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Barriers to the adoption of artificial intelligence in medical diagnosis: procurement perspective

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ABSTRACT

The aim of this research is to identify adoption barriers to the implementation of artificial intelligence in medical diagnosis using the Technology Acceptance Model and the Theory of Planned Behaviour. A qualitative case study in Dutch hospitals involved eight semi-structured interviews with stakeholders. In this study, it became clear that the stakeholder's intention to adopt artificial intelligence in medical diagnosis is influenced by the perceived barriers. The adoption intention is characterized by the factors of perceived usefulness, attitude, subjective norms, and perceived behavioural control, which can have a negative or positive influence on the intention. For example, perceived usefulness has a positive influence when work efficiency or quality increases, but a negative influence if there are significant potential risks involved in implementing AI. If there is a positive attitude or positive subjective norms, then this positively influences the intention to adopt AI. For example, if important stakeholders have a positive attitude, it can serve as a driving force because they have more impact on the implementation process than other stakeholders. It was found that the barriers that influence the intention are knowledge and expertise, data availability, ethical considerations, the business case of AI, resistance to change of physicians, and life-cycle management. This study was carried out with a small research sample of eight participants of which seven of the eight participants work in hospitals in the Netherlands, and one is a human-AI expert that provides expertise to hospitals. This limits the external validity of the findings since they might not be the same in different parts of the world. This study could be expanded to other countries to validate the findings. Furthermore, another limitation is the purchasing department's involvement in the implementation process. Artificial intelligence is still a relatively new topic in healthcare companies, and comparable research may be conducted after it has become more established. There has been limited research on the use of artificial intelligence in medical diagnosis from the procurement department's standpoint. The developed artificial intelligence adoption model provides fresh perspectives on this topic. Furthermore, the different factors that have a positive or negative influence on the artificial intelligence adoption process is a new aspect that got introduced to the research field.

Keywords – Hospital Purchasing, Value-Based Procurement, Artificial Intelligence, Technology Acceptance Model, Theory of Planned Behaviour, Technology adoption barriers.

PREFACE

This research is written for the Master’s Thesis in Business Administration in the track Purchasing and Supply Management at the University of Twente. This thesis is the effort of about 6 months of writing and conducting research.

The subject of my thesis has been chosen based on my interest in artificial intelligence and the purchasing process of innovation. Unfortunately, more respondents could not be included due to the limited availability of healthcare organizations that have implemented/are implementing artificial intelligence in medical diagnosis. Furthermore, it was discovered that the purchasing department only has a limited role in the purchasing process of AI in medical diagnosis, making an in-depth analysis of the procurement department's role not possible.

I would like to thank all people that I was able to interview and especially the people that were able to help me get in contact with other stakeholders. Furthermore, I would like to thank all people that supported me during the writing of my thesis.

Lastly, I want to thank my thesis supervisors, Dr Carolina Belotti-Pedroso and Dr Frederik Vos from the University of Twente, for giving me feedback and guidance while writing my thesis.

Rick Dellink
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Table of Contents

INDEX OF TABLES

INDEX OF FIGURES

1. INTRODUCTION

Artificial intelligence (AI) is defined as "the theory and development of computer systems able to perform tasks that normally require human intelligence, such as visual perception, speech recognition, decision-making, and translation between languages" (Knowles, 2006). AI has the potential to revolutionise the healthcare business. By analysing medical images and other patient data, it can improve illness diagnosis (Mirbabaie et al., 2021), and it has already been shown to be helpful in the detection of dementia (Mazzocco & Hussain, 2012) and cancer (Lu et al., 2020). Moreover, AI can help create personalized treatment plans by analysing a patient's genetic and electronic medical record (EMR) data, which is a key objective in personalized medicine (Thrall et al., 2018; Williams et al., 2018). In addition, AI can support population health management by analysing data from electronic health records and other sources to identify health trends in specific populations (Zeng et al., 2021). AI has been used, for instance, to detect infectious disease outbreaks like influenza (Șerban et al., 2019). These applications for artificial intelligence are made possible by the growth of data in the healthcare business (Davenport & Kalakota, 2019). While the growth of data allows for the use of AI, the implementation of innovation in healthcare is challenging, and effective procurement strategies are vital (Belotti et al., 2022).

The procurement department is responsible for purchasing goods and services for an organization. In the healthcare industry, procurement is gaining importance as a way of enabling the adoption and implementation of innovative technology (Edler & Georghiou, 2007). Value-based procurement, which focuses on selecting suppliers based on objective and verifiable proof of past performance rather than merely the lowest price, is gaining favour in the healthcare industry (Meehan et al., 2017). This strategy is intended to ensure that the procured innovation will be accepted and used efficiently to create value for stakeholders, such as patients and healthcare professionals. Taking a value-based approach to the procurement of artificial intelligence is crucial because the costs of AI are not directly related to a profit increase (Sun & Medaglia, 2019) and products that offer greater long-term cost advantages are rarely rewarded in price-based approaches (Geitona, 2012).

The shift towards value-based procurement and the adoption of AI in healthcare has been slow, but the potential benefits of AI in healthcare make it an important area to pursue. Implementing AI in the workflow of physicians can help improve processes and can lead to improved patient outcomes (van Leeuwen et al., 2021), more efficient and accurate diagnoses (Kaul et al., 2020), reduced healthcare costs (Reddy et al., 2019), and better disease prevention and management (Vaishya et al., 2020).

The adoption of AI in healthcare also poses a variety of ethical and patient-related problems, such as those about mistake liability (Reddy et al., 2019), patient privacy (Panch et al., 2019), and transparency (He et al., 2019). These barriers arise due to the potential risk and unintended consequences of using AI in healthcare settings. Making a decision that is partly or completely based on AI can still result in mistakes but then the question arises of who is responsible for this outcome. Similarly, AI needs a lot of data, patient data, and this opens the possibility of for example a data leak. Petersson et al. (2022) identify that a lack of confidence in AI technology and insufficient training for healthcare practitioners could be obstacles to the extensive implementation of AI. This lack of confidence can come from the fact that AI is often seen as a ‘black box’ that is not well understood. Besides ethical difficulties, the adoption of AI in healthcare faces practical obstacles, such as the necessity for regulatory clearance for models that evolve rapidly (Yu et al., 2018), the high cost of implementation (Panch et al., 2019), and the lack of experienced experts to build and manage AI systems (Sun & Medaglia, 2019). Yu et al. (2018) explain that regulatory approval is necessary because an AI model may be better on average, but it could be worse on a subgroup of patients.

To improve the adoption and successful implementation of AI in healthcare, it is critical to investigate how these barriers may be overcome. By overcoming these obstacles, healthcare organisations will be able to leverage AI and make sure that patients benefit from this technology. AI may also be required to address the growing demand for healthcare services and enhance healthcare delivery effectiveness due to the ageing population and the need for healthcare services (Meskó et al., 2018).

Even though the potential benefits of AI in healthcare are well known, the adoption of these technologies has been slow. A key factor that may contribute to this issue is the existence of barriers that can hinder the successful implementation of AI in healthcare. While some studies have explored these barriers, there is still a gap in the literature regarding the role that procurement can play in addressing these barriers. Therefore, this study's objective is to identify the main barriers that the purchasing department encounters while implementing artificial intelligence in medical diagnostics and explore the specific role that procurement can play in addressing them. The study focuses on understanding the obstacles the procurement department faces when fostering innovation in healthcare. The key problem that this study aims to address is:

"What are the primary barriers to the adoption of artificial intelligence in medical diagnosis from the perspective of the procurement department?"

Which will be examined using a qualitative approach including case studies and semi-structured interviews. The case study focuses on healthcare organizations that have attempted or successfully adopted artificial intelligence into their workflows. This should allow the collection of information regarding the precise barriers these companies have experienced, as well as any strategies they have implemented to overcome these obstacles.

This study is guided by the Technology Acceptance Model (TAM) (Davis, 1985), and the Theory of Planned Behaviour (TPB) (Ajzen, 1991). The TAM focuses on the individuals' perceptions of usefulness and ease of use as determinants for technology adoption, while TPB considers the role of attitudes, subjective norms, and perceived behavioural control on behavioural intentions. By using these two models, this paper seeks to provide a detailed understanding of the intricate AI adoption process in healthcare. This theoretical framework is used to guide the analysis of data collected through qualitative semi-structured interviews to answer the research question.

The academic relevance of this thesis lies in its investigation of the barriers that influence the adoption of artificial intelligence in medical diagnosis, particularly in the context of value-based procurement. By using both the Technology Acceptance Model (TAM) and the Theory of Planned Behaviour (TPB), this research attempts to give a thorough understanding of the factors that impact the adoption of artificial intelligence (AI) in healthcare. This study has the potential to contribute to the current body of knowledge by providing insight into the implementation barriers and opportunities associated with the adoption of AI in healthcare, as well as how value-based procurement might influence these issues.

The practical relevance of this thesis lies in its potential to influence procurement procedures in the healthcare industry, particularly in terms of the adoption and deployment of artificial intelligence (AI) technology. By recognising and resolving the issues and barriers that may occur during the procurement of AI in healthcare, the results of this study may promote the effective adoption of AI by healthcare organisations.

The research paper is organized as follows. The second chapter will consist of a literature review on value-based procurement, technology adoption in healthcare, the theoretical framework, artificial intelligence in healthcare, and AI adoption for medical diagnosis. The third chapter describes the data collection and analysis methodology. The fourth chapter presents the research question's findings and hypotheses. Discussion, implications, limitations, and recommendations for future research are included in the fifth chapter.

2. LITERATURE REVIEW

2.1. Value-based Procurement

Purchasing is an essential part of all organisations, including healthcare. Healthcare procurement costs make up to 40 per cent of hospital expenses (McKone-Sweet et al., 2005). There has been pressure to reduce these costs and healthcare has been very cost-based focused, ensuring that it spends the least amount of money possible through competitive tendering (Lian & Laing, 2004). This focus on reducing costs has been subject to competition because there are concerns that innovative products may be disadvantaged (Sorenson & Kanavos, 2011). According to Ann Allen et al. (2009), health systems are responsible for allocating public resources in order to improve the overall health of a defined population. These public resources can be used for the procurement of innovation in healthcare because they can provide substantial value to individuals and society (Nolte & Organization, 2018).

Procurement can act as a professional intermediary to implementing innovation in healthcare, by using calculative tools to establish the details of procurement situations and make it possible to calculate some measures of value (Miller & Lehoux, 2020). In the procurement literature, there has been a shift from a narrow price-based focus towards a broad value-based perspective that includes innovation that comes from collaborative relationships (Corsten & Felde, 2005).

This form of procurement is called value-based procurement (VBP) and is used to describe a method of purchasing products and services that puts stakeholder value above cost considerations. In healthcare, value is the improvement in health outcomes compared to the overall cost of treatment (Porter & Teisberg, 2006). It is a strategy that focuses on the long-term benefits of building strong relationships with suppliers and on getting better results for both patients and hospitals (Belotti et al., 2022). Artificial intelligence is an innovation that is focused on delivering value to patients by improving healthcare outcomes (Kaul et al., 2020). Implementing AI in healthcare can therefore be seen as a way of applying value-based procurement.

In an increasing number of healthcare systems throughout the globe, value-based purchasing is being used. The UK's National Health Service (NHS) has been making the switch to VBP since the early 2000s. NHS England created a VBP framework to enhance patient outcomes and cut costs (Blumenthal & Jena, 2013). Canada has also started to transition to value-based procurement for the same reasons NHS (Prada, 2016). The Danish Ministry of Health implemented a VBP framework in 2016 to start the growth of value-based purchasing in the Danish healthcare industry (Belotti et al., 2022). Belotti et al. (2022) looked at the effectiveness of VBP in healthcare and showed that VBP may encourage innovation in the sector.

Several difficulties may be faced while adopting value-based procurement in the healthcare industry. In the paper by Meehan et al. (2017), they classify the barriers into two categories: relational barriers and resource barriers. The resource barriers are capacity and capability issues, while the relational barriers are myths, mistrust, and perceptions of procurement.

Meehan et al. (2017) claim that relational barriers create obstacles for stakeholders that are needed for a value-based approach. Relational barriers such as myths are often based on the way things have been in the past. These include beliefs that procurement is inefficient and has no product knowledge, that clinicians don't trust procurement, or that procurement is only focused on reducing cost. These myths can create mistrust and perceptions that hinder the implementation of value-based procurement methods. On the other hand, resource barriers relate to more tangible challenges. Capacity issues can present themselves as a lack of resources and capability issues can be a lack of knowledge. A lack of resources used to exist in managing the buyer-supplier relationship, as it was often neglected. As a result, suppliers frequently circumvented procurement to discuss innovation issues. The lack of knowledge can be found in the required skills and understanding that personnel and organizations have in effectively implementing a value-based approach.

Next to relational and resource barriers, healthcare professionals may be resistant to change because they question the effectiveness of value-based healthcare (Health, 2020). Another barrier that organizations may encounter is the lack of regulatory support for value-based purchasing. Public procurement guidelines require openness, equal treatment, and objectivity in the sourcing process that is carried out by healthcare providers (Bulens et al., 2018). There is no clear and fair evaluation between suppliers in value-based purchasing. It is difficult to objectively compare key performance indicators (KPIs) for value-based purchasing which makes it difficult to follow procurement guidelines.

Key performance indicators can be used to measure the success of value-based procurement. According to Damberg et al. (2014), some examples of indicators are the total cost of care, length of stay, patient safety and patient experience. There is no best way to measure the success of value-based procurement and KPIs have to be determined based on a learning process (Belotti et al., 2022).

In conclusion, value-based procurement in healthcare is a strategy that encourages long-term partnerships with suppliers to improve patients outcomes while maintaining or lowering costs. The adoption of AI faces several barriers, including a lack of regulatory support, resistance to change, and doubts regarding the value AI creates in healthcare. Value-based procurement may assist in overcoming some of the barriers by prioritizing stakeholder value above costs. The value of AI in healthcare is not immediately measured by an increase in profits, but rather by its capacity to improve the delivery of medical treatment and health outcomes. By implementing a value-based approach, healthcare organisations may more effectively analyse and integrate cutting-edge technologies, such as AI, whose value is not visible in cost reduction, resulting in improved patient outcomes and more efficient medical treatment delivery.

2.2. Technology Adoption in Healthcare

According to Agarwal et al. (2010), technological adoption in healthcare is important because healthcare information technology (HIT) has the potential to fundamentally transform almost all areas of health services. They say that there is a general understanding that the digital transformation of healthcare through information technology may cut costs and enhance quality. For instance, lower mortality rates and improved patient satisfaction can increase quality. Increasing productivity and efficiency can reduce costs, but there is not any solid, conclusive proof of this. This may be due to the fact that many healthcare organisations have had difficulty properly managing the implementation process to translate HIT investment into practical advantages.

Despite the strong need for knowledge and education, as well as an educated workforce, the application of information technology in the healthcare business has been slow (England et al., 2000). The healthcare industry's innovation process has its own set of unique challenges. The innovation process involves five key stakeholders, each with their own unique needs. Table 1 gives an overview of these stakeholders and their needs as explained by (Omachonu & Einspruch, 2010). Physicians and other caregivers are the primary users of healthcare technology, and they can be one of the barriers to implementing healthcare technology. New technology is often disruptive and influences or changes the current workflow by replacing existing technology (Miller & Sim, 2004). If a physician is determined to not use the technology then its adoption rates will be low (Bhattacherjee & Hikmet, 2007). A physician's willingness to use the technology is crucial to its adoption and considering physicians' perceptions and feelings is key to successful implementation. Physicians' perceptions and feelings are likely impacted by the change in their work behaviour and increased workload from the new technology (Lin et al., 2012). The patients' needs also play a large role in the innovation process as they are the core of healthcare organizations. Improving patient experience, reducing waiting time and improving patient outcomes are key to implementing new technology (Omachonu & Einspruch, 2010).

Another barrier is financial factors including capital requirements and maintenance costs. In a study by Jha et al. (2009), about the barriers and facilitators of electronic health records, they observed that hospitals that did not implement electronic health records had concerns about high costs in regard to the purchase and maintenance of the technology. The needs of healthcare organizations are more realistic, with an emphasis on enhancing efficiency and improving patient outcomes while controlling costs. Innovation companies share the desire to improve patient outcomes, but they also want to improve their revenue, which contradicts the desire of healthcare organizations. Instead, regulatory agencies want to lower risks and improve patient safety, which could go against the interest of cost containment or profit.

Table 1. Key stakeholders of the healthcare innovation process (Omachonu & Einspruch, 2010)

Stake Holders	**Needs, Wants & Expectations**
Physicians and Other Caregivers	Improved clinical outcomes, improved diagnosis, and treatment
Patients	Improved patients' experience, improved physiological well-being, reduced waiting time, reduced delay
Organizations	Enhanced efficiency of internal operations, cost containment, increased productivity, and quality and outcomes improvement
Innovator companies	Profitability, improved outcomes
Regulatory agencies	Reduced risks and improved patient safety

Next to barriers, some drivers promote the implementation of technology. According to Bernstein et al. (2007), there have been five constants that drive the process of integrating new IT in healthcare namely, budget, supportive leadership, project management, implementation and end-user involvement. Each of these drivers presents its unique problems, but collectively they motivate healthcare managers to find new methods to enhance their approach to innovative technologies. But it is becoming increasingly difficult to keep up with new advances in technology as they become more complex. Having an IT budget that allows for sufficient personnel is critical for the IT team to work efficiently and effectively, i.e., there are enough people to do the work. It is also necessary that the valuation of new technology is not only based on increased profit or decreased costs. In healthcare value also lies in intangible quantities such as improved patient outcomes. The second driver, leadership support, is important because healthcare organizations have to align organizational objectives to implement new technology, which allows the necessary change in the organization. Good use of project management is the third driver, as it enables the creation of realistic expectations. New technology is unlikely to produce immediate results, and its benefits may take time to materialise. Furthermore, the fourth driver implementation, says that implementation should be structured so that each step is clearly defined, which prevents valuable resources are wasted.

The fifth driver that Bernstein et al. (2007) name, end-user involvement, aligns with the barrier of a user's willingness to adopt the technology. Involving the end user through the integration process can assist with aligning their interest with those of adopting the new technology.

As is evident from the barriers and drivers, as well as the many stakeholders that are involved with technology adoption in healthcare, the introduction of innovation in healthcare is a complex process that requires careful consideration of its barriers and drivers. The successful adoption of technology in healthcare depends on a variety of factors such as a user's willingness to adopt the technology, and the availability of resources to support the technology. A theoretical framework can guide the implementation of technology and is needed to explain the factors that influence the adoption and use of technology in healthcare. The technology Acceptance Model (TAM) (Davis, 1985) and the Theory of Planned Behaviour (TPB) (Ajzen, 1991) are two theoretical frameworks that can be used to understand technology adoption. The TAM is focused on the role of perceived usefulness and perceived ease of use in a user's behavioural intention to use the technology, while the TPB is also focused on external factors that may influence an individual's behaviour. Together, these frameworks provide a comprehensive understanding of how technology adoption happens in the complex environment of hospitals, where a variety of stakeholders are involved. The next section describes the TAM and TPB more in-depth and explains how both theories are used to explain the research question.

2.3. Theoretical Framework for exploring technology adoption in Healthcare

2.3.1. Technology Acceptance Model

This study aims to understand the barriers that influence the adoption of artificial intelligence (AI) in medical diagnosis. To gain a comprehensive image of the adoption of AI in healthcare, both the Technology Acceptance Model (TAM) and the Theory of Planned Behaviour (TPB) are used as theoretical frameworks.

The Technology Acceptance Model is a framework that aims to explain how and why individuals or organizations adopt and use new technologies (Davis, 1985). According to Davis (1985), the model has identified that the user's actual usage of the technology is mainly determined by the user's overall attitude towards using it. The attitude determines the behavioural intention and is a combination of two major beliefs, namely perceived usefulness, and perceived ease of use. Perceived usefulness is the degree to which a person feels that using a certain system will improve his or her work performance. Perceived ease of use is the extent to which a person believes that using a specific system would not need any physical or mental effort. There is a direct relationship between perceived ease of use and perceived usefulness because a system that is simple to use will result in a direct performance increase. That is because when technology is easy to use they are more productive in using the technology and will therefore become more productive in that part of their job. Then there are external variables that do not directly influence the attitude towards using the technology but influence the perceived usefulness and perceives ease of use. The external variables are for example technology-specific design features. TAM or an extension of TAM have been widely employed in healthcare to forecast and comprehend the adoption and use of technologies (Holden & Karsh, 2010).

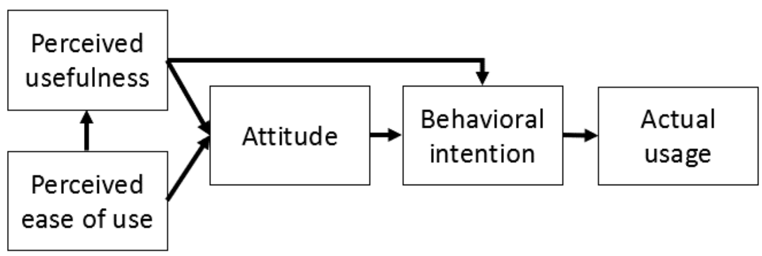

Figure 1. Technology Acceptance Model (TAM) (Davis & Venkatesh, 1996)

In the paper by Hu et al. (1999), they used TAM to examine physicians' acceptance of telemedicine technology. They found that the perceived usefulness of telemedicine has a significant influence on physicians' intention to use the technology, but perceived ease of use was found to have no significant effect on behavioural intention and perceived usefulness. One plausible argument they give is the possibility that the perceived ease of use component of the TAM might not apply to individuals with above-average intelligence, such as physicians. The model appeared to have a weaker utility for explaining physician's attitude formation and intention development, PU and PEOU explained 37% of the variance, in comparison to other studies that reported between 65% and 73% (Hu et al., 1999).

The extended technology acceptance model (TAM2) has been used to examine the physician's intention to adopt internet-based health applications (Chismar & Wiley-Patton, 2003). TAM2 includes two additional external variables that influence perceived usefulness: cognitive instrumental process and social influence processes. Their results indicate that TAM2 was partially adequate and applicable in the professional context of physicians. That is because perceived ease of use did not predict the physician's intention to use internet-based healthcare applications, but perceived usefulness was found to be a significant determinant. The external variables that were of significant influence on perceived usefulness were job relevance and output quality. This means that physicians value technology that is relevant to their job and increases the quality they deliver. Chismar and Wiley-Patton (2003) also indicate that physicians are likely to adopt beneficial applications even if they may not be easy to use.

2.3.2. Theory of Planned Behaviour

The Theory of Planned Behaviour is a theory that aims to explain and predict human behaviour (Ajzen, 1991). It is considered an extension of the Theory of Reasoned Action (TRA) which was proposed by Ajzen and Fishbein (1980). The theory of planned behaviour is focused on an individual's intention to perform a given behaviour. Intentions capture the reasons why someone does something and show how hard people are willing to try and how much effort they plan to put in to do the behaviour. In general, the more strongly someone wants to do something, the more likely it is that they will do it. The theory identifies attitude, subjective norm, and perceived behavioural control as significant determinants of the behavioural intention and therefore the behaviour.

The theory argues that perceived behavioural control influences the intention and the behaviour and refers to the degree to which an individual believes they have control over performing a particular behaviour. Perceived behavioural control is based on past experience, available resources, and situational factors. If a person believes that they have control over the behaviour because for example, they have done it in the past and that it is relatively easy to perform they are more likely to intend to engage in that behaviour. For example, a person can believe that their behaviour determines their outcomes but at the same time, they can still believe that their chances of curing cancer are very slim. Attitude relates to an individual's overall assessment of behaviour. It is the extent to which a person feels favourable or unfavourable feelings about performing the behaviour. These feelings are influenced by a person's experiences, prejudice and cultural factors. For instance, a person who grew up in an environment where data privacy was a priority is likely to have negative feelings about adopting AI, given that AI requires a large amount of data, which is frequently gathered through data sharing. Subjective norms relate to the perceived social pressure to perform or not perform a behaviour. This social pressure can come from friends, family, or colleagues. Subjective norms are influenced by normative norms, which are based on an individual's perception of social norms. For example, the thought of what your friends, family or colleague would or would not approve of can also be a form of social pressure. If a person believes that their social network expects them to engage in a specific behaviour, they are more likely to have a favourable attitude towards that behaviour and a higher intention to engage in it.

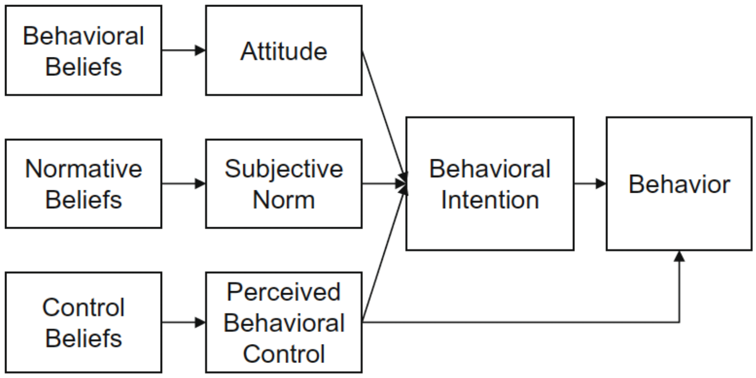

Figure 2. Theory of Planned Behaviour Model (TPB) (Ajzen, 1991)

In the paper by Arkorful et al. (2020), the intention to use technology among medical students has been evaluated using an extended model of the theory of planned behaviour. They conducted a field study with 322 medical students from various medical institutions who were completing obligatory clinical rotations in Ghana. The core constructs of TPB were able to explain 26% of the variance in technology adoption, and including the extension construct, and descriptive norm, the model was able to explain 33% of the variance. It is stated that TPB is a promising paradigm with a higher probability of accurately predicting intention. The fact that they did not define the type of technology was a limitation of their study, as they claim that doing so would have made the research more robust, distinct, precise, and effective.

The study by (Deng et al., 2021) aims to identify the factors that predict physicians' utilization behaviour of contrast-enhanced ultrasound (CEUS). They integrated the technology acceptance model and the theory of planned behaviour into a single model. A survey was conducted among 309 physicians in China. They found that physicians' intention to use CEUS was directly associated with utilization behaviour. They also found that attitude, subjective norm, perceived behavioural control and perceived usefulness are significant influences on physicians' intentions. Their results indicate that physicians are more likely to adapt technology to make their work more efficient and effective. Also, it was found that perceived ease of use has no direct relationship with a physician's intention.

2.3.3. Technology adoption model

In the past sections, the TAM and TPB have been explored separately. In this section, the TAM and TPB are combined into a single model, shown in Figure 3, to capture a larger range of determinants that influence a user's intention to perform a certain behaviour.

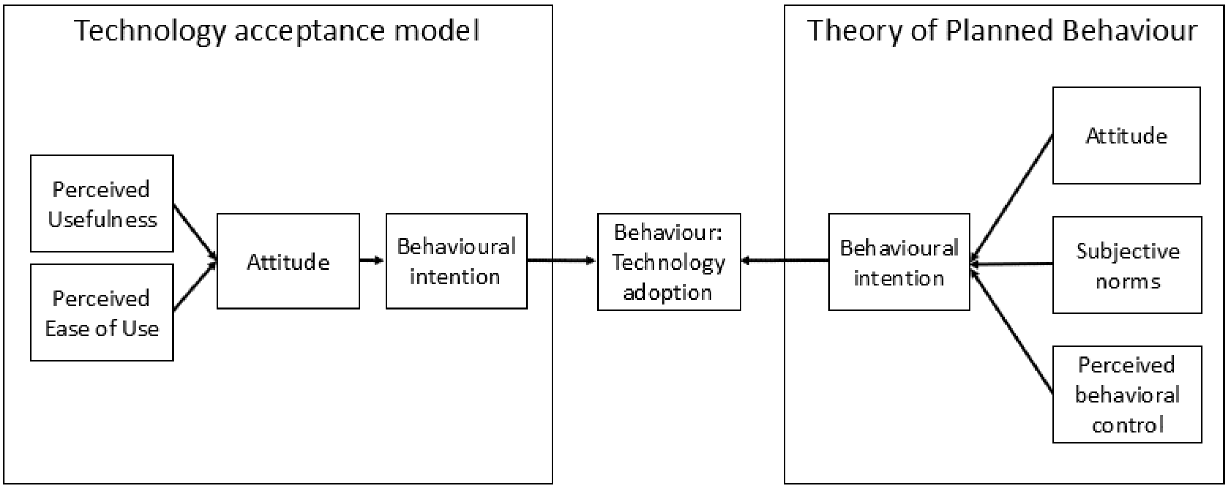

Figure 3. Technology adoption in general (No focus on artificial intelligence)

The TAM offers generic information on users' thoughts of the system, while the TPB provides more particular data to better guide the development (Mathieson, 1991). TAM is a useful framework to understand why a stakeholder intends or does not intend to adopt a specific technology. The TAM can be used to explore operational barriers such as system complexity, the requirement for specialized training, and the integration of technology with existing workflows. These operational barriers are represented in the perceived usefulness and the perceived ease of use constructs in the TAM. However, to gain a comprehensive understanding of the factors that influence technology adoption it is necessary to also consider the environmental barriers. The TPB can help to understand the environmental dimensions that influence technology adoption in healthcare. The TPB believes that the behavioural intention to perform a certain behaviour, in this case, adoption, is influenced by subjective norms. Subjective norms are the perceived social pressure to perform or not perform a specific behaviour. These subjective norms can be influenced by environmental factors such as social influences, cultural values, and institutional policies. Together the TAM and TPB are more capable of explaining the barriers to the adoption of technology in healthcare because they complement each other's weaknesses.

So, a general technology adoption model is developed based on the TAM and the TPB. The following section will describe what literature says about artificial intelligence in healthcare. The history, types, advantages and barriers of AI implementations are described, which are then used to develop different propositions for AI adoption in medical diagnosis.

2.4. Artificial intelligence in healthcare: history, types, advantages, barriers

In this section, the term artificial intelligence (AI) is being used as an umbrella term for machine learning, natural language processing, deep learning, and other AI enabled tools whose purpose it is to assist, and improve medical diagnosis, patient treatment, and outcomes. This section is organized as follows: first, a historical and evolutionary overview of AI in the healthcare sector is provided. The types of AI used in healthcare are then described. In the third section, the benefits of using AI in healthcare are discussed, and in the fourth section, literature-based barriers to the implementation of AI in healthcare are presented.

2.4.1. Overview of the "History and Evolution of AI in the healthcare sector"

Artificial intelligence has been present in healthcare since it was first described in 1950. AI began as a simple set of "if, then" rules and has evolved over several decades to incorporate increasingly complicated algorithms that function similarly to the human brain. However, the limitations of early models hindered their general adoption and medical use (Kaul et al., 2020). The history of artificial intelligence in healthcare may be divided approximately into three time periods: 1950 to 1970, 1970 to 2000, and the current period from the 2000s. In the first period, from 1950 to 1970, the focus of early AI was on producing robots with the ability to make judgements previously made only by humans. One early example is the computer program Eliza, introduced by Joseph Weizenbaum in 1964, which is one of the earliest algorithms capable of mimicking human conversation using natural language processing (Haenlein & Kaplan, 2019). During this early period, the adoption of AI in medicine was slow but it sparked the digitalization in healthcare that was necessary for the future growth of AI in medicine (Kaul et al., 2020).

The second period of the history of AI in healthcare, from 1970 to 2000, is referred to as the "Winter of AI" by Greenhill and Edmunds (2020). During this period initial interest in AI had declined and it was assumed that it would take decades for AI to enhance productivity. The high costs of AI research and the pessimistic outlook of the future capabilities of AI were some of the factors that led to this decline in interest (Haenlein & Kaplan, 2019). The decline in interest was matched by a decline in funding for AI research. Despite the lack of interest and funding during the AI winter the research did not stop. In 1972 MYCIN was developed, this was an expert system that uses clinical decision criteria of experts to advise physicians on the selection of treatment for bacterial infections (Shortliffe et al., 1975). MYCIN was not used because it was not notably better than human diagnostics, and they were badly integrated with clinical workflows and medical record systems (Davenport & Kalakota, 2019).

In the 2000s, the increase in data in the field helped artificial intelligence in medicine overcome one of its key obstacles, a shortage of data. In addition to the rise in data, the success of AI is enabled by the exponential growth in computing power and the wide adoption of cloud computing (Greenhill & Edmunds, 2020). The current period is characterized by the rise of deep learning, a type of AI that utilises large data sets to solve problems that have proven difficult for other types of AI to answer (Lecun et al., 2015). Before this increase in data, deep learning was not working as effectively because if it is trained on smaller data sets it runs into a problem called "overfitting" (Ying, 2019). In 2015 AlphaGo, which is a program made by Google, was able to beat the champion in the complex game Go which has an enormous search space and difficulty in evaluating board positions and moves (Silver et al., 2016). AlphaGo employs deep neural networks and demonstrates the ability to manage large datasets and make complicated judgements. IBM has attempted to train its artificial intelligence Watson to recommend personalized cancer treatments for patients (Strickland, 2019). This attempt to improve cancer care has been heavily criticised since, according to some, it delivered ineffective and sometimes even harmful recommendations. While cancer therapy may not be the best application for Watson, there are successful cases where Watson appeared to add value. It can be a source of medical information for clinicians when deciding on a treatment plan, which is one way it can add value. (Strickland, 2019).

2.4.2. Types of AI used in Healthcare

The healthcare sector consists of businesses that provide goods and services to treat patients. There is a growing need for healthcare services which has created a shortage of healthcare practitioners, with an emphasis on doctors (Kirch & Petelle, 2017). The shortage of healthcare professionals makes it a crucial matter that medical professionals' time is spent in areas in which it contributes most, caring for patients (Spatharou et al., 2020). The interest in implementing artificial intelligence in healthcare to improve patient care and outcomes is increasing (Davenport & Kalakota, 2019). Currently, several types of AI are already used in healthcare, such as machine learning, natural language processing, and cognitive systems. To comprehend the potential of AI in healthcare, it is necessary to examine the types of AI already used in the field.

Machine learning (ML) can identify patterns in data which can be used to understand the current world or make predictions (Wiens & Shenoy, 2018). The objective is to build a model that describes the data as well as possible and therefore it needs a large dataset. There is a great deal of data in healthcare due to the use of electronic health records (EHRs). This data is useful for a wide range of clinical tasks. It can be used in the critical care unit to predict ICU mortality rate and length of stay (Gutierrez, 2020). It can also be used to detect high-risk and high-cost patients. This is crucial for creating value because the limited resources that healthcare has can be used more effectively, where they are most needed (Bates et al., 2014). However, machine learning has some drawbacks, including the necessity for huge datasets to train the model, the need for data preparation, and the possibility of bias in the algorithm's predictions (Panesar, 2019). Lately, the application of deep learning in healthcare has made AI more effective and overcomes some of machine learning's limitations (Gupta et al., 2021). Deep Learning is a process that involves deep-layered neural networks (Panesar, 2019) where neural networks analyse problems in terms of inputs, outputs and weights of variables that relate the input to the output (Sordo, 2002). Deep learning integrates data at multiple levels which makes it a more adaptable algorithm with greater precision and accuracy than traditional machine learning algorithms. Deep learning has the potential to further improve the applications of AI in healthcare and is a powerful approach for complex problems that involve large amounts of data (Miotto et al., 2018).

Another type of AI used in healthcare is natural language processing (NLP) which is used to analyse data, such as speech and text (Chowdhary, 2020). Speech and text are unstructured data, and EHRs include a large amount of this data which in the future can be used for NLP (Esteva et al., 2019). Iroju and Olaleke (2015) identified applications of NLP in healthcare, some examples are information extraction, information retrieval, user interfaces, and document categorization. The healthcare industry faces high error rates (Bock et al., 2005), by extracting relevant information from EHRs, NLP can help minimise error rates by improving decision-making, hence reducing costs and enhancing healthcare processes. Another example is the usage of speech recognition-based user interfaces, which may enable people to speak with computer systems to aid with simple manual tasks in an effective manner (Hirschberg & Manning, 2015). Patients can interact with a computer and can ask it health-related questions or obtain information about upcoming treatments.

Computer vision focuses on understanding images and videos and includes problems such as image categorization and object recognition (Esteva et al., 2019). The use of computer vision in healthcare has the potential to increase diagnostic accuracy and patient care (Gao et al., 2018). One example is in the radiology field in which computer vision can be used to pre-screen images and identify features, effectively reducing the input needed by trained radiologists (Hosny et al., 2018). Computer vision also has shown great potential in surgery, where it has been used to enhance certain features and skills such as suturing and knot-tying (Bohr & Memarzadeh, 2020).

Expert systems are rule-based systems that turn the knowledge of experts into a set of rules (Seto et al., 2012). They are algorithms that simulate the decision-making skills of humans and are therefore considered AI (Saibene et al., 2021). Expert systems are a convenient and easy-to-use way to get professional expertise and can relieve human experts from some workload (Saibene et al., 2021). While expert systems can help physicians in the decision-making process, they have several problems and limitations, two important limitations are knowledge bottleneck and performance brittleness (Duan et al., 2005). An expert system is only as good as the knowledge it is based on, and its scope is also limited by this knowledge. They are slowly being replaced by approaches that are based on data and machine learning algorithms (Davenport & Kalakota, 2019).

2.4.3. Advantages of AI in the Healthcare Sector

The healthcare industry is facing a rising demand for healthcare services primarily due to an ageing population, high acuity care, and new infectious diseases (Oulton, 2006). While the demand for healthcare services increases, several countries are experiencing a shortage of healthcare practitioners, particularly physicians (Bohr & Memarzadeh, 2020). This increase in demand is worrisome because it leads to poorer patient outcomes and increases the cost of care (Oulton, 2006). To address this issue the healthcare sector is turning towards artificial intelligence to help improve patient care and outcomes (Meskó et al., 2018).

AI could improve patient outcomes by, among other things, improving diagnostic precision and efficiency (Kaul et al., 2020). Precision diagnostics involves accurately controlling a patient's healthcare model and identifying specific diseases. An AI that is trained on a large set of medical diagnosis data can help clinicians quickly and accurately diagnose patients. Hence, clinicians have to spend less time tracking patient data and can spend more time treating the patients. In radiology, AI can be integrated into the workflow to make the workflow more efficient by assisting in analysing medical images to detect, characterize and monitor diseases (Hosny et al., 2018). This can improve patient outcomes by decreasing reading time and earlier detection of critical findings (van Leeuwen et al., 2021). In oncology, AI has to potential to be a key driver to transform healthcare into personalized medicine (Shimizu & Nakayama, 2020). It is a real challenge to create medicine that is expected to improve the outcome of many patients. Due to the increase of data in the field, AI can classify patients into different groups based on their predicted response to medicine or risk of disease, thereby improving patient outcomes.

In the paper by (Reddy et al., 2019) they explain how the application of artificial intelligence might reduce the cost of health care by forecasting the outcomes of terminally sick and cancer patients and by monitoring disease outbreaks. In a time when the demand for healthcare is rising medical personnel is sometimes forced to choose which patients get the scarce resources of the hospital, which is a very difficult decision (Cookson, 2000). Using a cost-effectiveness analysis for healthcare resource allocation could be a way to determine who gets the scarce resources (Eichler et al., 2004) and AI can help determine the treatment effectiveness by forecast the healthcare outcomes. In case of disease outbreaks, AI can be used for early detection and diagnosis of the infection, monitoring the treatment, and contact tracing of the individual's (Vaishya et al., 2020). Therefore, reducing the number of resources required for the disease outbreak eases the burden on those resources. AI can also help reduce costs in drug discovery, which is a time-consuming and expensive process that can be made more efficient and effective by using AI that can analyse large amounts of data (Chan et al., 2019).

The use of artificial intelligence (AI) for administrative tasks frees up time for healthcare employees to devote to other crucial responsibilities. Approximately one-fourth of a nurse's time in a hospital setting is now dedicated to administrative responsibilities rather than direct patient care. (Commins, 2010). AI can be used for several healthcare applications, including claims processing, clinical documentation, revenue cycle management, and medical records administration (Davenport & Kalakota, 2019).

2.4.4. Barriers to the Implementation of AI in Healthcare

Artificial intelligence has the potential to change the healthcare industry, but several barriers hinder its adoption in healthcare. These barriers can be broken down into legal and ethical concerns, technical issues, organizational barriers, and regulatory barriers.

Table 2. Overview of barriers found in literature

Category	**Barrier**
Legal and ethical	Data sharing (He et al., 2019) (Jiang et al., 2017)
	Transparency of AI algorithms (Hashimoto et al., 2018) (Char et al., 2018)
Technical	AI needs constant development (He et al., 2019)
Organizational	Knowledge and expertise of medical personnel (Briganti & Le Moine, 2020)
	Resistance to change medical personnel (Sun & Medaglia, 2019 (Petersson et al., 2022)
Regulatory	Country specific regulations (Sun & Medaglia, 2019).
	National security risk (Sun & Medaglia, 2019)

The implementation of artificial intelligence in healthcare raises several legal and ethical concerns. One of these concerns is data sharing, as artificial intelligence requires a large amount of data to work properly; data are abundant in healthcare, but the majority of this data is patient data. Patients must consent to the use of their data, and the data must be anonymised and deidentified, to protect their privacy (He et al., 2019). Another issue is that there is now little incentive for data sharing in the United, but there is a reform in the way that shifts the physician's focus away from treatment volume towards treatment outcomes (Jiang et al., 2017). This should encourage healthcare providers to gather and share data to get the best treatment outcomes. Furthermore, the transparency of AI algorithms is also a significant problem. AI systems that are based on for example neural networks have a “black box” design, that is nearly impossible for humans to analyse and verify. This leaves a significant accountability hole because if physicians cannot check the output of AI, the question of who is accountable for errors arises (Hashimoto et al., 2018). Another transparency issue is the potential for bias. This is possible when the data it is trained on has an unequal representation of certain populations, which can lead to unequal healthcare outcomes (Char et al., 2018).

For optimal performance, AI needs constant development which will necessitate continual maintenance and updates to software algorithms. Without the assurance that AI will provide value to healthcare, this is a costly endeavour and it is unclear how the use of AI will be reimbursed (He et al., 2019). This is illustrated by IBM's artificial intelligence Watson, which has been used in public healthcare in China. Patients thought a visit with Watson is too expensive, and the hospital also found Watson to be costly because they did not realise any revenues from utilising Watson (Sun & Medaglia, 2019). Making sure that patients' sensitive data is handled securely introduces another economic challenge because, on average, a breached health record costs $355 (Gerke et al., 2020), and because AI must be trained on a large dataset, this expense will be substantial.

Furthermore, medical personnel must be trained to handle the digital shift and to educate patients and colleagues (Briganti & Le Moine, 2020). The workforce should be aware of both the benefits and drawbacks of AI; ideally, they should also understand how algorithms are designed. This knowledge is essential for healthcare practitioners to maximise their role in human-machine teams (He et al., 2019). While the benefits are apparent, healthcare professionals must be able to observe their value; otherwise, they will be unwilling to drive the adoption ahead (Petersson et al., 2022). Thus, artificial intelligence's value must be assessed before it can be utilized in the healthcare industry. The general public's lack of confidence in AI-based decisions presents doctors with a second adoption barrier. Due to the historical importance of face-to-face communication between patient and physician, the necessity for physicians to interact with a machine for important decision-making raises trust issues. (Sun & Medaglia, 2019).

Government policymakers and healthcare professionals in China have underlined the possible threat to national security when a foreign business obtains and keeps significant amounts of personal data on Chinese patients. They fear that this data can be exploited for harmful purposes, including biological warfare (Sun & Medaglia, 2019). Another barrier identified by policymakers is the lack of regulation; there is no accepted definition of artificial intelligence, no official norms for how AI may be used, and no official standard for evaluating its performance. Lastly, there is the issue of countries having different regulations. AI can for example come up with a treatment that is legal in for example the United States but is illegal in China (Sun & Medaglia, 2019).

2.5. Artificial intelligence adoption in medical diagnosis

In the past sections, a general model is developed for technology adoption (see Figure 3). In this model, the TAM and TPB are combined into a single model to capture a larger range of determinants that determine a user's intention to perform a certain behaviour. Furthermore, an overview of artificial intelligence in healthcare is provided. The following section will describe the general technology adoption model in the context of artificial intelligence. Different propositions will be developed and will be divided among the technology acceptance model and theory of planned behaviour determinants of technology adoption. At the end of this section, a model will describe the expected factors that will positively influence the willingness to adopt AI in medical diagnosis. This model will be used as the base of the interviews.

<u>TAM framework factors</u>

A factor described in the technology acceptance model that can influence stakeholders' intention to adopt AI is the perceived usefulness of AI. If a stakeholder perceives artificial intelligence to be a useful tool to successfully assist in a patient's medical diagnosis, then their perceived usefulness will be high. Perceived usefulness in the context of physicians and other caregivers might be explained by considering the value that AI can generate in medical diagnosis. Value for a physician can be created by improving patient outcomes or by decreasing costs (van Leeuwen et al., 2021). This could be achieved by for example enhancing diagnostic accuracy (Kaul et al., 2020), increasing productivity (Meskó et al., 2018), and improving patient care (Davenport & Kalakota, 2019). A physician who sees the use of adopting AI in medical diagnosis may be more likely to adopt it, whereas a physician who does not see its value may be less likely to adopt it. Healthcare organizations, patients, innovator companies and regulatory agencies all share this core need to improve patient outcomes. If the adoption of AI in medical diagnosis improves patient outcomes, then the stakeholders are more likely to adopt this new technology as it fulfils an important need for innovation. Based on this information the first proposition can be developed:

Proposition 1: Perceived usefulness of AI in medical diagnosis positively influences the intention to adopt it.

Another factor that is described in the technology acceptance model is the perceived ease of use. In the context of physicians and other caregivers, perceived ease of use could be defined as the fact that the implementation of technology does not require disruption in their traditional practice patterns (Yarbrough & Smith, 2007). This disruption in their traditional practice patterns is the additional time that is required when implementing a technology. Physicians' time is limited and disrupting their workflow cuts down their productivity. Physicians may need training and additional support when technology problems arise. The high initial physicians' time costs can be a significant barrier when implementing and adopting a technology (Miller & Sim, 2004). A physician that foresees a lot of work in the adoption of AI in medical diagnosis and who does not want to change their workflow is likely to have a lower intention of adopting AI. The inverse is also true: a technology that is easy to use and thus provides a direct productivity boost without the need for additional time investment might increase a physician's willingness to use AI in medical diagnosis. This aligns with the interest of healthcare organizations as their expectation of innovation is that it enhances the efficiency of internal operations and increases productivity. Innovation that is easy to use does not require additional training and this should help contain the costs, which is another important need for healthcare organizations. Easy-to-use innovation should also lower the potential risks of making mistakes which aligns with the interest of regulatory agencies. Based on this information the second proposition can be developed:

Proposition 2: Perceived ease of use of AI in medical diagnosis positively influences intention to adopt it.

<u>TPB framework factors</u>

The first factor in the TPB framework that is used to explain the intention to adopt AI in medical diagnosis is the attitude towards AI. When a physician must implement a technology in their workflow their attitude towards this technology can impact their willingness to do so, because implementing a new technology is often disruptive to the existing workflow (Miller & Sim, 2004). A physician's attitude is influenced by their experiences, prejudice, and cultural factors. If they have positive prior experiences with implementing technology, then it is more likely that their attitude towards implementing technology is more positive than if they had a negative prior experience (O'Donnell et al., 2018). A positive attitude can be supported by the early involvement of stakeholders in the implementation process, where a positive attitude is a state of mind that anticipates and hopes for favourable outcomes. This helps to ensure that their concerns are recognised and addressed proactively, which leads to a better user buy-in (Ahmad et al., 2012). Creating a positive attitude towards AI in medical diagnosis is deemed essential and can be achieved by aligning the interest of the stakeholders with the benefits of AI adoption. For example, innovator companies can be shown how profitable it is to develop and implement AI in medical diagnosis and regulatory agencies can be reassured how safe and effective AI technology is through an extensive validation process. If stakeholders have a positive attitude towards AI, they are more likely to support its adoption because they see the favourable outcomes. Based on this information the third proposition can be developed:

Proposition 3: A positive attitude towards AI in medical diagnosis positively influences the intention to adopt it.

The second factor in the TPB framework is subjective norms. Subjective norms are associated with perceived social pressure to perform or not perform a behaviour. Physicians can feel social pressure from colleagues who have a clear opinion about the use of AI. If their colleagues have a negative opinion towards AI, then this might influence the perception of the physician's opinion about AI as well (Chau & Hu, 2001). Having a social network that has a positive attitude towards AI could be a crucial determinant for the success of technology adoption. Subjective norms are also influenced by organizational culture and norms. Social pressure can also come from the potential value that AI in medical diagnosis can deliver. If the expected value is high, then the pressure to oblige to adopt AI is likely to be high as well. Physicians, healthcare organizations and other stakeholders' main objective are to create value for patients (Porter & Teisberg, 2007). An innovation that is seen by society as a high-value innovation, that will create a lot of value, is more likely to be adopted due to the social pressure to create value. Furthermore, an organization that values innovation is more likely to support AI because AI is potentially a significant innovation. In contrast, if the organizational culture is resistant to change or lacks support for AI implementation, it may create conflicting subjective norms that hinder adoption. Subjective norms can be a significant determinant in the reason to adopt AI in medical diagnosis. Based on this information the fourth proposition is developed:

Proposition 4: Positive subjective norms will positively affect the intention to adopt AI in medical diagnosis.

The third factor in the TPB framework is perceived behavioural control. Perceived behavioural control is associated with an individual's perception of their ability to perform a certain behaviour (Ajzen, 1991). In the case of AI adoption in medical diagnosis for physicians and other caregivers, this control is determined by their perception of their ability to use AI. Their perception is likely to be influenced by the complexity of working with the AI and the transparency of the algorithm. AI algorithms are currently nearly impossible to analyse and verify which leaves a gap in who is accountable for possible mistakes in medical diagnosis (Hashimoto et al., 2018). If physicians have no insights into how the AI makes decisions, they will perceive little to no behavioural control. Next to this, a physician must have the proper training and resources to effectively implement AI. If there is a lack of training and resources, then their ability to adopt AI will be limited (Petersson et al., 2022). AI will also require proper technical support in case of technical problems, if sufficient support is available then perceived behavioural control will also be higher. Therefore, a complex non-transparent AI algorithm is less likely to be adopted. Furthermore, complex, and non-transparent AI algorithms are also difficult for regulatory agencies, who want to reduce risks and improve patient safety. Breaches of patient health data costs $355 (Gerke et al., 2020), which are substantial costs for hospitals if there is a data breach. Complex AI algorithms need extensive and complex rules and regulations to cover all the potential risks. This negatively influences regulatory agencies to adopt AI while they cannot be certain if they have covered all the risks. Based on this information the fifth proposition is developed:

Proposition 5: Perceived behavioural control over AI in medical diagnosis positively influences the intention to adopt it.

The propositions developed in this section shed light on the factors that are expected to positively influence the intention to adopt artificial intelligence in medical diagnosis. The different propositions are described in Figure 3 and are divided into the Technology Acceptance Model and Theory of Planned Behaviour. The expectation is that the stakeholders' intention to adopt AI is high if perceived usefulness and perceived ease of use are high. The desire to adopt AI can be stimulated by a positive attitude and positive subjective norms, but not if they are negative. A low perceived behavioural control over using the AI is likely to result in a low intention from the stakeholders to adopt AI, whereas a high perceived behavioural control is expected to have a positive influence on the intention.

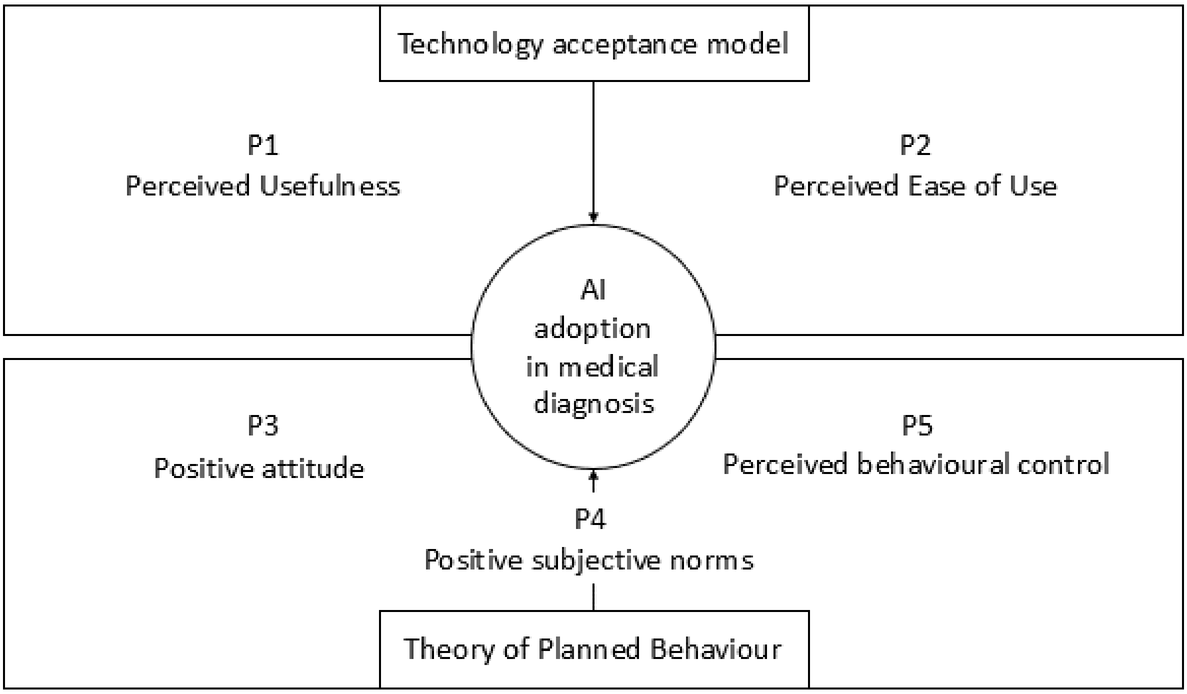

Figure 4. Expected positive influences on AI adoption in medical diagnosis

3. METHODOLOGY

3.1. Research Design

This study took a qualitative research approach, to answer the research question:

"What are the primary barriers to the adoption of artificial intelligence in medical diagnosis from the perspective of the procurement department?"

This approach is suitable because there is a lack of understanding about this topic from the perspective of the procurement department. A qualitative research method can help in gaining insights and a better understanding of this topic (Merriam & Tisdell, 2015).

Quantitative research involves the collection of numerical data through surveys (Bryman, 2012). Qualitative research is about understanding the social world by analysing different interpretations of people through observations and interviews (Bryman, 2012). Qualitative data gathering generates a detailed representation of a participant's thoughts and views, while quantitative data fails to interpret the actions of people (Rahman, 2020). The use of qualitative data gathering is deemed most suitable, while the successful implementation of AI in medical diagnosis depends on the intentions and readiness of stakeholders to use and embrace the technology.

This study uses a multiple-case study approach. A case study is suitable when the study focuses on investigating and answering real-life phenomenon (Yin, 2009). A case study enables the collection of many viewpoints on this real-world phenomenon (Cooper et al., 2003). The aim of this study is to describe a real-life phenomenon, namely potential barriers to the adoption of AI in medical diagnosis. There are single-case study and multiple-case studies. A single case study is an appropriate design when the case represent an unique or extreme case (Yin, 2009). A multiple-case study enables the examination of differences between cases and gives a more complete understanding of the phenomenon (Dubois & Araujo, 2007). Assessing if findings apply to multiple cases also enables a more robust theory development (Eisenhardt & Graebner, 2007). The flexibility of the case study allows for multiple participants in the organization to tell their experience, which leads to a deeper understanding of the phenomenon (Cooper et al., 2003)

This is a suitable method for this research, because implementing AI in medical diagnosis is a complex and rapidly changing phenomenon. Multiple stakeholders are involved in the implementation process, and the flexibility of a case study allows for multiple stakeholders in the same organization to explain their perspectives.. This allows for a better understanding of the potential barriers and the behavioural intention to adopt AI in medical diagnosis. The implementation of AI in medical diagnosis is also a recent topic and not much information is available, and the case study methods provides the opportunity to uncover new information

3.2. Data collection and Sample Definition

Semi-structured interviews are used to gather primary data. This type of interview enables a two-way conversation, in which interviewees can answer freely which may lead to a deeper understanding of the research question (Tong et al., 2007). This type of interview allows the study to gain a better understanding of the procurement process and the behavioural intent of stakeholders to use AI.

The sample selection criteria include stakeholders from three to five different healthcare organizations, encompassing a diverse group of healthcare professionals and purchasers involved in the adoption of AI in medical diagnosis. The healthcare organizations are selected on the requirement that they have recently implemented or are implementing AI for medical diagnosis. The research participants are selected based on their expertise and function within the organization, especially individuals with experience in implementing new technology in medical diagnostics and procurement decision-making. A total of 3 purchasers, 1 data scientist, 1 human-AI expert, 1 program manager, 1 innovation manager and 1 business manager medical support services are included in the sample.

The interviews are conducted in several healthcare organizations in the Netherlands to strengthen the validity of the research (Flick, 2004). The number of interviewees per healthcare organization is determined by the availability and willingness of relevant respondents. If surgeons and/or physicians are involved in the implementation process, then their insights and interpretations can sketch a larger picture and are therefore considered relevant participants. Similarly, if additional personnel are assigned to implementing and adopting artificial intelligence, all personnel are deemed relevant for this research. Assuming that they all fulfil a different role in the implementation process. The implementation of AI in medical diagnosis is a very recent topic that not many hospitals are currently working on. This severely limited the availability of potential interviewees.

The interviewees were asked a series of questions, which may be viewed in Appendix A. The questions can be roughly divided into sections. The first section consists of introductory questions about their role in the organization and involvement in decision-making. The second section contains questions regarding the stakeholders that are involved in the implementation process. The third section contains Technology Acceptance Model-related questions. The interviewees were questioned about their perceptions of AI's usefulness and ease of use for medical diagnosis. The fourth section consists of questions related to the Theory of Planned Behaviour. This part asks questions about the respondents' AI-related attitudes, skills, and societal norms. The last section consists of two more broad questions that allow the respondent to freely answer and give more insights into AI adoption barriers and possible solutions to these barriers.

3.3. Data Analysis

The primary data of this research will consist of 8 in-depth semi-structured interviews. To avoid any potential language barriers for the respondents, the interviews are conducted in Dutch. All interviews are recorded and transcribed with the permission of the participants. From the transcriptions relevant quotes are extracted that describe the propositions and research question. The duration of the interviews is approximately between 30 and 50 minutes. The variation in length can be explained by how involved the respondent was/is in the AI decision-making process in medical diagnosis. The more involved a person is, the better they were able to answer the interview questions.

Table 3. Qualitative sample overview

Respondent	Hospital	Function	Duration
1	A	Lead applied data science team	39:19
2	B	Purchasing manager	31:46
3	C	Purchasing manager	48:27
4	D	Purchasing manager	51:31
5	D	Program manager	51:31
6	E	Innovation manager	31:30

7	E	Business manager	47:20
8	-	Human-AI expert	44:28

3.4. Coding Process

The transcripts are coded through an inductive two-step coding process. The first step is open coding which allows the data to be broken down into first-level concepts. The open coding is used to identify the different barriers and barrier reductions. The second step is axial coding in which the open codes are compared and combined into overarching categories. The final categories that are used: B1: Knowledge, B2: Data, B3: Ethical, B4: Value, B5: Resistance, R1: Knowledge sharing, R2: Training. The personal questions and the process implementation questions are not coded while their results are purely descriptive and do not fit into categories. The questions regarding the propositions are coded as follows:

P1: Rejection, P1: Acceptance, P2: Rejection, P2: Acceptance, P3: Acceptance, P3: Rejection, P4: Acceptance, P4: Rejection, P5: Acceptance, P5: Rejection.

The transcripts are read multiple times in order to find connections and to assign the correct code. After the coding process, common views and interpretations are used to support the propositions, while uncommon contradictory responses are used to discuss the propositions (Bryman, 2012)

4. RESULTS

This chapter will describe the results of the interviews. The first part will explain the characteristics of each organization that was interviewed. By doing so the gathered data can be contextualized and the findings can be better understood within the specific organizational context. The second part of the results will explore the AI diagnosis implementation process. The third part describes the findings of the propositions and the research question.

During the interviews, it became clear that the implementation of AI in medical diagnosis is still in the rudimentary steps. All healthcare organizations that were interviewed are still in the process of implementing AI or are just starting to explore the possibilities. During the interview respondents were very eager to talk about the barriers to the adoption of AI in medical diagnosis, even before the question was asked or the interview started. Furthermore, the role of the purchasing department in the implementation process was still very limited or sometimes still non-existing. Many respondents explained that the knowledge and expertise necessary to do so were simply not present in the purchasing department. In-house AI projects were often run by the department that wanted to implement AI and had little to no intention to hand over control to the purchasing department.

Hospital A is an academic hospital that has many resources and capacity for setting up innovation initiatives. They have a digital health department with a data science team that is led by respondent 1. Hospital B is a general hospital that is focused on providing healthcare for regional patients and patients that need acute clinical care. Their approach to implementing new technology as respondent 2 mentioned: *"We take a 'wait and see' approach. Let's observe first and see how things unfold. We don't rush to be at the forefront; instead, we learn from others. If they can do it, we can do it too."* This approach is necessary while respondent 2 mentioned: *"You need capacity to thoroughly investigate all of this."* Hospital C is also an academic hospital and is therefore in a similar situation as hospital A. That means that next to the focus on patient care they are also focused on doing medical research. Hospital D is like hospital B a regional hospital. Hospital D, on the other hand, is in a unique circumstance in that it was chosen to be one of the few hospitals to participate in nationwide research of healthcare algorithms. This provides them with a distinct viewpoint on the implementation process. Respondent 8 works in an applied knowledge institute in the Netherlands, where they frequently collaborate with hospitals and conduct AI research. As a result of their expertise in

AI research and collaborations with hospitals, respondent 8 may provide useful practical insights. Hospital E is a general hospital that has put time and money aside to invest in AI applications.

Table 4 shows some characteristics of the researched hospitals. More information regarding the type of AI implemented, the involved stakeholders and the role of the stakeholders can be found in Table 5, Table 6, and Table 7

Table 4. Characteristics of researched hospitals

Hospital	**Type of hospital**	**Project leader of AI implementations**
A	Academic	Data science manager
B	General	-
C	Academic	-
D	General	Program manager
E	General	Innovation manager

4.1. Findings: AI implementation process

In this section, the findings of the implementation process of AI in medical diagnosis are shown. The section is divided into subsections headed: the type of AI implementations, steps of the implementation process, stakeholders involved in the implementation process and the stakeholders' involvement, role and dynamic in the implementation process.

4.1.1. The type of AI implementations

The AI implementation projects in healthcare organizations range from individual hospitals implementing AI on a small scale with limited resources to a group of hospitals representing a healthcare network implementing AI on a large scale with extensive resources. The individual hospitals are focused on specific processes in departments that can benefit from AI implementations, such as the radiology department, where a radiologist must be available twenty-four hours a day, seven days a week to analyse images of emergency patients. The healthcare network is implementing projects that are intended to have a large impact, on an entire department, such as determining the length of stay of patients in the emergency department. An overview of the types of AI that the researched hospitals have implemented or are currently implementing is shown in Table 5. The AI implementations are categorized into the following categories: clinical decision support systems, imaging and radiology, predictive algorithms, and patient support.

Table 5. AI implementations in healthcare mentioned by the respondents

	Type of AI implemented	**Hospital**
Clinical decision support systems	Risk management for premature and preterm infants	A
	Discharge from ICU model	A
	Clinical decision support system	A
	Diagnostic support systems	-
Imaging and radiology	Not specified AI implementation for radiology	C
	Bone fracture image recognition	E
Predictive algorithms	Algorithm predicting likelihood of admission from the emergency department	D
	Algorithm predicting the length of stay for patients in the emergency department	D

	Algorithm predicting duration of hospitalization for those in the clinic	D
Patient Support	Lifestyle advice systems for patients	-

The respondents mentioned that actual AI implementations are still lacking. Part of the reason that actual AI implementations are lacking is due to the fact that there are not many suppliers that are mature enough to implement AI, respondent 1 mentioned: *"Yes, well, you can see that in the field of AI, there aren't many companies that are very active or mature enough to implement it."* Even when a supplier has developed an AI solution the question is how well it functions, respondent 1 mentioned*: "But even then, you can see that there is still quite a lot of discussion about how well it is functioning."* However, some companies are further in developing AI implementations for radiology and pathology, as respondent 1 mentioned: *"However, in radiology, you do see a few companies that are further along, as well as in pathology."*

Due to the fact that there are not many mature companies that have well function AI implementations, some hospitals have started to co-develop AI implementations with suppliers. One of those hospitals is hospital C, they are in the process of co-developing an AI implementation for the radiology department, respondent 3 mentioned: "*We have a collaboration with a supplier, a procurement project specifically for radiology."* Furthermore, in hospital A there is a co-development project to create a clinical decision support, according to respondent 1: *"We have been collaborating with a supplier to create a clinical decision support system designed for the medical department, offering advice based on data."* Academic hospitals hospital A and hospital C both have abundant resources for research, however general hospitals do not have as many resources as these academic hospitals. In general hospital B, they are postponing the implementation of AI since they are unable to devote enough resources to a co-development project with a supplier, respondent 2 mentioned: "*We take a 'wait and see' approach. Let's observe first and see how things unfold. We don't rush to be at the forefront; instead, we learn from others. If they can do it, we can do it too."* However, that does not directly mean that all general hospitals are unable or unwilling to dedicate resources. In hospital E they are working on an AI implementation for radiology and oncology, respondent 6 mentioned: *"In radiology, we're working on image recognition to detect bone fractures. We're also involved in oncology, specifically gastrointestinal and liver* *surgery, utilizing machine learning. Within paediatric and allergy departments as well."* Cooperating with other general hospitals is another approach for general hospitals to create and use AI solutions. The SAZ hospital network in the Netherlands unites and coordinates the efforts of 29 general hospitals. Hospital D is part of this hospital network and is currently in the implementation phase of a large research project that seek to develop healthcare algorithms for predicting capacity management. Their aim is to develop an AI algorithm for the emergency department, respondent 5 mentioned: *"There are three algorithms being implemented, the first one determining the likelihood of admission from the emergency department. The second one is an algorithm predicting the length of stay for patients in the emergency department, and the third one predicts the duration of hospitalization for those in the clinic."*

4.1.2. Steps of the implementation process

AI diagnosis implementation consists of many steps. During the interviews, all of the respondents were asked to comment on the steps that are/were taken during the implementation process. From these interviews, a broad outline of the implementation process's steps is derived, which is shown in Figure 5.

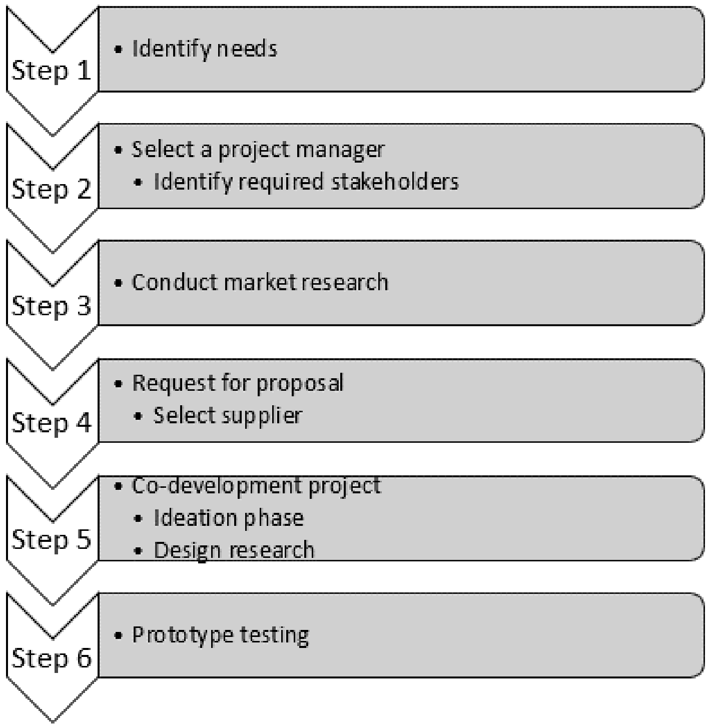

Figure 5. General overview of the steps taken during implementation process

In general, the first step is to identify the needs by assessing which process or department would benefit from implementing AI, as respondent 6 mentioned: *"We start with identifying the need. Then we proceed to map out the functional requirements."* After identifying the project's needs, a project manager is selected and given responsibility for the project, respondent 3 mentioned: *"Once we have a project leader who can organize the meetings, we can proceed to develop the program of requirements."*. Once the project leader has been selected and the required stakeholders have been identified, the project leader and the stakeholders develop a program of requirements, respondent 5 mentioned: *"Well, it certainly involved a comprehensive project plan from the beginning, with a series of documents and a focus on defining the requirements."* Then, market research is conducted to gather market information and determine if the requirements can be met, respondent 6 mentioned: *"Next, we conduct market research to identify the potential vendors or parties that can provide solutions. It could* *be one or multiple parties, and we may need to go through a selection process."* After conducting market research, the procurement process is initiated and a request for proposals is issued to identify a suitable supplier, respondent 6 mentioned: *"Subsequently, the procurement team becomes involved in the more commercial aspects and checks are performed in areas such as safety and privacy."* The next step is initiating a co-development project with a supplier who can meet the specified requirements. In the co-development project, they will undergo a phase of ideation in which the possibilities and ideas are defined, and an AI system is simultaneously designed in parallel. After a system has been designed, the testing phase begins, during which the AI is rolled out gradually to ensure and test its reliability.

4.1.3. Stakeholders involved in the implementation process

The stakeholders involved in the process vary across organizations and this section presents the different configurations that were found in each hospital. The involvement and role that each stakeholder plays in the implementation process and the dynamic between the stakeholders are described in section 4.1.4. Table 6 lists the various stakeholder structures that have been observed in the hospitals under investigation.

Table 6. Involved stakeholder configurations in the researched hospitals

	Involved stakeholders										
		Departments					**Information officer**			**Manager**	
Hospital	**Physicians**	**Data science**	**Information technology**	**Information communication**	**Legal**	**Purchasing**	**Security**	**Medical**	**Nursing**	**Business**	**Innovation**
A	X	X	X	X	X	X	X				
B	X			X	X	X	X				
C	X		X			X					
D	X		X	X		X		X	X		
E	X			X		X	X			X	X

In hospital A the involved stakeholders are the data science team, the medical specialist, the IT department, the ICT department, the information security officer, the legal department, and the purchasing department. In hospital B the configuration was found to be slightly different, namely the medical specialist, the ICT department, the information security officer, the legal department, and the purchasing department. A potential explanation for hospital A having a data science team, while hospital B does not is that hospital A is an academic hospital which has extended resources for research purposes. Because hospital A has its own data science team, they have the capability to develop its AI solutions internally, which they have been doing, as respondent 1 mentioned: *"In our project portfolio, we mainly focus on developing AI implementations at the moment."*

In hospital C the approach is to create a project group of all stakeholders, respondent 3 mentioned: *"One approach could be to create a select group of key users selected from these departments who participate in the project group and provide input."* The project group is formed by members that are involved in the use case and should have a voice in the procurement process, according to respondent 3: *"If you are working on patient monitoring systems, you would need involvement from departments involved with patient monitoring. These departments should have a say in the procurement process."* In hospital C as mentioned by respondent 3 the following stakeholders are involved in AI implementation, the IT department, the medical specialist, and a project leader from the procurement department.

Hospital D is leading a large AI implementation project for a large group of hospitals. The stakeholders involved in this project as explained by respondent 5 are medical specialists, team managers, the project leader, the executive board, the IT department, the ICT department, the medical information officer (MIO), and the nursing information officer (NIO). The MIO and the NIO are responsible for making IT applications more compatible with medical practice. The team managers of the medical specialists are just as important as the medical specialist because they are crucial in allocating time for their employees to participate. Respondent 5 mentioned that the executive board is also a stakeholder, while the other respondents did not. Respondent 5 mentioned the executive board as a stakeholder because the implementation does not provide immediate rewards, and the board must support this endeavour. The project currently has no commercial purpose and therefore the procurement department is not included as a stakeholder in this project, as respondent 4 mentioned: *"In terms of procurement, we currently do not have a specific role in this regard. However, if the situation becomes more commercially driven in the future, our role will become more significant."*

In hospital E when it comes to AI the directly involved parties are the ICT team, the medical specialist, the business manager, the innovation manager, the procurement department, the privacy officer, the security officer, or a legal specialist. The privacy and security officers are not actively involved in the implementation process, which means that they are not working on it on a daily basis, but more sporadically. They are called in once an issue arises that requires their expertise. The innovation manager is responsible for the financial or operational aspects, including procurement, of a new innovation project. The goal of the innovation manager is to drive and oversee innovation within the hospital to improve the ability of the hospital to deliver care in a more efficient manner, as mentioned by respondent 6: *"It's about approaching healthcare in a different way, exploring how we can utilize technology, for example, to improve the organization of our hospital or to deliver care in a more efficient manner."* Once the hospital explores new technological developments the innovation manager is the client or sponsor of the pilot project. The business manager is in charge of the hospital's financial and operational aspects; once an innovation project has gained traction and has left the pilot phase, then the business manager takes over the role of the innovation manager as project sponsor.

Respondent 8 also provided the necessary stakeholders for implementing lifestyle advice and diagnostic support. The stakeholders for lifestyle advice are patients, general practitioners, and dieticians. For diagnostic support the key stakeholders are the physicians, as mentioned by respondent 8: *"The key stakeholders for diagnostic support are the end-users, doctors, surgeons, and specialists."*

4.1.4. Stakeholders' involvement, role, and dynamic in the implementation process.

The stakeholders' involvement in the decision-making process seems to be dependent on their role in the implementation process. Stakeholders with a more important role have a large involvement in decision-making because their expertise and opinions carry more value. The stakeholder dynamics seem to be multifaceted and interconnected in most of the healthcare organizations researched. That means that the actions and decisions of one stakeholder can have implications for others. For example, the IT department pushing for progress, while the legal department is pulling back to focus on the legal aspects. An overview of the different roles that the stakeholders have is shown in Table 7.

Table 7. Role of Stakeholders in the implementation process of AI

Stakeholder	**Role**
Physicians	Provide feedback on AI
Data science team	Project lead and development of AI
IT/ICT department	Managing servers and data
Legal department	Oversees legal requirements
Procurement department	Create program of requirements, involve right stakeholders, select a supplier
Information security officer	Ensure data security
Medical information officer/ Nursing information officer	Responsible for making IT applications more compatible with medical practice
Business manager	Translate the strategic direction that is set by the board of directors into tactical plans
Innovation manager	Client for pilot projects
AI experts	Provide AI expertise

The role of the stakeholders is to provide advice in their area of expertise, respondent 1 mentioned: "*Everyone has an advising role in their expertise.*" Their expertise is required at the different go-no-go decisions in the innovation funnel, respondent 1 mentioned: *"We have an innovation funnel from idea to implementation. In this funnel, we handle different go-no-go decisions and at every decision, we consult the appropriate stakeholder."* The security officer for example must ensure data security and a jurist must oversee the legal aspects, respondent 2 mentioned: *"For example, the security officer ensures data security over the network, and a jurist oversees legal aspects. We also have someone dedicated to personal data protection."* The role of the IT department is to handle the technical infrastructure, by setting up the servers and managing the data: *"Our IT department, specializing in healthcare and information technology, is responsible for setting up the servers and managing the data."* The AI experts role is to advise stakeholders regarding the challenges and possibilities of AI in healthcare, respondent 8 mentioned: *"I do provide advice here and there regarding the challenges and possibilities of AI systems."* Furthermore, the role of the stakeholders is to create the program of requirements, in which their needs determine the requirements, as respondent 3 mentioned: "*The stakeholders create the program of requirements, which essentially outlines why you want to use AI."* In hospital E they have an innovation manager whose role is to be the client for pilot projects. These pilot projects are initial trial projects where the impact of several AI applications is examined on work processes, respondent 6 mentioned: *"If you look at the AI project within radiology, from my role as an innovation manager, I am the client for the pilot or the initial trial project where we try out several AI applications and see how they affect our work processes."* Once the pilot project ends the project is passed on to the business manager whose role is to translate the project outcomes into a more tactical plan, respondent 7 mentioned: *"I translate the strategic direction set by our Board of Directors into tactical plans and work on implementing those plans."*

The involvement of the stakeholders differs in the researched hospitals. In hospital A the decision-making process is led by the data science team, respondent 1 mentioned: *"Our involvement is quite extensive because we mainly focus on developing our own solutions and we act as experts and support the process".* However, in hospital B the decision-making process is led by the IT department, respondent 2 mentioned: "*Sometimes, IT is approached first in these matters because they are primarily concerned with the technical aspects."* This is also the case for hospital C, as respondent 3 mentioned: *"Well, we're not quite there yet. When it comes to AI, I won't have much input. That falls more under the responsibility of IT and BI."* In all researched hospitals, one similarity is that the procurement department's involvement in the decision-making process is limited. That is because the decision-making process in all hospitals is usually led by the department that possesses the most knowledge and expertise on AI. That also explains why the data science team in hospital A is responsible as the data science team possesses specialized knowledge on the functioning of AI. As mentioned by respondent 1: *"There is a team in the procurement department that handles medical technology and purchases medical instruments. In the case of software as a medical device, it would make sense to go through that route. However, the expertise in that area is currently more concentrated within our department."* The involvement of the procurement department becomes more active from the commercialization stage, as mentioned by respondent 4: *"In terms of procurement, we currently do not have a specific role in this regard. However, if the situation becomes more commercially driven in the future, our role will become more significant."* Before the commercialization stage the procurement department is involved in engaging the right stakeholders at the right time, respondent 2 mentioned: *"I am involved in engaging the right stakeholders."* With the exception of hospital A, where the data science team oversees every step of the AI deployment process and consequently consults with the stakeholders as needed, respondent 1 mentioned: *"During implementation, we ensure that the right stakeholders are involved at the right time."* Furthermore, due to the data science team's involvement, hospital A's procurement department has a limited overall responsibility, respondent 1 mentioned: *"In the procurement department, there is currently relatively less involvement in AI."* The physicians are actively involved in shaping the AI implementation and have to adapt their workflow to use the AI, respondent 5 mentioned: "*They need to adjust their workflows and actively contribute to shaping the appearance and functionalities of the new implementations."* As the physicians are the end-user of the AI their involvement in the decision-making process should be significant. In hospital A, this is the case as they indicated that the final decision lies with the physicians, as mentioned by respondent 1: *"The final decision lies with a physician, someone who is medically responsible in the healthcare process and has the relevant expertise."*

The dynamic of the AI implementation can be seen as a push-and-pull process, in which some stakeholders are open to the idea of an AI project and others are not. Respondent 8 mentioned: *"It can be a push-and-pull process, as not all stakeholders are initially open to the idea, especially at the beginning of such projects."* The dynamic is a balancing act between the stakeholders. For example, the IT department is eager to push for progress and wants to ignore the concerns that the legal department and the experts raise, respondent 2 mentioned: *"It is a balancing act between concerns that are raised by experts and stakeholders that are very eager to push for progress."* Sometimes stakeholders need to be convinced to change their mindset and start seeing the potential rather than just the problems, as mentioned by respondent 8: *"Along the way, I have noticed that many stakeholders do become more receptive and start* *considering possibilities instead of focusing solely on problems.* This shift in mindset occurs when the experts provide a demonstration of what is feasible, as respondent 8 mentioned: "*This shift occurs as we provide demonstrations, develop concepts together, and explore what is feasible and what is not."* The final decision-making authority lies with the board of directors and they can chose to ignore or address the concerns, respondent 6 mentioned: *"Ultimately, it's up to the Board of Directors, the highest governing body in the hospital, to make the decisions, and they can bypass those objections if necessary."* The implementation of AI in hospital D, where the AI project took an additional year, has shown that the dynamics between stakeholders can change over time. Because their time may be needed for other projects, certain stakeholders may become less involved in the project as a result, as indicated by respondent 5: *"It has now taken an additional year, which has greatly influenced the dynamics, while we are also engaged in other IT implementations."* The fact that stakeholder dynamics change over time, is also mentioned by respondent 8: *"It does happen regularly that the initial set of stakeholders diminishes over the course of the project."* The same reason as respondent 5 was given by respondent 8: *"We often encounter that there is a relatively small group of people who have the time, availability, and genuine interest to remain engaged throughout the project."*

4.2. Findings: Propositions

In this section, the findings of the propositions are shown. The section is divided into subsections headed by perceived usefulness, perceived ease of use, attitude, subjective norms, and perceived behavioural control. In Table 8 a cross-case analysis of the propositions is shown. For each propositions, the table indicates whether the response from each hospital is "yes" or "no" and provides additional information on the reasons or beliefs behind their answers. The naming of the hospitals in the table has been shortened, for example, hospital A in the table is presented as A. The table does not provide a comprehensive view of all hospitals, but rather the primary reason respondents provided, as interpreted by the interviewer, as to why the proposition is true or false.

Table 8. Cross-case analysis of propositions

Propositions	**Yes**	**No**
usefulness	A: Increased efficiency B: Increase healthcare capacity C: If all risks are managed D: Increase efficiency E: Increase healthcare capacity	
Ease of use	A: Complex AI lowers adoption E: Standardization simplifies use and adoption.	B: Not considered in purchasing process C: Safety is more important D: Other factors are more important
Attitude	A: Avoid damaging stakeholder sentiment B: AI acceptance depends on population C: Positive attitude is necessary driving force D: Key stakeholders require positive attitude E: Positive attitude is a key point	
Subjective norms	A: Strategy includes digital transition B: Organization environment affects adoption C: Pressure to perform as well as others D: Positive colleague experiences aid adoption.	

	E: Patients can demand to be treated by AI	
Behavioural control	A: Already considering future AI control B: Wait for others' AI success stories C: AI must stay controllable D: Black box AI would be rejected E: Control is only possible when AI is fully understood	

For the proposition about perceived usefulness, all hospitals agreed that an increase in efficiency is where they perceive AI to be useful for and therefore stimulates the intention to adopt AI. Before AI is perceived as complete useful, hospital C emphasized the importance of managing all associated risks of using AI in medical diagnosis. Perceived ease of use is a proposition in which the cases responded differently. As complex AI systems are more difficult to use and a standardized format for AI systems can make it simpler to work with, hospitals A and E believed that perceived ease of use was a significant factor in AI adoption. However, hospitals B, C, and D believed that other factors, such as safety, are more important than the ease of using AI which is why they believed that ease of use is not stimulant for AI adoption. All hospitals acknowledged that a positive attitude toward AI adoption was a significant driving force. Hospital A emphasized the importance of maintaining positive stakeholder sentiment, whereas hospital B suggested that AI acceptance may vary based on the characteristic of the population. However, hospital D explained that they encountered that only key stakeholders are required to have a positive attitude as they have a more substantial influence on the success of the implementation. All hospitals believed that positive subjective norms can stimulate the intention to adopt AI, but their arguments differ. Hospitals A and B considered organizational factors when adopting AI. Hospital C believed that hospitals will feel pressure to adopt AI to meet future industry standards. Hospital D found that positive coworkers increase AI adoption intentions. Hospital E believes that in the future patient demand could drive AI adoption. They considered the expectation of patients to be treated by AI to be a driving force for adopting AI. All hospital showed a risk-averse approach as they believed that control over the AI is necessary for adoption. Hospital A planned proactive AI control measures for successful implementation, whereas Hospital B took a more cautious approach, waiting for successful AI examples to gain confidence in adoption. Hospital C, D and E emphasized the importance of controllable AI, focusing on oversight and governance.

4.2.1. Perceived usefulness

All respondents mentioned that perceived usefulness is a significant determinant for the adoption of AI in medical diagnosis because, without it, nobody would want to go through the effort of implementing it. The respondents also mentioned the importance of risk management, the usefulness has to outweigh the risks. Perceived usefulness is understood by the respondents as the degree to which a person feels that using a certain system will improve work performance and it is present in healthcare organizations by the following means: improved efficiency, improved work quality, and increased value. Table 9 shows the factors that the respondents mentioned when they were asked if perceived usefulness is or is not a stimulant for AI adoption.

Table 9. Factors influencing perceived usefulness as a stimulant for AI adoption in medical diagnosis

Perceived usefulness	**Influence**
Increased efficiency	(+)
Improved work quality	(+)
Potential risks of implementing AI	(-)
Good system for managing quality	(+)

(+) Positive influence, (-) negative influence

Respondent 1 believes that AI clinical decision support is the future because they perceive the future usefulness of clinical decision support to be very high, respondent 1 mentioned: *"If you ask me whether AI clinical decision support is the future, the answer is simply yes."* Hospital A has been developing AI solutions internally, and when they show it to their medical specialists, they want to use it because they believe it will improve their clinical practice, respondent 1 mentioned: *"When we show the things we have developed internally, people say, Yes, that is something I would have wanted earlier. It greatly helps me in my clinical practice."* Another example of where improved efficiency increased the intentioned to adopt AI is in drug dosage application in rheumatology, respondent 1 mentioned: "*We made a drug dosage application in rheumatology, and we hear that this really improved physicians' efficiency and that it is the reason they use it."* The fact that hospital A is internally developing their AI solutions also gives credibility and confidence which help to stimulate its adoption, respondent 1 mentioned: *"If we offer it and people have confidence in it, and it is credible, especially credibility, then people will use it."* The intention of adopting new technologies in hospitals is to improve healthcare. Respondent 4 believes that AI will be able to improve healthcare in the future and therefore believes the intention to adopt AI in healthcare is stimulated by the perceived usefulness of AI, respondent 4 mentioned: *"I do believe that perceived usefulness can be an adoption stimulant. Our intention is always to improve healthcare and AI is likely able to do this in the future."* The expected usefulness of AI, and thus an element of how it will improve healthcare, is to save time and labour by achieving results with fewer people, as respondent 2 mentioned: *"The expected benefit of AI is saving time and labour by accomplishing tasks with fewer people, thus achieving results more efficiently."* However, improved efficiency can also hinder the intention to adopt AI because people are afraid that they will be replaced by the AI. Respondent 2 mentioned: *"Sometimes people find it challenging to envision their own actions being automated."* An example of this behaviour is when hospital B wanted to implement an orthopaedic robot that could improve positioning, but some orthopaedic surgeons believed that they could do their work better than a robot, respondent 2 said: *"We had the plan to implement an orthopaedic robot that could improve positioning, but some orthopaedic surgeons believe they are more capable of doing it than a robot."* Resistance to change is an aspect that can increase when the threat of losing your job increases due to an increased work efficiency, but this depends on whom you ask. That is what respondent 2 mentioned: *"It depends on whom you ask and whom it replaces, as well as the workload."* That is in-line with what respondent 6 mentioned: *"Yes, it varies depending on the application, but certainly when it comes to AI, there is also a bit of a threat involved for the specialists."* The threat is due to the AI possibly taking away work from the specialist, respondent 6 mentioned: *"It takes away a part of their role. The question, if their work will be automated, is naturally threatening for the specialist."* If the workload that AI will replace is a non-enjoyable workload that is manual work intensive then it's likely that an increased efficiency stimulates the intention to adopt AI, as respondent 2 mentioned: *"For instance, in radiology, all the images they used to manually review and annotate can now be done by AI, and they are very pleased with that because it's not particularly enjoyable for them."* However, AI does not have to be threatening to the specialist but can also be seen as a solution to staffing shortages, respondent 6 mentioned: *"It is mainly seen as a solution for staffing shortages or, in our case, the workload during shifts."* Another example of how AI can reduce the workload of radiology is with acute requests for image evaluations. Medical emergencies may necessitate an assessment by a radiologist in the middle of the night, while they are off shift, as respondent 6 mentioned: *"The radiologist's evaluations of images need to be done 24/7, so even at night, someone may arrive at the emergency department with a leg that needs assessment, and these* *are all sort of acute requests that the radiologist receives."* The use of AI for immediate assessment of the images can make it so that the radiologist only has to review the examinations at a planned time, which greatly improves their workflow. That is what respondent 6 explained: *"By utilizing AI, we have ensured that the acute process can continue, based on the AI's conclusions, and the radiologist can review all the examinations from the past few hours at a later scheduled time. The main difference is that it becomes plannable and that is very useful."* Respondent 7 used the same example when explaining how AI can add value: *"Yes, I do have that expectation, especially when considering the relief of the radiologist, particularly during shifts; it has significant added value."*

Physicians, according to respondent 3, are always resistant to change. However, if you can demonstrate that you can deliver quality, you can gain their trust and they will come to you for assistance the next time, as respondent 3 explained: *"Doctors often want proof you can deliver quality and once you showed them once you are capable of delivering quality then they keep coming to ask for your help."* Showing that you can deliver quality in the implementation process is key to overcoming resistance to change. Therefore, hospital A has been developing a quality management, to show the stakeholders that they can implement AI safely and cleanly. Respondent 1 mentioned: "*We are building a quality management system to show we have the required expertise and knowledge. By doing so we hope to show the stakeholders that we can implement AI safely and cleanly."* Showing stakeholders the value of AI in improving their work is also a strategy that is used by AI experts to increase physician adoption, according to respondent 8: *"Physicians first have to see what makes AI so useful before they want to implement it, it's often because they have difficulty grasping what AI can actually do, what its capabilities are, and how it can fit into their work."*

Regarding the value-added by AI, the respondents agree that increased efficiency and improved work quality can stimulate the intention to adopt AI. However, improved efficiency and work quality are not the only influencing factors on the adoption intention. The concerns of risks regarding the implementing an AI can lower the perceived usefulness. Respondent 3 mentioned: *"Yes, I do. I think that AI definitely has value. What I'm more concerned about is, how can you ensure safety?"* The AI contains a large amount of data on which it bases its decisions; however, the decisions it makes are not transparent because the reasoning behind the outcomes is often not presented. This impacts the reliance of the AI and its uncertain how to safely interpret the outcome, respondent 3 mentioned: *"Look, with a doctor, you're always* *reliant on one doctor, but with AI, you're essentially relying on all the knowledge, so it's much broader in scope. How will you ensure that this happens safely?"* It is very important to note that hospitals have an organizational culture that is characterized by risk avoidance. This is in line with the interviewees, as Respondent 1 mentioned: *"At the same time, a hospital environment is very risk-averse, so you also see that people are inclined to prioritize building even greater safety."* Respondent 5 also explained that they want to minimize the risks that arise during AI implementation too: *"As an organization, it is important for us that we are completely certain of how to implement AI so that we minimize the risks."* Potential risks lower the perceived usefulness while hospitals want to leverage the benefits of AI to enhance patient care and the consequences of those risks lead to the opposite. A risk could be the AI's accuracy, which is defined as how often it predicts the same outcome as a physician. In order to manage this risk and to measure the value of the AI, hospital D is slowly rolling out the system step by step, as respondent 5 mentioned: "*We roll out the system step for step, but we do this on purpose to check the value of the AI."* As a consequence of slowly rolling out the system hospital D believes that medical professionals will first perceive a low usefulness of AI, while it does not bring them any value yet. That is what respondent 5 mentioned: *"Perceived usefulness for medical professionals will start low while only implement the AI step for step."* Respondent 3 also mentioned the importance of risk management: *"If you manage to eliminate all the shortcomings, then it's definitely a win-win situation for both the patient and the hospital."*

As can be seen in Table 9 there is enough information to support proposition 1. All respondents indicated that perceived usefulness is a significant determinant for the intention to adopt AI in medical diagnosis. The table includes factors that respondents mentioned when they explained why they believe perceived usefulness is an important stimulant for AI adoption in medical diagnosis.

4.2.2. Perceived ease of use

The perceived ease of use varies among the healthcare organizations researched. The respondents is understood by the respondents as the extent to which a person believes that using a specific system would not need any physical or mental effort. Most organizations explained that perceived ease of use is no consideration in the implementation process because they prioritize other factors such as improved work efficiency and quality. While perceived ease of use varies throughout healthcare organizations, the emphasis is generally on the potential benefits and outcomes that AI can bring to patient care rather than just on the convenience of using the technology. AI is often implemented and created in a co-development project, so physicians are involved and are thus familiar with how to use the AI. Table 10 shows the factors that the respondents mentioned when they were asked if perceived ease of use is or is not a stimulant for AI adoption.

Table 10. Factors influencing perceived ease of use as a stimulant for AI adoption in medical diagnosis

Perceived ease of use	**Influence**
Not considered in purchasing process	(-)
Reliability and added value take precedence	(-)
Including end-users reduces complexity	(-)
Adjusted AI systems to align with current workflow	(+)
Easy-to-use AI systems do not require additional effort	(+)

(+) Positive influence, (-) negative influence

The complexity of the AI diagnosis machine influences the stakeholders willingness to adopt it. Respondent 1 mentioned: *"If an AI implementation is more complex then it is less easily adopted by stakeholders."* However, in the purchasing process, perceived ease of use is rarely considered. Respondent 2 mentioned: *"As a purchaser, we really do not think about the perceived ease of use."* That is the case because AI is often not delivered as a final product but developed in a co-development project. Respondent 2 also mentioned: *"AI is one of those products that does not get delivered as a final product but will need more of a co-create approach."* When a product is co-created with a supplier, perceived ease of use is not taken into account because stakeholders were involved in the product's development process. Perceived ease of use could be an add-on for safety, where safety is defined as the AI's ability to predict correct outcomes. If the AI is reliable, perceived ease of use should follow naturally because no physicians can trust the outcome and no is required to check the outcome. Respondent 3 mentioned: *"Well, when it comes to user-friendliness, as I mentioned earlier, it ultimately comes back to safety. If it's 100% safe, then user-friendliness increases significantly."* That is consistent with respondent 4's explanation, which is that perceived ease of use is related to the AI's transparency. The more transparent the AI, the more interpretable the outcome, giving the user more control over the AI and making it easier to use. Respondent

4 mentioned: *"Perceived ease of use is related to how much control you have over the AI, and thus how transparent the algorithm is."*

Hospital D is in the beginning of the implementation process of an AI algorithm and has not found perceived ease of use to be an important concern right now. Respondent 5 mentioned: *“I do believe that perceived ease of use is important in the end but at the start of implementation the concern is on the prerequisites that are important for giving the implementation a go.”* However, that does not mean that usability is not important but it’s not as important as other factors such as added value and quality. Respondent 5 also mentioned: *“Well, I think actually usability might be very important, as I mentioned. Of course, it needs to be easy to use, but what's especially important is that it delivers added value to the healthcare process and that it makes a difference. That the quality is good, that it's reliable—those aspects, in my opinion, are much more important than just having an AI that works easily.”* Although hospitals might care most about added value there are physicians that struggle with using AI and for them an easy to use AI could be essential for adoption. Respondent 8 mentioned: *“Not all specialists respond this way, but there is a group who often think that AI is complex and difficult to handle. They may even start with the notion that they won't be able to cope with it.”* Although these physicians can be involved in the design phase which decreases the complexity and increases their willingness to adopt the AI, as respondent 8 mentioned: *“When they actively participate in designing an interaction that suits their preferences, they are more willing to embrace the system.”* During implementation respondent 8 found that by presenting the data in a way that physicians are familiar with that can increase the ease of use and improve their willingness to use the system. Respondent 8 mentioned: *"Their willingness to use the AI system increased by having it show the previous cases and patients which were similar to their current cases, as they do in their own diagnoses."* Furthermore, having a uniform platform for all AI implementations can make it easier for users to adopt AI. Respondent 7 mentioned: *“Having a platform where tools are provided brings more uniformity, making it easier for users to adopt and utilize the tools.”* A consistent platform makes it easier to integrate and use various AI tools, and it can be more standardized. Respondent 7 explained: *“Instead of each individual coming up with their own layout, structure, and functionality, having a standardized platform simplifies the process of incorporating and using the tools.”* Respondent 6 elaborated that although medical specialists are intelligent people they still like to be relieved of having to learn new systems. Respondent 6 mentioned: *“Medical specialists are intelligent people who are quick learners, but they do not complain if they are maximally relieved of burdens.”*

As can be seen in Table 10 there is not enough information to support proposition 2. The remarks of the respondent demonstrated that perceived ease of use was not a key determinant for the intention to adopt AI in medical diagnosis. End-users are involved in the implementation process which eliminates any concerns regarding the perceived ease of use of the system.

4.2.3. Attitude

The attitude of the stakeholders involved in the process can influence AI medical diagnosis adoption. A positive attitude is perceived as the extent to which a person feels favourable about performing the behaviour. According to the respondents, without a positive attitude, no one in the organization feels inclined to implement anything in the first place. The attitude towards AI is likely influenced by the organizational culture of the organization. Organizations that foster innovation and research have employees that are more fascinated by new innovations, such as AI and are therefore more likely to have a positive attitude towards AI. Furthermore, only the key stakeholders are required to have a positive attitude because they have more influence on the implementation process. Table 11 shows the factors that the respondents mentioned when they were asked if a positive attitude towards AI is or is not a stimulant for AI adoption.

Table 11. Factors influencing positive attitude as a stimulant for AI adoption in medical diagnosis

Positive attitude	**Influence**
Positive attitude is essential for successful implementation	(+)
Physicians require a positive attitude for adoption	(+)
Key stakeholders need a positive attitude	(+)
Innovation oriented organizational culture	(+)
Positive attitude serves as a driving force	(+)

(+) Positive influence, (-) negative influence

A positive attitude toward AI implementation is dependent on the feeling the stakeholders have on its actual implementation. For example, respondent 4 mentioned: "*If we do not have a positive attitude towards AI then it's never going to be implemented in the first place.*" A medical specialist requires a positive attitude towards the adoption of AI otherwise they are not willing to adopt it. Respondent 8 mentioned: *"I observe that doctors need to have a positive* *attitude towards AI in order to be willing to adopt it, but I believe this applies to everyone and not only doctors."* Medical specialist are the end-users of the technology and without a positive attitude they are more difficult and critical about embracing the technology. This does not necessarily imply that they are the most difficult stakeholder to convince, but if they do not adopt AI, they will not use it in medical diagnosis.

Respondent 8 elaborated on this: *"If you encounter a doctor who is quite negative or pessimistic about AI, it becomes challenging to get them to engage in constructive thinking. It feels like everything you propose is immediately dismissed or overly criticized, but they are the ones who need to embrace and utilize the technology."* It is impossible to ensure that everyone who is involved in the implementation process has a positive attitude towards AI, but this should not be an issue. In the AI implementation process of hospital D, they found that only the key stakeholders required for the implementation process need a positive attitude. Respondent 5 mentioned: *"There will always be people that are involved but do not have a positive attitude, but what matters is that the key people that you need to have a positive attitude."* The key stakeholder s can make or break the implementation process because their support can be necessary which is also what respondent 5 encountered. Respondent 5 mentioned: *"We spent a lot of time changing the attitude of one of our key stakeholders while it was essential to have her support."*

A positive attitude towards AI can also be influenced by the organizational environment, respondent 1 mentioned: *"In our Academy, there is a fairly positive attitude because, being a research environment, there are many people involved in AI research."* An academic hospital is focused on research and the people working at an academic hospital in general have an interest in research. Doing research means exploring new ideas and concepts that show potential for the future and AI is one of those new ideas and concepts. Respondent 1 provided an example of how their organizational environment influences their members' attitudes toward AI. Hospital A organized a meeting in response to new developments in large language models, and many interested members of the organization attended because they were curious what these new developments could mean for them. Respondent 1 mentioned: *"Next week we have organized a meeting based on various aspects of chat GPT and other open and large language models. They came up with a catchy title, and the event is completely booked. People are very curious about what this can mean for them."*

The population in which one grows up may also have an impact on one's attitude toward AI. Respondent 2 mentioned, for example, that they believe a younger population is more likely to be positive about AI. Respondent 2 mentioned: *"I suspect that the attitude someone has towards AI is dependent on the population. A young population is more likely to have a positive attitude."* One possible explanation is that AI is currently gaining traction, with many people having fascinating first experiences with AI. For example, respondent 2 mentioned that people are probably being influenced by current discussions about AI in the news: *"People's attitudes are probably being influenced by current discussions about AI."*

The project team that is implementing AI may require a project leader who is enthusiastic about AI to be the project's driving force. This can result in a compelling story that will inspire other project members and stimulate their curiosity. Respondent 3 mentioned: *"I think you'll need a driving force, someone who is enthusiastic and willing to take the lead. Having a team with a learning mindset and enthusiasm in every project is crucial. When you have a compelling story to support your ideas, it becomes easier to approach others."* However, we may need more evidence of the value of AI before we can be confident in AI. Respondent 3 mentioned: *"However, who is currently so positive about AI we need to see some evidence first."*

Respondent 6 explained that the adoption of AI is determined by one's attitude towards AI, which is dependent on how threatening the AI is perceived to be. The more threatening the AI is the more negative the medical specialists' attitude is towards AI. Respondent 6 mentioned: "*If the AI jeopardizes job security, then medical specialists are not likely to adopt the AI."* However, if the medical specialist are comfortable with the AI taking away some of their workload then their attitude towards the AI is positive. Respondent 6 also mentioned: *"But when everyone feels comfortable with AI solving the challenge of finding a new radiologist, then it can be seen as a viable solution."*

As can be seen in Table 11 there is enough information to support proposition 3. A positive attitude is important for AI adoption while the intention to adopt AI with a negative attitude is lower and more likely to not succeed.

4.2.4. Subjective norms

Subjective norms are understood as the individual's perception of social expectations or pressures regarding a specific behaviour or action. They represent individuals' beliefs and attitudes toward the norms and values of their social groups or communities. In the case of AI adoption in healthcare organizations, they represent the social expectation or pressure from patients or colleagues to adopt AI. Table 12 shows the factors that the respondents mentioned when they were asked if positive subjective norms are or are not a stimulant for AI adoption.

Table 12. Factors Influencing Positive Subjective Norms for AI Adoption in Medical Diagnosis

Positive subjective norms	**Influence**
Organizational structure supports digital transition towards AI	(+)
High expectations of AI	(+)
Success stories showcase benefits of AI	(+)
Pressure to perform as well as other hospitals	(+)
Highly ranked doctors with a positive attitude influence others	(+)

(+) Positive influence, (-) negative influence

The pathway to digital transition has impacted AI medical diagnosis implementation positively for some healthcare organizations. Respondent 1 mentioned that: *"We have truly incorporated in our strategy since 2020 that we will undergo the digital transition."* Hospital A has high expectations of AI in medical diagnosis, these high expectations can reflect the perceived social pressure to adopt AI and influence the subjective norms in the organization. Respondent 1 mentioned: *"We have high expectations for digital technology as a solution to several challenges in our hospital."* Incorporating innovation into the organization's strategy has also been mentioned by respondent 7: *"We have incorporated innovation into our strategy for the second time now."* Social pressures include public expectations, patient demands, and peer influence. For example, the public can expect hospitals to keep up with new AI developments, with the expectation that their healthcare organizations will also benefit from AI. Patients may also request to be treated at hospitals that have implemented artificial intelligence, knowing that it may improve their medical diagnosis. For example, respondent 6 mentioned: *"Currently, it's still somewhat perceived that the medical specialist is the best person to examine your images. But I do think that will change more, and patients will increasingly see the added value of a computer performing that task."* Colleagues from other hospitals or departments that have already adopted AI may put pressure on other medical specialists to do the same. Respondent 1 mentioned: *"Some physicians feel the need to implement AI as there is this social pressure from their colleagues."* In hospital A, they are showcasing the innovative applications of AI in order to create a positive image of AI that can generate peer pressure from patients and colleagues to adopt AI. Respondent 1 mentioned: *"I show people the cool things that others are doing with AI."* Respondent 3 agreed that success stories and peer pressure from colleagues can be motivating factors, and mentioned: "*Positive subjective norms, such as peer pressure from colleagues or success stories, can be motivating factors."* Respondent 4 provided a similar example of how success stories are used to gain stakeholder support for future AI applications, and mentioned: *"You're actually pre-selling them a success story for the future, showing them that we have been able to do well, and in the future, we will do this with an even more significant application."* Success stories are able to influence people because they provide concrete evidence of the positive outcomes and benefits that can be obtained by implementing AI in medical diagnosis. Respondent 2 mentioned: *"People are by definition influenceable and think something and react accordingly."* The availability of clinical evidence of AI implementation is key to motivating medical specialist to adopt AI in medical diagnosis. Respondent 2 also mentioned: "*The people who work in a general hospital, including the doctors, first want to see if it has been successfully done somewhere else. If that's the case, then we adopt it too."* Hospital C is constantly looking for clinical evidence of what other hospitals have done in order to learn from their experience and replicate their success. Respondent 3 mentioned: *"We always look at what other hospitals have done. Can we replicate it? Can we learn from their experience?"* If other hospitals received benefits from implementing AI, this can generate interest and the expectation that they, too, must implement AI in order to obtain the same benefits. For example, respondent 3 mentioned: *"When a different hospital consistently performs well for two consecutive years, it catches attention. The Board of Directors takes notice of their success."* Success stories from others can address resistance to change by showing the potential benefits and therefore lead to a shift in subjective norms. Collaborating with successful organizations can improve the attitude of medical specialists, which has been mentioned by respondent 7: *"Pathologists may not have been enthusiastic about AI, but the organizations we collaborate with and the advancements they have made in implementing AI in imaging and related areas are encouraging."*

If there is one pessimistic doctor in a group of doctors, he or she can set the tone for the other doctors and negatively influence their attitude toward AI, but the opposite is less likely.

However, if the optimistic individual holds a higher position in the hierarchy, think about a department head versus an intern, then they will have more influence on others. A person with a higher rank might have more weight and credibility, and as a result, their positive attitude may have a greater influence on the opinions and attitudes of others. As respondent 8 mentioned: *"When the optimistic person holds a higher position in the hierarchy, then they have more influence on others."*

As can be seen in Table 12 there is enough information to support proposition 4. Having the right positive subjective norms, such as an innovative organizational culture or success stories of AI implementations can stimulate the adoption of AI in medical diagnosis.

4.2.5. Perceived behavioural control

The perceived behavioural control is considered as significant factor by most of the organizations researched. Perceived behavioural control is the extent to which an individual believes they have control over their own behaviour and the factors that influence it. In the context of AI implementation, perceived behavioural control refers to individuals' belief in their ability to control and manage the AI implementation and overcome any challenges or barriers that may arise. Table 13 shows the factors that the respondents mentioned when they were asked if perceived behavioural control is or is not a stimulant for AI adoption.

Table 13. Factors Influencing Perceived Behavioural Control in AI Adoption for Medical Diagnosis

Perceived behavioural control	**Influence**
Inadequate aftercare for AI implementation	(-)
Providing own data increases control	(+)
Small scale implementations enhance control	(+)
Transparent AI algorithm	(+)
Early involvement of physicians	(+)
Continuous involvement of physicians	(+)

(+) Positive influence, (-) negative influence

Healthcare organizations are currently not designed for complex AI implementations, which lowers perceived behavioural control. Respondent 1 mentioned: *"Healthcare organizations are not yet designed for complex AI implementations."* One of the aspects of why healthcare organizations are not yet designed for complex AI implementations is the concern of how to manage the AI after implementation. Respondent 1 mentioned: *"Yes, I do find that a very exciting thing, you know? How it all goes after implementation because everyone talks about the wonderful successes leading up to the implementation."* Aftercare for an AI implementation necessitates knowledge and input from many different fields, and no one is presently considering how to manage that aspect of an AI implementation. Respondent 1 continued: *"What do we do after a year passed and it's not just one implementation anymore, that is a very big issue because handling the aftercare of AI implementations takes knowledge from multiple disciplines and how do we manage that?"* Furthermore, existing hospital infrastructure is often not sufficient for handling the large amounts of data and systems that have to be run on it.

Control over the AI may be achieved by controlling the data on which the AI model is based. That is due to the fact that different hospitals label their data different. The meaning of the labels can be completely different from each other and can lead to incorrect assessments. For example, respondent 3 mentioned: *"If one hospital receives patients via helicopter, they may label those patients accordingly. However, if our hospital does not receive patients via helicopter, this data would be incorrect for us."* Providing own hospital data ensures that the data is relevant and accurate and therefore the outcomes are more relevant and accurate. Respondent 3 mentioned: *"As long as we provide our own data for the AI algorithms then we can ensure that we have control over the AI."* Therefore, in order to maintain control AI implementations it would be better to use data from known hospitals and therefore use a smaller dataset that is more controllable. Respondent 3 mentioned: *"As a result, I believe that implementing AI on a smaller scale is more controllable, because we do not include data from all over the world, which would never provide us with a sense of control."* In the future this might be different once AI gains more acceptance worldwide. For example, respondent 7 mentioned: *"We do want to maintain control over those tools. However, we don't scrutinize image processing programs that perform their tasks effectively. They are already widely used worldwide, and it will likely be the same for AI in the near future."*

Medical specialists are the end-users and need to feel a sense of control over AI otherwise they are less willing to use it, respondent 6 mentioned: *"Medical specialists will only embrace it once they truly understand what it does."* By including medical specialist in the development process they can pertain a sense of control over the AI, respondent 4 mentioned: *"Medical* *specialists are naturally involved in the development process which helps to pertain that sense of control for them."* Medical professionals who are unable to participate in the implementation process must also have control over the AI. This may be accomplished by displaying the variables and the weight that the AI assigned to these variables. Effectively this means that the reasoning behind the outcomes of the AI are more explainable and this should stimulate medical specialist intention to adopt AI in their work. Respondent 5 mentioned: *"The AI we are working with shows us the weights it gives to the factors that are used to come to a conclusion. This helps give this sense of control that I believe is so necessary."* This is also known as explainable AI. Explainable AI also allows medical specialist to contribute their own expertise to the AI which should help them to maintain their sense of control. Respondent 8 mentioned: *"By implementing explainable AI, our aim is to support them in a way that allows them to contribute their own expertise, which seems to have a positive effect on the acceptance of such systems."* Therefore, allowing the AI to be more than just a black box system and to be closely integrated with medical specialist their workflow by providing them more relevant information. Respondent 8 explained: "*It ensures that the AI system is not just a black box that communicates and operates independently, but rather is closely integrated with their workflow and provides them with relevant information. In this way, they have control over the ultimate decision-making process and how the AI system functions."* This is in-line with what respondent 5 mentioned: *"I do think that perceived behavioural control is necessary for the adoption of AI, and therefore we do not work with a complete black box implementation."* By keeping medical specialist continuously involved in the system they can adopt more easily to new developments and helps to ensure their sense of control and their willingness to keep using it. Respondent 8 mentioned: *"The idea is to ensure that when applying the system in a specific domain, doctors can stay involved and adapt to new developments."* Keeping the medical specialist continuously involved should ensure their sense of control and their willingness to keep using it.

As can be seen in Table 13 there is enough information to support proposition 5. All respondents stated that they believe that perceived behavioural control is a stimulant for AI adoption, and then summarized their reasoning which is shown in Table 13.

4.2.6. Final Model

Figure 6 shows the final model with all influences on AI adoption in medical diagnosis that is derived from the interviews. The plus icon means a positive effect on the corresponding factor. The minus icon means a negative effect on the corresponding proposition. All factors except for perceived ease of use have shown to be a positive stimulant for the adoption of AI in medical diagnosis. Perceived ease of use has shown to be not significant enough or rarely considered.

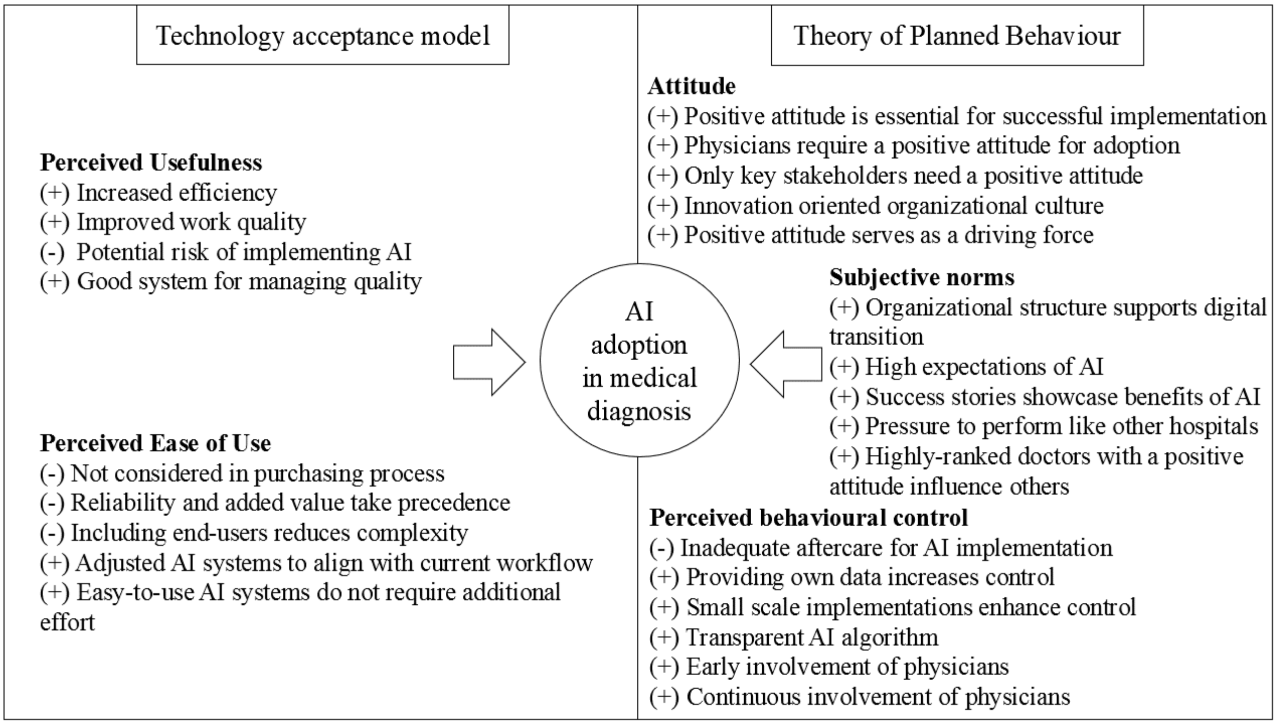

Figure 6. Influences on AI adoption in medical diagnosis elaborated by the author (2023)

4.3. Findings: Research Question

4.3.1. Main Barriers

In the previous section, a model has been developed that intends to explain the users' intention to adopt AI in medical diagnosis. This model aims to provide a comprehensive understanding of the factors that influence technology acceptance and behaviour change. The respondents answered the questions related to the TAM and TPB model and while doing so often had specific barriers in mind as most indicated during the interview. It was found that while the respondents had specific barriers in mind, they were focused on answering the specific question and often did not mention the barriers they had in mind. Therefore, all respondents were asked to identify the main barriers to the adoption of AI in medical diagnosis. A general overview of the identified barriers is shown in Table 14. The barriers relate to the previous model because, they give insight into the challenges and obstacles that influence users' attitudes, intents, and perceived behavioural control when it comes to implementing AI in medical diagnostics.

The implementation of AI in medical diagnosis requires a lot of knowledge and expertise from various stakeholders to be successful. Next to knowledge and expertise, respondents identified data availability as a barrier. AI models require a large amount of data on which to train the models, and hospitals currently lack the necessary IT infrastructure to store and share all of the data in one location. Because AI in medical diagnosis makes decisions that affect patient well-being, ethical considerations are a barrier. If the AI makes an incorrect decision, for example, because its reliability is too low, it can harm patients. What is considered to be acceptable reliability for AI is an ethical consideration. Furthermore, the business case for AI is still unclear because the potential benefits of AI are not directly measurable, whereas the costs are. Physicians' resistance to change is a barrier because if they are unwilling to adopt and use AI, the implementation process will fail. This resistance to change may come from concerns about the AI's reliability or from feeling threatened by the AI taking over some of its work. The last barrier is lifecycle management. The lifecycle management of AI is not mentioned in the literature because most hospitals are still concerned with implementing AI and are not considering what needs to be done after the implementation. In the long run, the AI model may change if the data on which it was trained changes, and who will ensure that the model remains valid is unknown.

Table 14. Main Barriers identified

Identified Barriers
Knowledge and Expertise
Data Availability
Ethical considerations
Business case of AI
Resistance to change physicians
Lifecycle management

Knowledge and expertise

The implementation of AI in medical diagnosis requires a lot of knowledge and expertise from various stakeholders. Most respondents mentioned this requirement to be one of the main barriers. Medical specialists must understand how AI works and how to correctly interpret the results. Data scientists and AI experts are needed for their technical skills in order to develop and deploy AI algorithms. The IT department must have the knowledge and expertise to manage the necessary infrastructure. The legal department must be knowledgeable about AI regulations. However, hospitals currently do not possess the required knowledge and expertise, respondent 1 mentioned: *"We do not have the proper knowledge in the hospitals to implement AI."* The organization structure of hospitals has not been adjusted yet to ensure that the mentioned required and expertise is provided, respondent 1: *"We do not have an organizational structure that enables the implementation of AI, because it's not a typical medical instrument."* Obtaining the required knowledge and expertise can be extra challenging when the necessary resources or expertise are not widely available, respondent 5 mentioned: "*Additionally, achieving successful implementation can be challenging if the necessary resources and expertise are lacking."* Furthermore, dedicated resources and specifically allocated personnel may be required to investigate and create the necessary capacity for AI implementations, respondent 2 mentioned: *"The knowledge and information required for thorough investigation demand dedicated resources. To properly explore these innovations, you need to allocate people and create the necessary capacity."* Not all hospitals are capable of dedicating the necessary resources and personnel to AI implementations. General hospitals often do not have the capabilities to investigate the implementation of new technologies, because their primary focus is on providing healthcare to people. Academic hospitals, however, have dedicated resources and personnel for research purposes and that is why resource-intensive innovations, such as AI, are more likely to be seen at academic hospitals. Respondent 2 also mentioned: "*This is why such innovations are often seen in academic settings where they have access to a larger pool of individuals who can be allocated to these tasks."* The short-term costs in academic hospitals are not very relevant because they prioritize development and in the long-term implementations are often profitable. Allowing academic hospitals to invest more in implementation projects although they are not likely to be profitable in the short-term. Respondent 3 mentioned: *"They often prioritize digitalization and development, and in my opinion, costs are not very relevant because it often leads to long-term profitability."*

Data availability

Data availability for AI implementations is important because AI models require large datasets to be trained on effectively. Data availability has been mentioned by almost all respondents to be a significant barrier. That is not as much due to the fact that data privacy is an issue, all respondents mentioned that data privacy is not an issue. There are already regulations and procedures in place to ensure that data is stored anonymously. The actual issue with data availability that respondents mentioned is data sharing because hospitals lack the necessary IT infrastructure. Data sharing between hospitals is also not possible because most hospitals store their data differently and adjustments to how data is stored would be required.

A prerequisite to starting the implementing process of AI is having the necessary data, as respondent 5 mentioned: *"Data is essential for implementing AI, and having the necessary data is a prerequisite for starting the process."* In order to obtain the required data hospitals first have to ensure they have the IT infrastructure available. At the moment IT infrastructure in hospitals is not sufficient as it is not capable of handling data sharing between systems. Respondent 1 mentioned: *"Current IT infrastructure is not capable of handling data transfer between systems."* Data sharing between systems is such a difficult problem because data in hospitals is often dispersed across various systems and storage spaces and therefore not available in a central dataset. Respondent 8 mentioned: *"It's often incorrect to assume that hospitals and general practitioner practices have a central dataset readily available. The data is dispersed across various systems and storage, making it nearly impossible to have a single centralized digital point where all the data comes together."*

While IT infrastructure is one aspect of data availability another one is the handling of personal data, as mentioned by respondent 3: *"The handling of personal data and ensure personal security within the system, considering the General Data Protection Regulation (AVG). It seems that the use of the system may not even be permitted under the AVG regulations."* The required data for AI models consist of personal data, which is protected under data privacy regulations. If data is kept in-house then privacy regulations are not an issue, but it does hinder the sharing of data between hospitals. That means that all hospitals either have to enter into a collaborative data-sharing agreement or have to produce their own data. Respondent 5 mentioned: *"Data privacy and confidentiality are maintained by keeping the data in-house."* Transferring AI systems that have been trained on specific data can also not be seamlessly transferred between hospitals. There is no standardization in how hospitals store their data, and AI systems to work in different hospitals take time and resources. Respondent 5 mentioned: *"It is challenging to adopt a system that has been trained on specific data to work with different data. it takes a lot of time and resources to make the necessary adjustments. It's not as simple as just transferring the system and expecting it to work seamlessly."*

Ethical considerations

The implementation of AI in medical diagnosis raises several ethical considerations and some of the respondents mentioned that ethical considerations are a barrier. In healthcare, ethical principles include the obligation to provide the highest level of care while avoiding harm to patients. Ethical considerations include the reliability of the AI and mistake accountability.

The respondents emphasized the importance of AI's ability to make accurate and trustworthy decisions. If the reliability of the AI cannot be assured then patients can be brought in unnecessary danger, by for example misdiagnosis or inappropriate treatment plans, and this is considered unethical. Respondent 3 mentioned: "*Reliability of the AI is a barrier while we need assurance that the decisions it makes are accurate and trustworthy.* The reliability of the AI can be determined by comparing the decisions of medical specialists with the decisions of the AI. The level of reliability necessary is also dependent on the use case of the AI if there is a potential for greater harm to the patients then reliability should be higher. For example, neurologists may be more concerned about using AI because they make high-risk decisions that can determine life or death. Respondent 7 mentioned: *"Neurologists may still have concerns and find it quite challenging to adopt AI."*

Not only reliability is an ethical consideration but also accountability. A medical specialist that makes a mistake can be held accountable for their mistakes if they have done something wrong. An AI is a software system that cannot be effectively held accountable for the mistakes it may make. It is still unclear who should be held accountable in the event of an AI error, but an answer to this question must be found before AI can be implemented. Respondent 2 mentioned: *"Ethical considerations are also taken into account, such as assigning responsibility for errors and understanding the reasoning behind certain conclusions."* Where to draw the line in relying on AI decision-making is also unknown; how much trust we should place in AI to make the best decision for a patient must be determined. Respondent 4 mentioned: *"Ethical considerations are a barrier because where do we put the limit of AI in medical diagnosis? How far do we rely on its insights?"* In hospital D they have been co-developing an AI implementation with a supplier that possesses expertise on AI. In their opinion, the supplier of AI remains responsible for delivering quality and to maintain certain standards. Respondent 5 mentioned: *"The expertise centre remains the supplier, so to speak, of such AI. They should be responsible for performing quality checks and maintaining certain requirements and standards."*

Business case of AI

The need for a business case is something that was brought up as a barrier by multiple respondents. These respondents often fulfil the project lead position and range from the data scientist to the business manager. A business case is a thorough analysis and justification for beginning a project or pilot. It also includes a financial evaluation of the project, which includes the estimated cost and estimated revenues. The business case for artificial intelligence is still unclear due to the fact that the value of AI is unknown, the majority of AI projects do not deliver a return on investment, and hospitals are not focused on co-developing with other hospitals, which would enable cost-sharing.

Implementing new technology requires a business case that demonstrates cost savings and quality improvement. As mentioned by respondent 3: *"Implementing new technologies requires a compelling business case that demonstrates cost savings and quality improvements, making it a worthwhile investment."* New technologies are only implemented if they are a worthwhile investment, that ultimately delivers results. Respondent 3 mentioned: *"You will only proceed with implementing it if it ultimately delivers results."* In the case of AI in medical diagnosis, the financial benefits are not immediately available and therefore its long-term value is still unclear. Respondent 7 mentioned: *"The benefits of implementing AI may not always be immediately quantifiable in financial terms."* The value that one hospital achieves with AI is not transferable to another because the value is dependent on the process, and different hospitals have different processes. Respondent 1 mentioned: *"The value of the AI is unclear and differs between hospitals. Value can be very dependent on process and hospitals can have different processes."* AI implementations often do not go past the development phase, and this means that most AI projects do not give a return on investments, making the incentive to implement AI solutions smaller. As respondent 5 mentioned: *"Often AI solutions do not go past the development phase."* As a consequence of most AI projects failing to be implemented, future projects are less likely to be started unless the business case is clear. Respondent 4 mentioned: *"If previous projects turn out to not be a success, then I believe that will form a large barrier for future projects."*

Not only do most AI projects fail to provide a return on investment, which is problematic for the business case, but funding for AI projects is also unclear. Respondent 1 mentioned: *"The funding of AI is a barrier because business and financing structure is still unclear."* Hospitals often receive government funding and are not a commercial entity. The costs of developing these AI models can therefore not simply be reimbursed by selling the AI to a different hospital while it's funded by the government. Respondent 5 mentioned: *"As a hospital, you're not a commercial entity, so you can't simply sell these solutions. There are considerations like state aid and conflicts of interest that come into play."* Because there is currently no viable business case, but there are potential benefits to patient care, respondent 8 believes that healthcare insurers should be the ones funding AI projects. One possible reason for healthcare insurers to fund AI projects is that in the long run, AI projects that provide preventive care and are intended to help people avoid hospitalization can be implemented. Therefore, insurance companies are in a good position to invest in AI implementations because they can improve patient outcomes and reduce health insurance costs in the long term. Respondent 8 mentioned *"But we also notice that healthcare insurers need to accept it; otherwise, there won't be any funding available. Without a viable business case, there's little incentive for the market to invest in these systems."*

Healthcare institutions that are working on AI implementations are focused on themselves and do not want to share ownership with other institutions, making cost-sharing and co-developing impossible. Respondent 5 mentioned: *"We are still too focused on developing solutions* *individually, and there's a lot of domain-specific thinking and competitive behaviour. Each institution wants to claim ownership over its developed solutions. As a result, it becomes difficult to implement these solutions elsewhere."* Hospitals also consist of two organizations: the hospital organization and the medical specialist company. Frequently, the hospital organization finances projects from which the medical specialist organization profits. Both organizations are focused on improving healthcare, but neither organization is willing to pay for the other. As a result, hospital funding structures have become extremely complex. Respondent 7 mentioned: *"As a hospital, you essentially have two organizations within the organization, due to the financing structure of hospitals. You have the hospital organization itself, and then you have the medical specialist company, which represents all the specialists who operate as a separate entity."* Respondent 7 also mentioned: *"The party benefiting from AI is actually paid by a different entity, so we bear the costs while someone else reaps the benefits."*

Resistance to change physicians

Physicians frequently develop routines and practices based on their training and expertise. They may be used to their current way of doing things and are thus hesitant to adopt new technologies that would disrupt their routines. AI is one of those technologies that has the potential to disrupt physicians' current workflow and requires time and effort to become accustomed to working with. The phenomenon of being unwilling to accept change is called, resistance to change, and is another barrier that has been identified by the respondents. Resistance to change occurs in the case of AI for medical diagnosis because medical specialists are afraid of being replaced by AI and are sceptical of AI. Scepticism arises from an inability or unwillingness to believe that AI has advanced sufficiently to be useful in their work.

Medical specialist that show resistance to change are unwilling to embrace the use of AI in their work. Respondent 3 mentioned: *"The willingness of doctors to embrace the use of AI is a barrier."* One possible reason medical specialists are hesitant to use AI is that they are frequently sceptical of new technologies because they are unwilling to accept evidence that it will benefit their work. In terms of AI, medical specialist often do not believe that it has sufficiently developed to be useful in their work. Respondent 8 mentioned: *"Well, the acceptance of our system is not very high. Quite often, doctors and specialists are quite sceptical. Partly because they still think, you know, technology hasn't come that far, despite the evidence that it can often work in a domain. They just don't see the most benefit for their* *own work."* Another possible reason why physicians are resistant to change was given by respondent 2. In the example, the hospital tried to implement an orthopaedic robot, but the physicians were not willing to use it as they believe they are more capable in doing their work than the robot. Respondent 2 mentioned: *"We had the plan to implement an orthopaedic robot that could improve positioning, but some orthopaedic surgeons believe they are more capable of doing it than a robot."* The same reasoning is mentioned by physicians right now about the use of AI in medical diagnosis. That is due to the fact that they often lack awareness of the full potential of AI in their field and are unaware of the possibilities and success stories of others. Respondent 8 mentioned: *"One of the challenges is that they often lack awareness of the full potential of AI in their field. It varies depending on whether they can relate to success stories and see the benefits first-hand."*

Because of the AI algorithm's lack of transparency, medical specialists are sceptical of it because they believe they have no control over the outcomes. Respondent 4 mentioned: *"I think that distrust of medical specialists is one of the largest barriers, if there is no transparency then they perceive no control."* Resistance to change can also come from a fear of being replaced by AI. In the current healthcare model, there is a need to hire a medical specialist to make diagnoses or decisions, but if AI can make these decisions then this threatens their job security. Respondent 6 mentioned: *"The current model in healthcare is such that hospitals hire medical specialists to make certain diagnoses or decisions, but if we have a working AI implementation, we do not have to hire medical specialist anymore."*

Life cycle management

Life cycle management is a Barrier that emerged on field, while the interviews were being conducted, and therefore they don't appear in literature. Life cycle management is the process of managing a product throughout its entire life-cycle. That is from development and implementation to retirement. AI life cycle management includes maintaining the quality and accuracy of the AI algorithm over its entire life cycle.

Life-cycle management as a barrier was brough up by respondent 1, the data scientist. Respondent 1 is responsible for the data scientist team in hospital A and leads the development of AI implementations. Life cycle management of AI is something that is still rarely considered to be an issue while most hospitals have not come this far yet in their implementation process, but hospital A is already concerned with this issue. Their hospital and data science team has gather knowledge and experience in AI implementations and have started to think about what happens after the AI implementation has been successful. Respondent 1 mentioned: *"Lifecycle management is a huge barrier while we have no clear image on how we should handle that."* The issue that arises after implementation is how to maintain the quality of AI models. Long term, it is possible that patient wellbeing is classified differently than at the start, implying that the data the AI is trained on is not the same as it was previously trained on. This can cause the model to produce different results than it did during the implementation phase, affecting its accuracy and reliability. It is also possible that over time a bias occurs in the model in which it could negatively affect a certain part of the population. Respondent 1 mentioned: *"Value should be measured in patient wellbeing, but we cannot be certain if AI models in the long term still classify patient wellbeing in the same way as it did at the start. How we validate and monitor these models is unclear."* Respondent 1 also mentioned: *"it's crucial to have knowledge and understanding in-house to successfully handle the entire monitoring of AI models, including the potential biases that may arise after implementation, the changes that can occur in your processes and patient population, and so on. Being able to comprehend and identify when things are not going well is essential."*

4.3.2. How to reduce barriers

After the respondents identified the barriers, they were asked how to reduce or eliminate these barriers. The answers of the respondents could be grouped into the following categories: knowledge sharing and collaboration, and skills and expertise.

Table 15. Methods to reduce barriers

How to reduce barriers
Knowledge sharing and collaboration
Skills and expertise enhancement

Knowledge sharing and collaboration

Knowledge sharing and collaboration were mentioned the most times. These elements are important because a lack of knowledge and expertise is one of the main barriers to the adoption of AI in medical diagnosis. By sharing knowledge hospitals can learn from each other and teach each other their best practices regarding AI in medical diagnosis. By collaborating with other hospitals the costs of developing AI can be shared. Also by collaborating with other hospitals it is possible to standardize data and therefore increase data availability.

Hospital A created a knowledge network in which they share best practices and learn from each other. This network consists out of other academical hospitals that are also researching and implementing AI in medical diagnosis. They share best practices with each other and use those as way of learning from each other's experiences. For example, respondent 1 mentioned: *"We have a knowledge network for AI implementation in healthcare, initiated by our hospital and involving other people as well. And well, there we learn from each other's best practices, so I see the real value in continuous learning and leveraging the network to learn by doing."* In hospital B they also believe in collaboration and they have established a partnership with five other hospitals. Their partnership exists around joint procurement and exchanging procurement knowledge. Respondent 2 mentioned: *"Collaboration is key, and that's what we observe. We have established partnerships with five leading hospitals, forming a group of pioneers. Our focus is not only on joint procurement but also on exchanging knowledge, including in the realm of procurement."*

In hospital C they are also involved in innovation-oriented partnerships in which they work together in order to share the costs of projects and to combine their knowledge on for example healthcare and AI. Respondent 3 mentioned: *"Working together means we can share the cost and knowledge."* Respondent 3 also mentioned: *"We have various purchasing projects, such as innovation-oriented partnerships and then together with the partner we decide an innovation we want to implement, such as AI."* Respondent 5 also mentioned there are added benefits from collaboration: *"From the Dutch AI Coalition project, we also believe that it has a lot of value to develop this together, collaboratively. So, by having multiple hospitals work together on the same use case, there may be additional benefits."*

Skills and expertise enhancement

While knowledge sharing and collaborations are useful to reduce barriers, the development of expertise and skills is also crucial. Skills and expertise can be defined as the specific knowledge, capabilities, and competencies possessed by individuals or teams in a specific domain or field. By raising awareness, they can help to prevent barriers. Artificial intelligence is a complex phenomenon that requires a thorough understanding of how it works and how it can be used in medical diagnosis. By enhancing skills and expertise regarding AI, the stakeholders involved in the AI implementation process are more capable of handling the problems that arise during implementation. For example, respondent 5 mentioned: *"Perhaps there should also be a national training program or something similar to address this because currently there is insufficient focus on these topics in medical and nursing education. That is an area of concern."* Medical and nursing students should be trained in AI to improve their awareness and expertise. For AI to be widely adopted and accepted, healthcare professionals must become more familiar with it, as they must understand how the AI decision-making process works to effectively adopt AI in their decision-making process. Respondent 5 mentioned: *"It is important for people to become digitally proficient in this field, both healthcare professionals and towards patients and citizens. It is crucial to understand how AI is being deployed in healthcare."*

Creating awareness of AI is an essential reason for enhancing skills and expertise. However, if AI would be less complicated and presented in a more understandable way, explainable AI, then this could also raise physicians' awareness. For example, respondent 8 mentioned: *"The focus of the project is to make the black boxes interpretable, which is why Explainable AI is also a pillar of the project. We recognize that if a physician is expected to work with such a* *system, they need to understand what they're working with to make informed decisions about whether to rely on the system's advice"* Involving stakeholders in the implementation process also increases awareness of AI because it allows for direct engagement and any questions or concerns can be discussed immediately. Respondent 8 mentioned: *"We always strive to involve the stakeholders, such as doctors and specialists, because there is a need for awareness in the medical domain."* Furthermore, it is important to gain practical experience by gradually implementing the changes in small steps, respondent 6 mentioned: *"Starting small and safely, but still exploring and experiencing it in small increments."*

5. DISCUSSION, IMPLICATIONS, LIMITATIONS, AND RECOMMENDATIONS FOR FUTURE RESEARCH

The aim of this study was to identify the main barriers to the adoption of AI in medical diagnosis from the procurement perspective. In this thesis, the Technology Acceptance Model and the Theory of Planned Behaviour were employed to explore AI adoption in this context. A new model has been developed that combines the TAM and TPB in the context of AI adoption, which shows the different factors that influence the intention to adopt AI in medical diagnosis.

The model is meant to discover what drives users' intention to adopt a new technology and therefore indirectly shed light on the barriers that end users may encounter. In the TAM model perceived usefulness and perceived ease of use are used to determine the users' attitude (Davis, 1985). When a user perceives significant barriers associated with the technology then their attitudes may become more resistant, leading to decreased acceptance. Similarly, the TPB model considers attitudes, subjective norms, and perceived behavioural control as determinants of intention and behaviour (Ajzen, 1991). However, during the interviews, it was found that the respondents were so eager to talk about the barriers that before the first question was asked several barriers were already mentioned. As a consequence, when the questions related to the model were asked, the respondents replied with their specific barriers in mind but did not directly mention the barriers that impact their intention to adopt AI. This highlights the significance of the identified barriers in the respondents' minds and how they were influenced by the barriers when considering their intention to adopt AI.

The study by (Kaul et al., 2020) presented a brief historical overview of AI in healthcare and the limitations that hindered the general adoption of earlier models in healthcare. Although these model limitations are no longer an issue, widespread acceptance, and utilization of AI for medical applications have not yet occurred. Literature has identified several barriers to the adoption of AI in healthcare. The study by He et al. (2019) stated that for widespread implementation of AI, data privacy would be a significant barrier. Because data would need to be anonymized and therefore, patient confidentiality and patient privacy may need to be reimagined entirely. During the interviews, it became clear that data privacy is not a barrier because healthcare data is already anonymized. Another study mentioned that biased outcomes are a barrier (Char et al., 2018). However, this barrier has only been found in hospital A and no other researched hospital has mentioned this. A possible reason for this could be that they are further along in the implementation process than many other hospitals and are therefore already considering the long-term consequences. Accountability is an important subject in healthcare organizations (Denis, 2014). In the study by Hashimoto et al. (2018), they identified a significant accountability issue due to a lack of clarity of error responsibility when working with AI. This issue is a particularity of healthcare and AI because AI is often not transparent (He et al., 2019), and physicians are therefore not able to verify the decision-making of AI. However, during the interviews, it became clear that the researched hospitals are currently not concerned with this barrier because they believe they do not influence this subject. This is in line with the study by Reddy et al. (2019) in which the authors state that the determination of liability regarding the use of the system is an area that legal and regulatory authorities have to consult with a wide variety of stakeholders. Healthcare organizations would be one of those stakeholders and therefore are involved in this barrier, but they are not responsible to make the regulations.

5.1. Theoretical and practical relevance of the research findings

This paper aims to clarify the barriers to the adoption of AI in medical diagnosis from the procurement perspective. It does this by employing the Technology Acceptance Model (TAM) and the Theory of Planned Behaviour (TPB). The findings of this thesis have academic relevance since it adds to the research of other scholars who have investigated the barriers to the adoption of AI (Char et al., 2018; Davenport & Kalakota, 2019; He et al., 2019; Sun & Medaglia, 2019). Previous literature has not investigated the barriers from the procurement perspective or has applied the TAM and the TPB framework to investigate what drives the adoption of AI in medical diagnosis. By applying these models, this research aims to contribute to existing literature and fill the gap by examining the specific barriers and factors that drive AI adoption in medical diagnosis. The final model, mentioned in Figure 6, contains influences that have not been mentioned in the literature before. Influences that determine the adoption of AI in medical diagnosis. These models have not been used for AI adoption in medical diagnosis but have been used in many other studies to describe a user's behavioural intention, in this case, they are used to study the behavioural intention to adopt AI in medical diagnosis. Therefore, giving new insights and reasoning into what drives or prevents people to adopt AI in medical diagnosis. Technology adoption in healthcare is different from other sectors as the healthcare sector is risk averse and the innovation process contains multiple stakeholders (Omachonu & Einspruch, 2010). Since, artificial intelligence is a very complex innovation, and the healthcare sector contains many stakeholders the factors that influence the adoption of AI in medical diagnosis were expected to be different than those of other innovations. This was indeed the case as during the interviews it became clear that there are AI-specific barriers in the context of the healthcare sector. In the healthcare sector data is not readily available and cannot be shared freely. As a consequence, companies have trouble obtaining healthcare data and cannot develop valuable AI models without cooperating with healthcare organizations. This has a direct impact on the purchasing department's involvement in the implementation process of AI in medical diagnosis. It was expected that the purchasing department plays a large role in the implementation process, as innovation often enters the organization through purchasing (Edler & Georghiou, 2007). During the interviews, however, it became clear that the purchasing department has limited involvement. At this moment there are not many companies that can deliver an AI implementation that is worthwhile to purchase. Therefore, during the interviews, it became obvious, that if a healthcare organization wants to implement AI in one of its processes it has to develop this AI together with a supplier. The purchasing department sometimes helps to select a supplier, but more often a supplier is directly in contact with the department that has knowledge and expertise on technology, for example, the IT department.

This study's findings have practical implications as well. As mentioned before the identification of the barriers to the adoption of AI in medical diagnosis can help overcome these barriers and successfully implement it. When healthcare organizations want to implement AI in medical diagnosis, they can consider the barriers identified in this study. By doing so the stakeholders in the implementation process are aware of the potential barriers they can run into and can prepare themselves for when the situation arises. For example, the purchasing department can set up a collaboration with other hospitals that are also interested in implementing AI in medical diagnosis and so create cost-sharing and knowledge-sharing benefits for the AI project. The model developed within this research can be used by purchasers to understand what drives the adoption of AI in medical diagnosis and to create a support base for the various stakeholders that are involved in the implementation process. For example, purchasers can use the factors that influence the perceived usefulness of AI in medical diagnosis and show the stakeholders how AI can be useful for them and therefore improve the intention to adopt AI.

5.2. Limitations and further research

This research also has its limitations. The study was carried out with a small research sample of eight participants in the Netherlands. Seven of the eight participants work in hospitals, and one is a human-AI expert. This study looked into the barriers to implementing AI in medical diagnosis. Because the implementation process involves numerous stakeholders, it is beneficial for the research to interview various stakeholders within each hospital. Only two of the five hospitals interviewed were willing and able to provide two stakeholders for interviews, so this was not possible. Furthermore, because the respondents were all from the Netherlands, the findings' external validity is limited because they may differ in other parts of the world. The study could be expanded to other countries and more stakeholders per hospital were interviewed to validate the findings.

A limitation of this research is the fact that the research topic is still in its rudimentary steps. Artificial intelligence is still being actively developed and evolving rapidly. Healthcare organizations have only recently started to implement AI in medical diagnosis, and most have not even started yet. It is recommended to investigate if the barriers to AI adoption in medical diagnosis change over time. What could be a significant barrier at this moment does not have to be a significant barrier in the future.

Another limitation of this research is the limited role of the purchasing department in the implementation process of AI in Medical diagnosis. Healthcare organizations have mainly been developing their own AI solutions or have been co-developing with other organizations. The purchasing department is important in obtaining innovative products from suppliers, but due to the scarcity of suppliers with significant AI solutions, the purchasing department's involvement is also limited. This will likely change in the future once companies become more mature in artificial intelligence and have more to offer to healthcare organizations.

During the interviews, it became clear that it is difficult to measure the value of AI implementations in medical diagnosis. In the short term, there are no indicators that can be used to measure the value, and the indicators that can be used in the long term are also still very uncertain. Out of this research the following questions came forward and are interesting for further research:

What key performance indicators can be used to measure the value of AI implementations in medical diagnosis?

Another interesting avenue of research is to investigate what the purchasing department can do to increase its role in the purchasing process of AI for medical diagnosis, it would be interesting to answer the following questions:

What roles and expertise are needed in the purchasing department to expand the purchasing department's role in purchasing AI for medical diagnosis?

As mentioned before there are many barriers to the adoption of AI in medical diagnosis. This research focused on identifying the different barriers, but not on how to reduce these barriers. It is interesting to investigate if there are different ways to reduce these barriers in addition to skills and expertise enhancement and collaboration and to answer the following question:

Which mechanisms can be used to reduce the barriers to the adoption of AI in medical diagnosis?

The role of collaboration between healthcare organizations seems to be important to overcome the barriers to the adoption of AI in medical diagnosis. It would be interesting to investigate how this process of collaboration works and if different types of collaboration have different effects in reducing the barriers. Thus, the following question would be interesting to answer:

What type of collaboration between healthcare organizations is most effective in reducing the barriers to the adoption of AI in medical diagnosis?

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APPENDIX A – INTERVIEW PROTOCOL

Adoption of AI in medical Diagnosis

1) Instruction to the interviewer
    a) Opening
       I would like to thank you once again for being willing to participate in the interview aspect of my study. As I have mentioned to you before, my study seeks to understand what the barriers are to the adoption of AI in medical diagnosis from the perspective of the procurement department. To find solutions to overcome these barriers and to successfully adopt AI in medical diagnosis. Our interview today will last approximately 30 minutes. Before we begin the interview, do you have any questions? [discuss questions] If any questions arise at any point in this study, you can feel free to ask them at any time.
    b) Clarify the Anonymity of the respondents/organizations and ask for consent.
2) Personal questions to be asked
    a) Personal information respondent
        - Can you describe your job and responsibilities?
        - What is your involvement in the decision-making process related to the adoption of AI in medical diagnosis?
        - What type of AI in medical diagnosis have you implemented?
3) Process Implementation
    - Which stakeholders were involved in AI medical diagnosis implementation?
    - What was the role of these stakeholders in the implementation process?
    - How would you describe the stakeholders' dynamics in the implementation process?
    - What were the steps of the implementation process?
4) Key questions propositions
    a) Do you think AI's <u>perceived usefulness</u> in medical diagnosis can encourage the intention to adopt it?
        - Why? Why not?
    b) Do you think the <u>perceived ease of using</u> AI in medical diagnosis can encourage the intention to adopt it?
        - Why? Why not?
    c) Do you think that a <u>positive attitude</u> towards using AI in medical diagnosis can encourage the intention to adopt it?
        - Why? Why not?
    d) Do you think that <u>positive subjective norms</u> about the use of AI in medical diagnosis can encourage the intention to adopt it?
        - Why? Why not?
    e) Do you think that the <u>perceived behavioural control</u> of using AI in medical diagnosis can encourage the intention to adopt it?
        - Why? Why not?
5) What do you think are the main barriers to adopting AI in medical diagnosis?
    - Data privacy?
    - Ethical considerations?
    - Value uncertainty
    - [Discussing different barriers]
6) How could these barriers be reduced?
7) Space for recording the comments
8) Thank the respondent for their time and effort