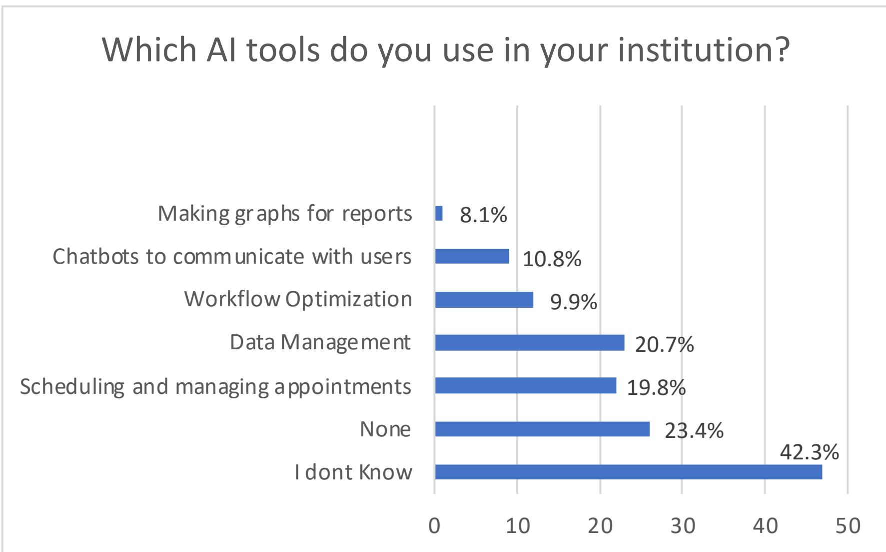

Figure 5- Identification of AI tools on professional practice

When asked about the clinical areas that could benefit the most from the utilisation of AI tools, from the figure 6 is possible to verify that, the professionals said that Clinical

Research will be the most suitable one (71.2%). On the contrary, they say that Surgery and Emergency assistance will be the least favoured areas (25.2%).

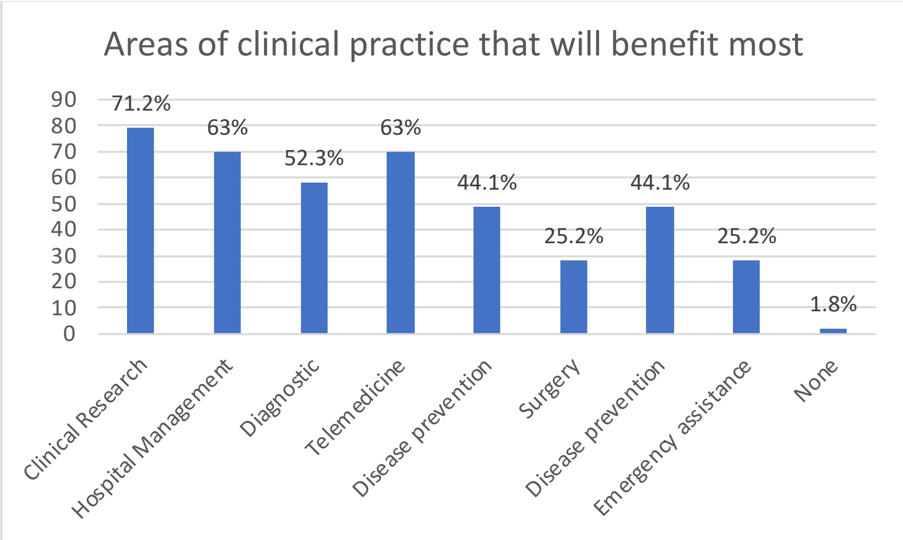

Figure 6- Identification of clinical practices that will benefit the most from AI tools

Considering the question "What do you consider to be the biggest challenges to adopt AI technology?" The obtained results seen in figure 7, the professionals consider Data Security, Ethical Concerns and Resistance as the top 3 of biggest challenges. This result may help to explain why the average of the descriptive variable 'Confidence' associated with the use of AI tools is so low.

Figure 7- Biggest Challenges of AI tools

To better understand the variable “Training”, figure 8 shows that the majority (54.5%) say that they have not received any type of training to use AI tools in healthcare. In addition, figure 9, displays the training they consider to be the most suitable for dealing with AI tools is on-the-job training and workshops with practical training. This additional information may help to explain the average obtained for the descriptive variable “Training”.

The final group of the questionnaire, designed so that professionals could provide a well-founded opinion on the use of AI in their professional practice, yielded 8 valid responses. From observing appendix II (Table 22), it is possible to verify that Lusíadas Hospital employs an AI-based consultation scheduling system, which, however, does not function as intended.

Nevertheless, the professionals acknowledge its potential benefits, ranging from decision support with fewer errors to greater diagnostic accuracy. In addition, it is also possible to see that the professionals’ express concerns about data protection, ethics, legal regulations, and the potential risk of dehumanization, which is a positive factor, as it shows they are conscious of the various aspects associated with the adoption of AI.

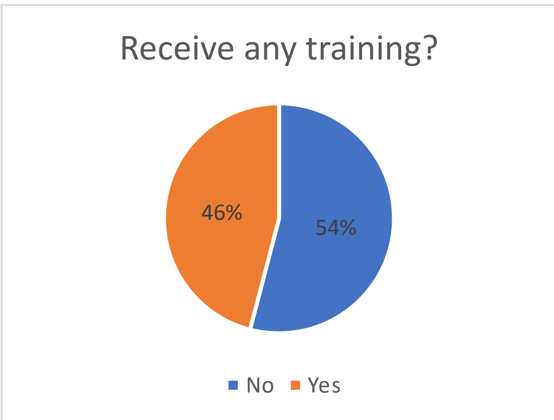

Figure 8- Received any type of training

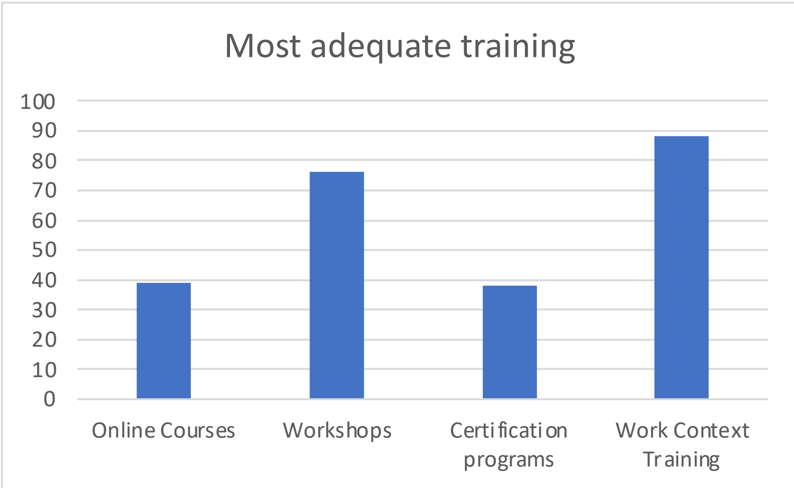

Figure 9- Most adequate training to deal with AI tools

4.5. Comparative analysis between groups

Considering other variables that are present in the study, which are intended to give valuable insights: Type of Institution where they work, Age Group, Familiarisation with AI, Professional Category, and Identification of AI tools in professional practice. The aim was to analyse the presence of statistical differences between them.

To carry out this analysis, the application of t-test for independent samples was initially considered to compare the means between the variables. However, before applying the aforementioned test, it was necessary to verify if the assumption of normality was met (Kim & Park,2019). According to Appendix 3 (Table 23, Table 24 and Table 25), it can be observed that, through the realization of Kolmogorov-Smirnov and Shapiro-Wilk tests, the significance value obtained was $p<0.05$, indicating that the variables did not follow a normal distribution for any variable. Given the violation of this assumption, it was necessary to find an alternative test to proceed with the analysis.

So, under these conditions, to carry out this comparative analysis, the Kruskal-Wallis test was the alternative, since compares differences in the values of a dependent variable and a categorical independent variable without assuming a normal distribution (McKight & Najab, 2010).

The first executed test intended to seek if the "Identification of AI tools" changes according to the "Type of Institution" where they work. To do so was considered the variable "Identification of AI tools" as the dependent variable, and after proper transformation of the independent variable, where "1=Public; 2=Private and 3=Other", the respective test was executed. As we can observe in Table 17, the significance ($p>0.05$) indicates that there is no statistical evidence to confirm that the identification of AI tools on professional practice changes between public and private institutions. However, this result may be related to the fact that the vast majority of the professionals who responded to the survey work in the public sector, which may condition this analysis, so it will be necessary in the future to further understand this phenomenon.

Table 17- Kruskal Wallis Test (Identification of AI tools and Type of Institution)

Test statistics[a,b]

	AI tools Identification
H de Kruskal-Wallis	2.185
df	1
Significance Sig.	.139

a. Kruskal Wallis Test

b. Grouping Variable: Type of institution

To understand if the age of the professionals might affect their ability to familiarise themselves with AI tools. The second test aimed to investigate if there were significant differences between the age groups and their level of familiarisation with AI. In this analysis, "Familiarisation with AI" was considered the dependent variable, while the independent variable "Age group" was categorised numerically for analysis purposes as follows: "1=20-29", 2=30-39,3=40-49,4=50-59, 5=60-69 and 6=+70', the test mentioned above was carried out. The results can be found in Table 18, where a ($p<0.05$) indicates that age significantly influences the familiarization with AI. An additional analysis was carried out to see which age group tends to be more familiar with AI and, looking at Table 18; it can be seen that the 20-29 age group has the highest average ($M=3.38$), followed by the 30-39 ($M=3.30$) and 40-49 ($M=2.89$) age groups. The older age groups have lower averages, reflecting a trend where younger professionals tend to be more familiar with AI tools.

Table 18- Kruskal Wallis Test (Familiarisation and Age) and Descriptive Analysis

Test statistics[a,b]

	Familiarisation
H de Kruskal-Wallis	14.926
df	5
Significance Sig.	.011

a. Kruskal Wallis Test
b. Grouping Variable: Age

Descriptive Analysis

Age	Mean
20–29	3.38
30–39	3.30
40–49	2.89
50–59	2.67
60–69	2.41

For the third and final test, was considered as independent variable the "Professional Category" and the dependent variable "Identification of AI tools on professional practice". After transforming the answer of the independent variable to "1=Nurse, 2=Doctor and 3=Other" was executed a test to understand if the identification of AI tools could be related with the professional category. According to the table 19, it is possible to verify that ($p>0.05$) indicates that does not exist statistically significant difference between professional category and the identification of AI tools in the workplace. However, the result obtained may be biased by the fact that the majority of health professionals who responded to the survey were nurses. This factor may explain the result, so further research is needed in the future to investigate this relationship.

Table 19- Kruskal Wallis Test (AI tools Identification and Professional Category)

Test statistics[a,b]

	AI tools Ident.
H de Kruskal-Wallis	2.270
df	1
Significance Sig.	.132

a. Kruskal Wallis Test
b. Grouping Variable: Professional Category

4.6 Discussion of the Results

The survey was essential for collecting data and analysing the proposed statistical model. The complementary analysis helps to understand the reasons behind some of the respondents' answers, and the results obtained are worthy of a more detailed reflection, which will follow.

From the analysis above, it is possible to verify that from the total of the hypotheses developed, five of them can be supported. Hypotheses H1 and H3 showed a positive and significant relation between "Training" (β=0.178) and "Confidence" (β=0.356) with Diagnostic Accuracy. To verify H4, which intends to evaluate the professionals' perceptions about her "Confidence" with Administrative Efficiency, was obtained the exact same conclusion, meaning that there is a positive and significant relation between those variables.

Previous studies have shown that "Training" and "Confidence" are crucial factors in the correct use of AI tools. According to (Mamdwar et al.,2021; Mulukuntla,2022; Dankwa-Mullan,2024), the training received ensures that the professionals are fully aware of how these tools work as well as the advantages and limitations of them. On the other hand, "Confidence" allows professionals to rely on AI tools to help them make decisions that can speed up diagnosis and eventually contribute to the patient's quality of life.

Nevertheless, the results obtained for H2 are not in line with the previously mentioned authors because there is no statistical evidence between the "Training" variable and Administrative Efficiency. This shows that although professionals recognise that higher levels of training are associated with diagnostic accuracy, the same is not true for administrative areas. This result could be associated with the type of training the professionals receive, which may be more associated with the clinical area, or also this reason could be explained by the fact that professionals inquired are more directly involved in clinical processes than in administrative ones.

To better understand the relationship between "Workload" and "Administrative Efficiency", since the automation of routine tasks may contribute to reducing Workload (Topol,2019), it is possible to understand that the results of this study indicate that although the majority of professionals still do not recognise a reduction in workload so far, the analysis of H5 revealed a statistically significant relationship, suggesting that when professionals perceive concrete benefits of administrative efficiency, they tend to associate them with a reduction in their workload.

It was tried to understand whether the "Patient Experience" could be improved through Administrative Efficiency, since according to the authors (Smeaton & Christie, 2020; Parry et al., 2023; Bhagat & Kanyal, 2024), this is often pointed out as one of the main advantages of adopting this type of tools to support administrative management. The results obtained for H6 are in accordance with the previously referenced literature, meaning that there exists statistical evidence to ensure that administrative efficiency contributes significantly to the perception of overall user satisfaction.

According to the comparative analysis between the groups, and since the fact that it was only possible to prove that the age range differs statistically in terms of familiarity with AI tools. It was also possible to verify that as age increases, familiarity with this technology decreases. The other tests are worthy of future investigation.

5. Conclusions, Limitations and Future Research

5.1 Conclusion

In this MFW, the objective was to understand the impact of AI on the healthcare sector. To do this, an intensive and comprehensive research was carried out, along with the most varied scientific articles available for consultation, where several areas were identified in which AI proves to be a fundamental aid for healthcare professionals. It was possible to verify that there already exists a huge diversity of AI algorithms for detecting the most varied types of disease, highlighting the growing role of AI in supporting diagnoses and clinical management.

As it happens with any technological innovation, the adoption of AI involves advantages but also challenges. Based on this principle, the aim was to find out what were the most relevant ones and understand what the opinions and perceptions of healthcare professionals regarding this topic would be.

From the diverse range of areas where AI is already been present, diagnoses accuracy and administrative efficiency were the reference to study the influence of different factors like Training, Confidence, Workload and Patient Experience.

The results obtained in the analysis of the collected data allowed to validate that the variables “Confidence” and “Training” contribute to increase diagnoses accuracy.

Additionally, the "Confidence" variable also demonstrated a positive influence on the perception of administrative efficiency. It was also possible to verify that professionals recognize that administrative efficiency can contribute to reduce the Workload, as well as reflecting greater patient satisfaction by measuring the variable "Patient Experience".

Although the positive perceptions, it was possible to identify that the professionals still have significant concerns about ethics, security, and data protection as well as lack of training to deal with this technology. Factors like these inevitably contribute to reflecting a certain resistance towards the adoption of AI, however, since professionals are so aware of the benefits and advantages that they can extract from the use of this promising technology, it will only be necessary for them to start seeing it with different eyes.

Considering the possible strategies to overcome this resistance, the need to invest in the development of skills and training stands out, mainly because they can contribute to better inform about the real risks to which they are exposed, in order to raise awareness, prepare and motivate professionals so that it will be easier for them to acquire mastery of these tools. It will also be necessary to establish consensual policies, both by governments and by health institutions. Finally, it is also suggested that these institutions work together with companies that provide AI software, in order to mitigate technological barriers and adapt solutions to the actual needs of the sector.

In short, these proposals should be regarded as a valuable contribution to the sector, so that professionals could use these tools in their daily practices in an ethical, safe, and effective way. And at the same time, contributing to the well-being of patients, reducing waiting times, accurate diagnoses, appropriate treatments and contribute to improve the quality of life of users.

5.2 Limitations and Future Research

Although all the efforts to make this dissertation as accurate as possible, there are limitations that should be considered for future research. When analysing the answers of the survey, it is possible to understand that the majority of professionals are nurses, this can be explained by the fact that they are the biggest professional group on healthcare sector but would be interesting to have a broader range of responses from other type of professionals.

The same happens for the type of sector where they work, as most of the professionals who were willing to respond to the survey belonged to the public sector, it was not possible to obtain a significant result between the differences perceived by professionals from the public and private sectors about the adoption of AI, so it would be interesting to make a comparison between them.

Given the high number of emails, a greater level of adherence from the professionals would be expected. On the other hand, because the use of this technology is very recent, it is possible that the obtained results from this sample are not representative of the reality felt by all health professionals.

The questionnaire was also made available in English, but unfortunately, no results were obtained in that language. It would be worthwhile to investigate this further in future research, and thus be able to compare the adoption of AI in different countries, considering political factors, technological investment, and organisational culture.

Lastly, it would be relevant to take into account the patients' perspective on the use of AI in healthcare, including investigating aspects such as trust, experience and satisfaction. And thus, compare them with the perception of healthcare professionals

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APPENDICES

Appendix 1: Survey

Concept	Code	Question	Scale
	DD1	Nationality	Portuguese; Other
	DD2	Qualifications	High School; Bachelor's Degree (or similar); Master; Post Grad; PhD
	DD3	Situation	Health Professional/Student; Other
	DD4	Area of Studies	Medicine; Nursing; Other
	DD5	Work area	Medicine; Nursing; Other
	DD6	Type of institution	Public; Private; Not Applicable; Other
Demographic Data	DD7	Public Institution	ULS Hospital; ULS-Centro de Saúde/Similar; ULS-Unidade de Saúde Pública; Other
	DD8	Private Institution	Hospital; Primary Aid; Clinic; Other
	DD9	Age	20-29; 30-39; 40-49; 50-59; 60-69; >=70
	DD10	Gender	Female; Male; Prefer not to say;

	DD11	Nº Years Working/Studying on health sector	<1; 1-5; 6-10; 11-20;21-30; >30

Concept	**Code**	**Question**	**Scale**
Diagnose Accuracy	DA1	Familiar with AI	5 points Likert Scale
	DA2	Identification of AI tools on professional practice	Yes; No; Don't Know
	DA3	Frequency of utilization of AI tools	Never; Rarely (1-2 times/month); Occasionally (1 time per week); Often (2-3 times per week); Daily; Not applicable
	DA4	The use of AI improves diagnostic accuracy	5 points Likert Scale
	DA5	AI tools contribute to faster diagnosis and help identify diseases more quickly when compared to traditional methods.	
	DA6	Monitoring health data through devices such as smartwatches and other devices can contribute to a more accurate diagnosis.	
	DA7	Main contributions of smartwatches to medical diagnosis	Constant monitoring of vital signs; Early detection of abnormalities and health patterns; Personalization of medical treatment; Reduced need for frequent face-to-face; examinations; None; Other

Concept	Code	Question	Scale
Administrative Efficiency	AE1	The use of AI simplifies administrative processes, such as scheduling appointments and managing medical data.	5 points Likert Scale
	AE2	In the institution where you work, is AI used to predict user absences or optimize workflows?	Yes; No; Don't Know
	AE3	How effective do you think AI solutions are in sending alerts and reminders to users?	5 points Likert Scale
	AE4	What AI-based administrative tools do you use in your institution?	Scheduling and managing appointments; Data management; AI-powered chatbots for communicating with patients; Workflow optimization; None; Other
	AE5	Does the use of AI contribute to improve overall user satisfaction (e.g., speed scheduling, accuracy of diagnoses and effectiveness of treatment)?	Yes; No; Don't Know
	AE6	In your institution, has the use of AI reduced the workload of healthcare professionals?	
	AE7	In your opinion, which areas of clinical practice could benefit from the use of AI?	Clinical Research; Disease prevention; Emergency care; Telemedicine; Diagnosis; Surgery; Hospital Management; None; Other

Concept	Code	Question	Scale
Perceptions and Challenges	PC1	The adoption of AI in healthcare faces resistance from professionals.	5 points Likert Scale
	PC2	Current AI systems are sufficiently reliable for complete integration into clinical processes.	
	PC3	User privacy is at risk when using AI technologies.	
	PC4	Biggest Challenges for implementing AI in your area?	High costs; Lack of training; Data security concerns; Resistance from professionals; Ethical risks (e.g., discrimination, reduced human interaction); Technological compatibility; None; Other
	PC5	Confidence about allowing AI to assist in decision-making regarding critical clinical decisions	5 points Likert Scale
	PC6	Has your institution implemented clear and strict guidelines to ensure the protection of users' personal data when using AI technologies?	Yes, there are clear regulations; There are some guidelines, but they are not strictly followed; There are no clear regulations; I don't know

Concept	Code	Question	Scale
Skills and Competences	SC1	Do you consider it important to receive training to adapt to AI tools in the health sector?	Yes; No; I ‘don’t Know
	SC2	Have you received any training on how to use AI tools in healthcare?	Yes, intensive training; Some training, but not enough; No, I learned on my own; No training at all

	SC3	What type of training do you consider most appropriate to improve the adoption of AI in your professional practice?	Online Courses; Workshops and practical training; Certification Programs; On-the-job training; Other
Concept	**Code**	**Question**	**Scale**
Final Comment		Is there anything you would like to add about the impact of AI on your professional	

Appendix 2- Logistical Model Overview

Table 20- Variable "Workload Reduction" explained by the model

Model overview

Stage	Log-2 likelihood	Chi-square Cox & Snell	Chi-square Nagelkerke
1	103.239[a]	.064	.101

Omnibus Tests of the Coefficient Model

	Chi-square	df	Sig.
Step	7.294	1	.007
Block	7.294	1	.007
Model	7.294	1	.007

Table 21- Variable "Patient Experience" explained by the model

Model overview

Stage	Log-2 likelihood	Chi-square Cox & Snell	Chi-square Nagelkerke
1	128.996[a]	.165	.224

Omnibus Tests of the Coefficient Model

	Chi-square	df	Sig.
Step	20.082	1	<.001
Block	20.082	1	<.001
Model	20.082	1	<.001

Table 22- Professionals opinion about the impact of AI on professional practice

- Training of users/general population
- Accurate and faster diagnosis
- Testing integrative models will be an asset for professionals and users, allowing them to move from decision support to an informed decision with fewer errors.
- I think that if used well, it is a tool that can bring progress and benefits. However, all this must be accompanied by ethics and legal regulations, so that there is no abuse. We're talking about healthcare, there can be no dehumanization.
- It's the future.
- I think it will be the future
- The Lusiadas hospital uses a program to schedule appointments using AI and it works very badly.
- Better understanding of how AI can coexist without losing human interaction

Appendix 3- Normality Test - a prerequisite for performing the T- test

Table 23- Normality Test (Identification of AI tools and Type of institution)

		Normality Test					
		Kolmogorov-Smirnov			Shapiro-Wilk		
	Type of Institution	Statistics	gl	Sig.	Statistics	gl	Sig
Identification of AI tools	1	0.391	50	<0.001	0.622	50	<0.001
	2	0.392	18	<0.001	0.624	18	<0.001

Table 24- Normality Test (Familiarisation and Age)

		Normality Test					
		Kolmogorov-Smirnov			Shapiro-Wilk		
	Age	Statistics	gl	Sig.	Statistics	gl	Sig
Familiarisation	1	0.174	49	<0.001	0.910	49	0.001
	2	0.311	62	<0.001	0.846	62	<0.001

Table 25- Normality Test (Identification of AI tools and Professional Category)

		Normality Test					
		Kolmogorov-Smirnov			Shapiro-Wilk		
	Professional Category	Statistics	gl	Sig.	Statistics	gl	Sig
Identification of AI tools	1	0.433	10	<0.001	0.594	10	<0.001
	2	0.350	44	<0.001	0.636	44	<0.001