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Healthcare in the Age of AI: A Qualitative Study on the Perceptions and Acceptance of AI Health Chatbots Among Patients and Healthcare Professionals

A Master’s Thesis by

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Abstract

Objectives: This thesis examines the acceptance and perceptions of Artificial Intelligence (AI) chatbots in healthcare among patients and healthcare professionals (HCPs). The primary objectives are to investigate the attitudes of patients and HCPs towards AI chatbots, to compare their perspectives, and to identify the motivators, facilitators, and barriers influencing AI chatbot acceptance.

Methods: The research employs a qualitative methodology, including a systematic literature review and interviews, guided by an interpretivist philosophy and an abductive research approach. The Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) serve as the foundational theoretical models for research. Following the literature review, twelve semi-structured interviews with patients (n=8) and HCPs (n=4) are conducted via video conferencing, collecting data about their experiences and perspectives. Interview transcripts are then coded and analysed via NVivo to identify key areas, which are organised into themes that answer the four research questions (RQ1-RQ4).

Results: The study finds that patients appreciate the potential benefits of AI chatbots, including accessibility and convenience, but hold concerns about lack of empathy, trust, and data security. HCPs acknowledge the potential benefits, particularly for routine tasks, but have concerns regarding implementation, potential for misdiagnosis, and lack of empathy. Both groups express more confidence in AI chatbots as supportive tools rather than replacements for human expertise. Shared and divergent viewpoints exist between patients and HCPs regarding AI chatbots, with trust, data privacy, social influence, and accuracy concerns being significant factors influencing acceptance.

Conclusion: The implications of these findings are significant, informing the design and implementation strategies for AI chatbots in healthcare settings. The study suggests the need for future research to further explore these attitudes and to identify strategies addressing concerns to ensure successful AI chatbot integration in healthcare. The research concludes with the recognition that AI chatbots have the potential to revolutionise patient care and transform health service delivery, subject to an understanding and accommodation of both patient and HCP perspectives.

1. Introduction

1.1. Opening section

The advent of artificial intelligence (AI) has brought forth a myriad of opportunities and challenges across various sectors, including healthcare. One of the most promising applications of AI in healthcare is the development and integration of AI-based health chatbots, which have the potential to revolutionise the way health information and services are delivered to patients (Laranjo et al., 2018). AI health chatbots are conversational agents that utilise natural language processing (NLP) and machine learning algorithms to interact with users, providing personalised health information, support, and guidance (Montenegro et al., 2019). These chatbots have the potential to improve patient outcomes, reduce healthcare costs, and increase accessibility for underserved populations (Bickmore et al., 2010).

Despite the rapid growth and potential benefits of AI-based health chatbots, there is a significant gap in understanding the perceptions, expectations, and concerns of patients and healthcare professionals (HCPs) regarding this technology. The lack of such insights presents a barrier to the successful integration of these chatbots into healthcare systems, a process that could lead to improved patient outcomes, cost reductions, and increased access to health services.

Therefore, this study aims to bridge this gap by exploring the attitudes and acceptance of AI health chatbots among patients and HCPs, and by identifying the factors that influence their acceptance and willingness to use and recommend this technology. This research will be underpinned by established technology acceptance models such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), providing a solid theoretical framework for understanding technology acceptance and use.

The introduction chapter of this paper is structured as follows. The opening section provides a general overview of the field and the research problem. Following is the study background, which delves into the definitions and origins of AI, the emergence of AI in healthcare, the use of AI chatbots in healthcare, and the purpose of technology acceptance research in healthcare. The next section presents the research gap, after which the problem statement and research questions are presented to provide clear directions for this study. The research scope and delimitations section will outline the boundaries and limitations of the study, before a final section summarises the chapter.

1.2. Study Background

Global healthcare systems are being challenged with escalating expenses and declining results (Topol, 2019). This situation confronts healthcare administrators with what is considered a “wicked problem”, characterised by multiple contributing factors that are difficult to fully grasp and define, thereby necessitating a multi-faceted approach to address it (Morley et al., 2020).

Against this backdrop, emerging technologies such as artificial intelligence present a promising avenue to explore. As we delve into the origins and definitions of AI and AI chatbots in the following section, we will examine its potential role in alleviating some of the pressures that contemporary healthcare systems face.

1.2.1. Artificial Intelligence: Definition and Origin

The term "artificial intelligence" (AI) was first coined by John McCarthy in 1956, marking the initiation of a new field of study that endeavours to create machines or software capable of exhibiting characteristics inherent to human intelligence. Russell and Norvig (2016) categorise AI into four types: systems that think or act like humans, and systems that think or act rationally. AI encompasses various sub-disciplines and applications, including machine learning, natural language processing, computer vision, and robotics.

While concluding on a universal definition of AI has been challenging, researchers have devised the "Turing Test" and "Subject matter expert Turing Test" to evaluate AI's ability to mimic human intelligence, aiming for "artificial general intelligence" that can transition between tasks (Turing, 1950; Feigenbaum, 2003).

In both research and everyday language, various terminologies are used interchangeably with AI, such as machine learning, natural language processing, robotics, expert systems, intelligent systems, and neural networks. While each of these terms has technical nuances, they collectively underscore the diverse manifestations of AI (Asemi et al., 2020).

As AI technologies continue to permeate various industries, from healthcare and finance to manufacturing and transportation, the potential for revolutionary change is palpable. Yet, the increasing prevalence of AI in our daily lives—from personal assistants like Siri and Alexa to self-driving cars and advanced medical diagnostic tools—brings with it a range of ethical considerations (Mintz & Brodie, 2019). These considerations, coupled with the exciting possibilities presented by AI, make it a compelling and crucial area of study.

1.2.2. Emergence of AI in Healthcare

The earliest applications of AI in medicine can be traced back to the 1960s and 1970s, where studies explored automating diagnostic systems for diagnosing heart disease (Warner, 1961) and tailored treatment recommendations (van Melle, 1978). In subsequent years, the focus shifted towards evaluating AI's diagnostic accuracy compared to human physicians, which saw improvements in diagnosis, decision-making, and patient outcomes (de Dombal et al., 1972; Adams et al., 1986). These strides in AI application allowed the technology to permeate a wide range of medical fields, with a focus on refining its use and addressing potential drawbacks, concerns, and uncertainties (Becker, 2019).

The potential of AI in healthcare is vast and can be divided into eight key areas:

- **Disease diagnosis and treatment:** AI plays a pivotal role in disease diagnosis and treatment by enabling the rapid processing of complex biomedical data, thereby aiding in the identification of disease markers and the prediction of treatment outcomes, such as the use of AI in interpreting radiology images for the detection of cancerous growths (Topol, 2019).
- **Medical image diagnosis:** AI systems, through techniques such as machine learning and deep learning, can enhance the analysis of medical images (like CT scans, X-rays, or MRIs), improving the precision of diagnoses and aiding in the early detection of conditions such as tumours, strokes, or cardiovascular diseases (Lundervold & Lundervold, 2019).

- **Drug discovery and manufacturing:** AI can expedite the discovery and manufacturing of drugs by predicting molecular behaviour, optimising pharmaceutical formulations, and streamlining manufacturing processes, thereby reducing time to market and improving patient access to essential medicines (Vamathevan et al., 2019).
- **Personalised medicine:** AI can facilitate personalised medicine by leveraging genetic, clinical, and lifestyle data to tailor treatment strategies to individual patients, thereby optimising therapeutic efficacy and minimising adverse effects (Johnson et al., 2020).
- **Physical robots:** AI-driven robots can assist in a myriad of clinical tasks, ranging from surgical interventions to patient care, thus enhancing precision in surgical procedures and improving patient outcomes (Hashimoto et al., 2018).
- **Administrative tasks and smart records management:** AI can streamline administrative tasks and enhance records management, thereby reducing the administrative burden on healthcare professionals, enhancing data security, and facilitating the sharing of patient information across healthcare systems (Shickel et al., 2018).

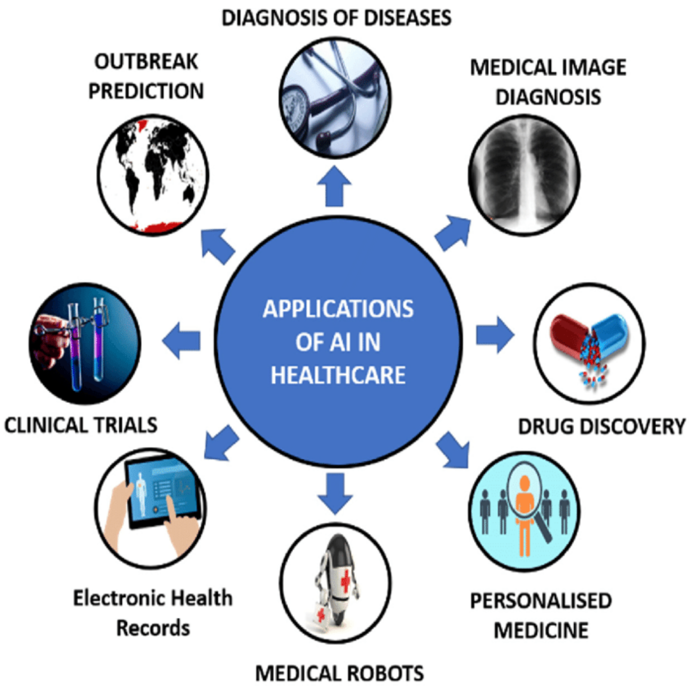

Figure 1. A representation of various applications of AI in healthcare. (Pandya et al., 2021)

Thus, AI's diverse applications highlight its potential to transform healthcare, boosting service efficiency and effectiveness, and improving patient outcomes. A rapidly evolving part of this technological transformation is the development of AI chatbots and their use in healthcare, offering novel ways to revolutionize patient care and interactions. The next section explores the specifics of AI chatbots, their healthcare application, and stakeholders' attitudes towards them.

1.2.3. AI Chatbots in Healthcare: History, Opportunities and Challenges

AI chatbots (also known as conversational agents, virtual assistants, or VAs) are complex computer programmes designed to emulate human conversation through text or voice interaction (Abu Shawar & Atwell, 2007). AI chatbots use technologies such as natural language processing and machine learning to understand and learn from user interactions (Abu Shawar & Atwell, 2007). Google Assistant, Amazon Alexa, and Apple's Siri are examples of well-known chatbots (Kepuska & Bohouta, 2018).

The emergence of AI chatbots can be traced back to Turing's proposition of machine intelligence in 1950, leading to the creation of ELIZA in 1966 as the first conversational agent (Weizenbaum, 1983). Advancements in AI brought forth PARRY, a chatbot simulating a schizophrenic patient's responses, in 1972, and later, Jabberwacky in 1988, which utilised AI more extensively (Adamopoulou & Moussiades, 2020). The new millennium saw an evolution in chatbot technology, with voice-activated personal assistants like Apple's Siri, IBM's Watson, Google Assistant, Microsoft's Cortana, and Amazon's Alexa (Adamopoulou & Moussiades, 2020). Most recently, the emergence of ChatGPT, a conversational large language model (LLM) developed by OpenAI, has shown increased user interest and adoption due to its ability to generate more human-like responses (Sallam, 2023; Biswas; 2023).

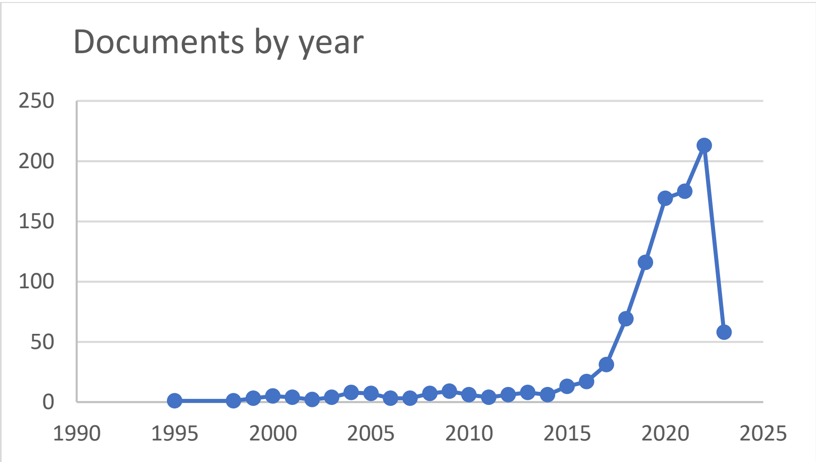

Figure 2. Search Results in Scopus (executed on 5th May 2023), from 1966 to 2023 for the keywords "chatbot" or "conversation agent" or "virtual assistant".

Chatbots can broadly be classified into two categories: rule-based and AI-powered. Rule-based chatbots operate within the confines of pre-determined commands and follow fixed decision trees. In contrast, AI-powered chatbots leverage machine learning algorithms, enabling them to understand context, make informed decisions, and, crucially, evolve from past interactions (Dale, 2016; Joseph, 2021). A brief overview and comparison between rule-based and AI-powered chatbots can be seen in Figure 3, which illustrates the fundamental differences in their operational characteristics and capacities (Joseph, 2021).

The healthcare sector, facing challenges such as HCP shortage, the COVID-19 crisis, rising digitalisation, and the imperative for patient engagement, has emerged as a fertile ground for the application of both rule-based and AI-powered chatbots (European Union ECE, FA, 2019). These chatbots offer improved accessibility to healthcare resources, cost efficiencies, and 24/7 availability.

They can aid physicians, nurses, patients, or their families better organise patient pathways, medication management, emergency situations, or first aid, and address specific issues in healthcare (Mesko, 2021).

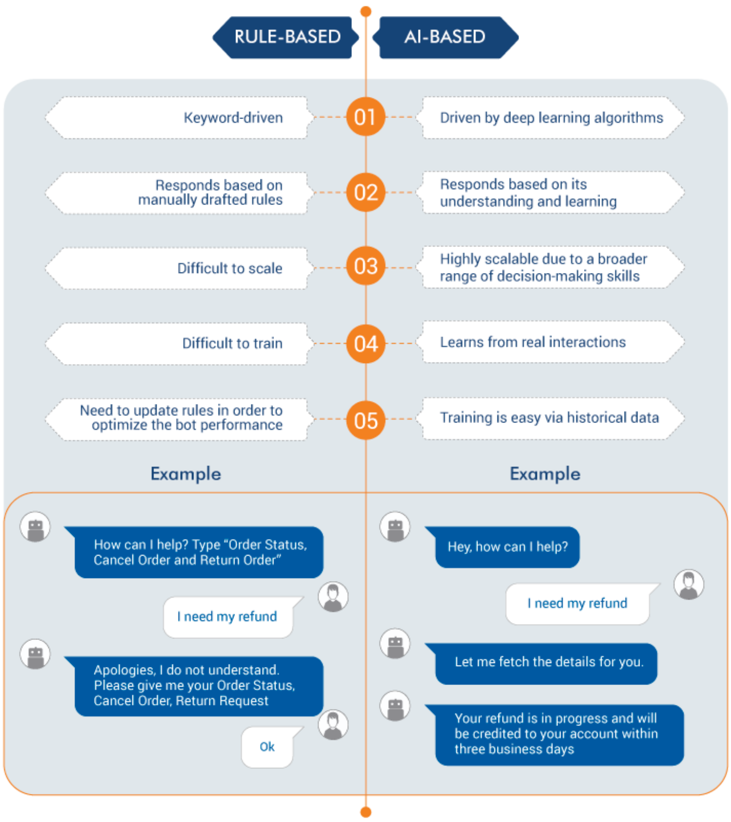

Figure 3. Technical and operational differences between rule-based and AI-powered chatbots. (Joseph, 2021)

AI chatbots have found impactful applications in patient education, self-diagnosis, and mental health support. "Babylon Health" and "Vik" exemplify chatbots effectively providing medical consultations and comprehensive disease information, respectively (Richens et al., 2020; Chaix et al., 2019). Chatbots like "Ada" have also demonstrated diagnostic accuracy, even with sensitive conditions, comparable to human clinicians (Middleton et al., 2016; Ghosh et al., 2018; Gräf et al., 2022; Fan et al., 2018; Meyer et al., 2020). Addressing the communication gap in mental health, chatbots such as "Woebot" have been successfully adopted as digital counsellors, using conversational therapy techniques to guide patients (van den Brink et al., 2019; Newall et al., 2014; Fitzpatrick et al., 2017).

However, despite their vast potential, AI chatbots also pose challenges, including lengthy implementation, data security, and user frustration (Zumstein & Hundertmark , 2017). The transition from traditional modes of communication, such as phones and emails, to chatbots, may be difficult, necessitating continued support for older platforms (Zumstein & Hundertmark , 2017). Data security is also critical, particularly for sensitive information and when hosted on third-party platforms (Zumstein & Hundertmark , 2017). Finally, chatbots often struggle with poor usability, including misunderstanding user intent, poor communication, and odd responses. Notably, a recent example of Bing's AI chat became newsworthy due to several unusual responses including threats, righteousness and even declaration of love, which users have flagged as "mind-blowing" and "creepy" (Leswing, 2023). Mitigating these challenges is adamant and can be achieved through strategies such as integrating chatbots with live chat services for unidentified inputs, using built-in quality assurance tools, specifying approved chatbot responses, and protecting critical transactions (Adamopoulou & Moussiades, 2020).

In summary, while the emergence of AI chatbots in healthcare promises revolutionary improvements in patient engagement, diagnosis, and mental health support, it is not without its challenges. These span from user adaptation and data security to understanding user intent, managing toxic content, and ensuring quality interactions. As we delve deeper into the utilisation of these digital tools in healthcare, it becomes imperative to consider the factors that determine their acceptance by both healthcare professionals and patients. The following section provides a detailed exploration of technology acceptance in healthcare, setting the stage for a nuanced understanding of how AI chatbots are perceived and used in this critical sector.

1.2.4. Technology Acceptance in Healthcare

User acceptance within the realm of technology usage holds a unique and central role. It signifies an individual's willingness to employ a novel technology or system, characterised by a favourable disposition towards the technology and a behavioural intention to utilise it (Davis, 1989).

In the context of healthcare, and more specifically with respect to AI chatbots, user acceptance is a crucial determinant of the effectiveness and success of health interventions (Or & Karsh, 2009). A variety of factors can influence user acceptance, such as perceived usefulness and ease of use (Davis, 1989), compatibility with existing workflows, and considerations related to patient care and data security (Holden & Karsh, 2010).

Studying technology acceptance in healthcare is crucial. As technology and digital health services rapidly evolve, understanding the factors that foster user acceptance can guide successful implementation strategies, especially for emerging technologies like AI chatbots (Chaudhry et al., 2006). Insights into user acceptance can inform technology development to suit user needs, enhancing satisfaction and healthcare efficiency (Fadzlah, 2018). Furthermore, understanding user acceptance aids in creating interventions to tackle technology use barriers (Gagnon et al., 2010), thereby facilitating adoption and progress in the digital health landscape. Pursuing these objectives can ultimately contribute to the optimisation of healthcare services and the enhancement of patient care.

In summary, the understanding and evaluation of user acceptance in healthcare - particularly in the context of AI chatbots - emerges as a cornerstone of effective technology implementation and healthcare service optimisation. It is within this context that the current study locates itself, positioning the discourse within the broader conversation surrounding the integration of technology in healthcare. However, despite the significance of user acceptance, there are gaps in our current understanding of the acceptance of AI chatbots in healthcare, particularly by patients and doctors. These gaps, along with the associated research problem, will be explored in greater detail in the subsequent section.

1.3. Research Gaps and Problem Identification

Despite the growing interest in AI chatbots and their potential applications in healthcare, there is a noticeable gap in the literature concerning the qualitative understanding of patients' and HCPs' perceptions, expectations, and concerns towards AI chatbots in healthcare.

1.3.1. Lack of qualitative and comparison studies

Most existing studies have focused on either patients or HCPs separately, with limited research comparing the attitudes of both groups (Laranjo et al., 2018; Palanica et al., 2019). Furthermore, much of the current literature has been centred around quantifying users' intention to use AI chatbots rather than exploring their underlying attitudes and experiences (Hoque & Sorwar, 2017; Nadarzynski et al., 2019). This highlights a need for a qualitative exploration, which can capture the nuances of user attitudes and experiences of different users.

1.3.2. Insufficient understanding of AI chatbot acceptance

There is also a need for deeper understanding of the acceptance of AI chatbots in healthcare. Studies have investigated user satisfaction (Zhang et al., 2020), trust (Coeckelbergh, 2021), and privacy concerns (Mittelstadt et al., 2016), as well as in applications of mental health support (Fitzpatrick et al., 2017) and patient self-diagnosis (Gräf et al., 2022). However, there is still a need for more extensive research on other healthcare applications.

1.3.3. Under-representation of middle-income countries

Finally, it is crucial to note that most existing studies have been conducted in selected high-income countries with advanced healthcare systems, such as… . As a result, there is limited information about how patients and HCPs from a combination of countries, including both high- and middle-income, perceive AI chatbots in healthcare settings. This lack of representation may hinder our understanding of potential barriers to adoption across different cultural contexts.

1.3.4. Sub-conclusion

In summary, the current literature presents several gaps that warrant further investigation:

1) Limited research comparing the perceptions of patients and HCPs, and a focus on quantifying user intentions rather than qualitatively exploring underlying attitudes.
2) Insufficient exploration of factors influencing acceptance across various applications within healthcare.
3) Underrepresentation of middle-income countries and a combination of countries in existing studies.

Addressing these gaps will contribute to a more comprehensive understanding of patients' and HCPs' perspectives on AI chatbots in healthcare settings. This study aims to inform future development strategies for more effective integration of AI chatbots into healthcare services.

1.4. Problem Statement and Research Questions

1.4.1. Problem statement

This study aims to explore the perceptions and acceptance of patients and HCPs regarding AI health chatbots and identify the factors that influence their willingness to use and recommend this technology to others. While there is a growing body of literature on AI in healthcare, studies providing an in-depth understanding the attitudes of both patients and HCPs towards AI health chatbots are limited. Hence, this research will seek to identify key themes in attitudes of patients and HCPs and compare perceptions between the two groups. The research questions focus on understanding the expectations of technology performance and required effort for both patients and HCPs, as well as identifying the motivations, facilitators, and barriers that may impact their use and recommendation of AI health chatbots. This study will be guided by established technology acceptance models such as TAM and UTAUT, which provide a theoretical basis for understanding technology acceptance and use.

1.4.2. Research questions

This study seeks to answer the following research questions:

- **RQ1:** What are **patients'** perceptions of AI health chatbots and their reasons?
    - ***RQ1a:*** What are their expectations of the technology's **performance**?
    - **RQ1b**: What are their expectations for the **level of effort** required to use it?
- **RQ2:** What are **HCPs'** perceptions of AI health chatbots and their reasons?
    - **RQ2a:** What are their expectations of the technology's **performance**?
    - **RQ2b**: What are their expectations for the **level of effort** required to use it?
- **RQ3:** How do the perceptions and attitudes of patients and HCPs towards AI health chatbots **compare and contrast**?
- **RQ4:** What factors would influence patients and HCPs to use AI health chatbots and recommend the technology to others?
    - **RQ4a*:*** What factors would **motivate** both users to use the technology and recommend it to others?
    - **RQ4b:** What **facilitators** do users expect to be in place in order to use the technology?
    - **RQ4c:** What factors would **discourage** both users from using the technology?

By addressing these research questions, this study seeks to contribute to a deeper understanding of the factors that drive the acceptance and adoption of AI health chatbots.

1.5. Research Scope and Delimitations

The scope of this study is defined by several aspects, including participants, applications of AI chatbots and study methodology. This section will also address some limitations to the scope.

Firstly, the study will include participants from Bulgaria, Bahrain, Denmark, and the UK to address the under-representation of middle-income countries in existing literature (Laranjo et al., 2018). Participants will consist of adult patients who have experience with or interest in using AI chatbots for healthcare purposes, as well as HCPs who are involved in patient care and may potentially interact with AI chatbots in their professional practice.

Secondly, while some previous studies have focused on specific applications of AI chatbots, such as mental health support (Fitzpatrick et al., 2017) and patient self-diagnosis (Gräf et al., 2022), this research will consider a broader range of healthcare applications, including but not limited to disease management, appointment scheduling, medication adherence, and health education.

Thirdly, this study will adopt a qualitative research design to address the gap in qualitative understanding of user attitudes towards AI chatbots in healthcare (Hoque & Sorwar, 2017; Nadarzynski et al., 2019) and capture the nuances in user perspectives.

Finally, despite its comprehensive scope, this study intentionally sets some delimitations related to its scope:

- **Lack of non-experienced users:** The research will only include adult patients with experience or interest in using AI chatbots in healthcare. Therefore, the perspectives of individuals unfamiliar with or uninterested in this technology, as well as those of minors, may not be fully captured.
- **Geographical representation:** While the study encompasses participants from Bulgaria, Bahrain, Denmark, and the UK, the results may not be representative of all high-income and middle-income countries. Cultural, economic, and infrastructural differences in other countries may lead to different perceptions and acceptance of AI chatbots in healthcare.
- **Additional stakeholders:** This research focuses on patients and HCPs, and as a result, it may not consider the perspectives of other important stakeholders in healthcare, such as policymakers, AI developers, and healthcare administrators.
- **Rapid development of technology:** The study is limited to AI chatbots currently available and in use. The rapid evolution of AI technology may result in the development of new features or capabilities that could influence user perceptions and acceptance in ways not captured in this study.

In conclusion, this study seeks to contribute valuable insights into the perceptions and acceptance of patients and HCPs regarding AI chatbots in healthcare by addressing gaps in existing literature related to qualitative understanding, factors influencing acceptance across various applications within healthcare, and representation of middle-income countries.

1.6. Structure of This Paper

This paper is structured in the following way. The current chapter (Chapter 1) serves as an introduction to the topic of AI chatbots in healthcare, their emergence and usage, and the technology acceptance in healthcare, leading to the identification of research gaps and the formulation of the problem statement and research questions. This is followed in Chapter 2 by an in-depth exploration of the theoretical background, including the Technology Acceptance Model (TAM), and the Unified Theory of Acceptance and Use of Technology (UTAUT), as well as their limitations and challenges in the healthcare domain.

Chapter 3 provides a thorough literature review focusing on the perspectives of patients and healthcare professionals. Subsequently in Chapter 4, the methodology employed for this study is outlined, covering our approach to the literature review, the philosophical underpinnings of the research, data collection and analysis techniques, and potential limitations.

In Chapter 5, the results from the study are presented, examining attitudes of healthcare practitioners and patients towards AI chatbots in healthcare. The discussion section (Chapter 6) then interprets these results, highlighting motivators, facilitators, and barriers to AI chatbot adoption, and proposes a newly constructed theoretical framework.

The paper concludes with a review of the study's limitations and recommendations for future research (Chapter 7), before the final conclusion (Chapter 8) that encapsulates the key findings and their implications. References and appendices with supplementary material follow at the end.

1.7. Summary of Introduction

AI chatbots have played a significant role in healthcare, leveraging technologies like natural language processing and machine learning to interact with users. Tracing their roots back to the 1950s, these conversational agents have evolved over time, witnessing a surge in applications post-2016, particularly in healthcare. As a result, AI chatbots have been instrumental in addressing the sector's challenges, including medical staff shortage and the need for patient engagement, by carrying jobs such as patient education, aiding self-diagnosis, and mental health support, with examples such as "Babylon Health," "Vik," "Ada," and "Woebot."

However, the deployment of AI chatbots in healthcare is not without its challenges. Transitioning from traditional modes of communication to chatbots requires user adaptation, and data security remains a significant concern. There are also issues with chatbots understanding user intent, managing toxic content, and ensuring quality interactions. As the use of AI chatbots expands in healthcare, user acceptance is vital. Therefore, understanding technology acceptance and the factors that affect it can guide successful implementation strategies, inform user-centred technology development, and promote technology uptake. While acceptance of AI chatbots is crucial to their widespread adoption, gaps exist in our current understanding of the perceptions of patients and doctors towards the technology, which is the key objective of this study.

This research explores patient and HCP attitudes towards AI chatbots, focusing on comparative perspectives and a broader range of healthcare applications. The study also includes participants from underrepresented middle-income countries. Despite its broad scope, it acknowledges limitations including the exclusion of non-experienced users, other healthcare stakeholders, and potential developments in AI technology.

2. Theoretical Background

The following section focuses on providing a comprehensive overview of the theoretical foundations that underpins the research study. The research question and hypotheses will be informed by a discussion of relevant literature, key concepts, and theoretical frameworks. The section first introduces the two theories that are most commonly used in technology acceptance research, namely the **Technology Acceptance Model (TAM)** and extensions, and the **Unified**

Theory of Acceptance and Use of Technology (UTAUT) and extensions. This part of the text addresses key concepts of both theories, along with their relevance, validity, and limitations when applied to technology acceptance research within the healthcare industry. Next, this section draws on research applying and modifying these two theories in order to establish a comprehensive overview of the acceptance and use of AI technologies by patients and practitioners. This chapter concludes by highlighting the limitations of these frameworks when studying user acceptance.

2.1. Technology Acceptance Model (TAM) and Extensions

The Technology Acceptance Model (TAM) is a widely used theoretical framework for understanding technology adoption and usage behaviour. It is founded on two prior IT-adoption theories: the theory of reasoned action (TRA) (Fishbein & Ajzen, 1975), and its successor, the theory of planned behaviour (TPB) (Ajzen, 1985). Developed by Davis (1989), TAM attempts to conceptualise and use. user acceptance specifically as it relates to technology use. Given its focus on user perceptions and attitudes, TAM and its extensions are particularly relevant to this study, which seeks to understand patient and HCP attitudes towards AI chatbots in healthcare.

2.1.1. Key Concepts and Variables in TAM and Its Extensions

TAM posits that perceived usefulness (PU) and perceived ease of use (PEOU) are the two primary determinants of technology acceptance (Figure 4). PU refers to the degree to which a user believes that using a particular technology will increase their job performance or facilitate task accomplishment (Davis, 1989), such as if the technology can help them accomplish a task quicker or more efficiently. PEOU refers to the degree to which a user perceives a certain technology to be simple, straightforward, and free of effort. In the context of AI health chatbots, PU might refer to patients or doctors believing that using the chatbot will enhance their health management or patient care, while PEOU could reflect their views on how easy and intuitive the chatbot is to interact with.

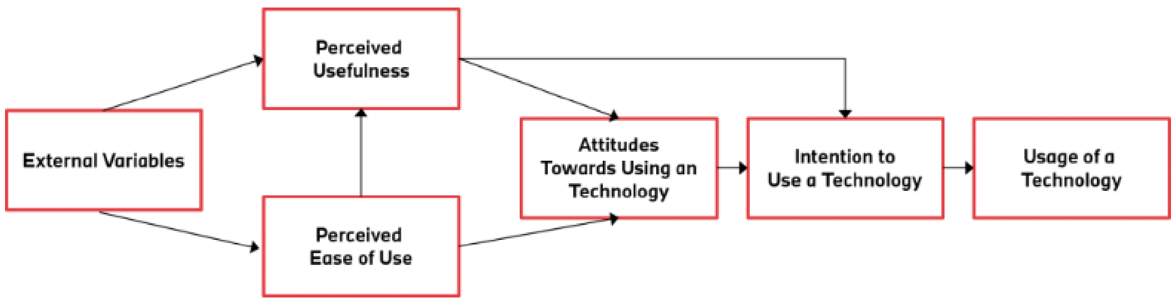

Figure 4. The Technology Acceptance Model (Davis, 1989).

In subsequent years, the original TAM was extended into TAM2 (Venkatesh & Davis, 2000) and later, TAM3 (Venkatesh & Bala, 2008). These extensions incorporated additional variables, which would increase the model's explanatory and predictive power (Figure 5). TAM2 introduced five additional exogenous variables and two moderators: *subjective norm*, *image*, *job relevance*, *output quality*, *result demonstrability*, *experience,* and *voluntariness*. The definitions of these variables are presented in Table 1. The five exogenous variables were set up to predict PU, while the two moderators (*experience* and *voluntariness*) moderated the variables' predictive powers.

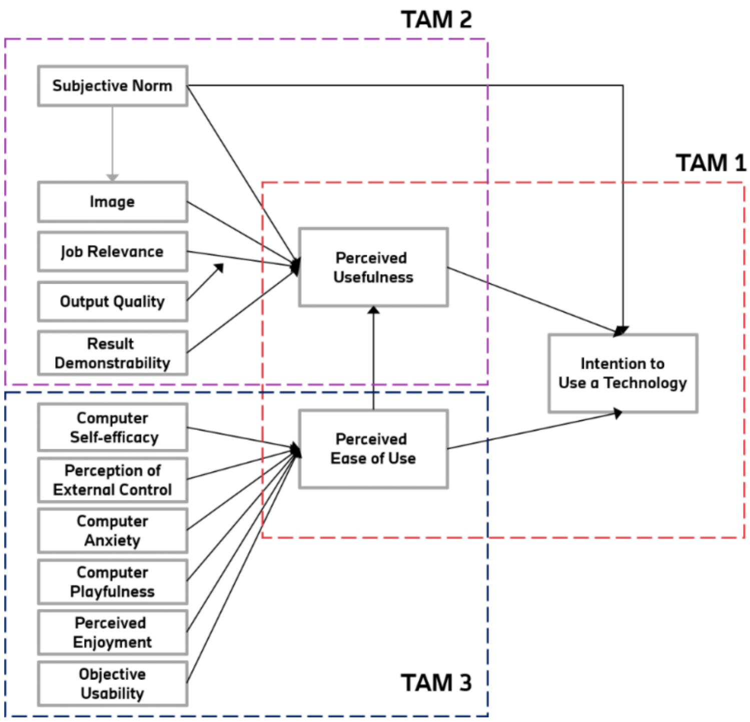

Figure 5. TAM 1, 2 & 3 (Davis, 1989; Venkatesh & Davis, 2000; Venkatesh & Bala, 2008).

However, TAM and TAM2 received criticism for their lack of usefulness in real-world settings, and thus TAM3 was developed in order to provide actionable advice for managers that seek to enhance the rate of technology adoption by their employees (Venkatesh & Bala, 2008). TAM3 introduced six additional variables as predictors of PEOU: *computer self-efficacy*, *perception of external control*, *computer anxiety*, *computer playfulness*, *perceived enjoyment*, and *objective usability* (Figure 5). A breakdown of all factors and their definitions is presented in Table 1.

Table 1. TAM and UTAUT constructs and definitions

Model	Construct	Definition	Reference
TAM / UTAUT	Behavioural Intention to Use	A measure of the strength of one's intention to perform a specified behaviour.	Davis, 1989; Venkatesh et al., 2003
TAM / UTAUT	Perceived Usefulness / Performance Expectancy	The degree to which a person believes that using a particular system would enhance their job performance.	Davis, 1989; Venkatesh et al., 2003
TAM / UTAUT	Perceived Ease of Use / Effort Expectancy	The degree to which a person believes that using a particular system would be free from effort.	Davis, 1989; Venkatesh et al., 2003
UTAUT	Social Influence	The degree to which an individual perceives that important others believe they should use the new system.	Venkatesh et al., 2003
TAM / UTAUT	Attitude Toward Using	An individual's positive or negative feelings about performing the target behavior.	Davis, 1989; Venkatesh & Bala, 2008

TAM2	Subjective Norm	An individual's perception that most people who are important to him think he should or should not perform the behavior in question.	Venkatesh & Davis, 2000
TAM2	Image	The degree to which use of an innovation is perceived to enhance one's status in one's social system.	Venkatesh & Davis, 2000
TAM2	Job Relevance	An individual's perception regarding the degree to which the target system is applicable to his or her job.	Venkatesh & Davis, 2000
TAM2	Output Quality	The extent to which the system performs its designated functions.	Venkatesh & Davis, 2000
TAM2	Result Demonstrability	Tangibility of the results of using the innovation, including their observability and communicability.	Venkatesh & Davis, 2000
UTAUT	Experience	The degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system.	Venkatesh et al., 2003
UTAUT	Voluntariness of Use	The extent to which potential adopters perceive the adoption decision to be non-mandatory.	Venkatesh et al., 2003
UTAUT	Facilitating Conditions	The degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system.	Venkatesh et al., 2003
UTAUT2	Hedonic Motivation	The fun or pleasure derived from using a technology.	Venkatesh et al., 2012
UTAUT2	Price Value	Consumers' cognitive trade-off between the perceived benefits of the applications and the monetary cost for using them.	Venkatesh et al., 2012
UTAUT2	Habit	The extent to which people tend to perform behaviors automatically because of learning.	Venkatesh et al., 2012
UTAUT Synthesis	Compatibility	The degree of suitableness of the technology to the user’s lifestyle	Blut et al., 2022
UTAUT Synthesis	Education	The user’s educational background	Blut et al., 2022
UTAUT Synthesis	Personal innovativeness	The degree of willingness of the user to try out new technologies	Blut et al., 2022
UTAUT Synthesis	Costs	The extent to which the user perceives the technology as costly	Blut et al., 2022

In summary, TAM is a model that focuses on the perceived usefulness and ease of use as primary determinants of technology acceptance, making it a useful framework for investigating acceptance of technology like AI chatbots in healthcare.

2.1.2. Validity of TAM, TAM2, and TAM3

After the development of TAM, PU was confirmed to be the strongest predictor of intention to use, with an effect size of 0.6 on average (Venkatesh & Davis, 2000). The original TAM explained more than a third of the variance in behavioural intention (Venkatesh & Davis, 2000). TAM2 increased explanatory power to between 37% and 52% of the variance in behavioural intention (Venkatesh & Davis, 2000). This increase was largely due to a rise in predicting PU, as the model was found to explain 60% of the variance in PU with the inclusion of the new variables. Finally, TAM3 explained between 40% and 53% of the variance in intention to use, which is similar to the explanatory power of TAM2 (Venkatesh & Bala, 2008).

When it comes to predicting technology use in healthcare, in general, the application of the TAM models has shown similar explanatory power. One meta-analysis (Holden & Karsh, 2010) of over 20 studies of clinicians using health IT for patient care reported that TAM explained an average of 40% of the variance in the intention to use, ranging between 29% and 70% across studies. (Chismar & Wiley-Patton, 2003) found that the TAM2 model explained 59% of the variance in physicians' intention to adopt internet-based health applications, while (Wu et al., 2007) reported that the model accounted for 70% of the variance in HCPs' intention to use mobile healthcare systems. However, as (Holden & Karsh, 2010) note, researchers should be cautious when interpreting the values of explanatory power from different studies because of study heterogeneity (e.g., some studies use the exact frameworks while others adapt them to the study).

In summary, TAM and its extensions have shown significant predictive power in technology acceptance, including in healthcare settings. However, variations in study design and model adaptation necessitate careful interpretation of these results.

2.1.3. Summary of TAM

The theoretical models TAM, TAM2 and TAM3, provide a comprehensive framework for understanding technology adoption, centering on usefulness and ease of use, and supplemented by additional variables introduced in the extensions. The models' validity has been confirmed in various contexts, including healthcare, demonstrating robust explanatory power for predicting technology acceptance and use, though caution is advised when interpreting results.

2.2. Unified Theory of Acceptance and Use of Technology (UTAUT) and Extensions

The Unified Theory of Acceptance and Use of Technology (UTAUT) is another prominent framework introduced by Venkatesh et al. (2003) to consolidate and integrate eight existing innovation acceptance models, including TAM. The UTAUT framework aims to provide a holistic view of all the factors that influence people's behavioural intention to use a new technology. While the original UTAUT was created to measure the use of new technology solely within an organisation, the two extensions (UTAUT2 and "UTAUT synthesis of extensions" by Blut et al.) can be applied to both consumers and employees (Blut et al., 2022).

2.2.1. Key concepts of UTAUT

UTAUT identifies four core constructs: *performance expectancy*, *effort expectancy*, *social influence*, and *facilitating conditions*. The model also considers four moderating variables: *gender*, *age*, *experience*, and *voluntariness of use*. Table 1 presents the definitions of each construct and its respective counterpart from the TAM models (if applicable).

In 2012, Venkatesh and colleagues published the extension UTAUT2, which adapted the model to consumer contexts (Venkatesh et al., 2012). UTAUT2 introduced three additional constructs: *hedonic motivation*, *price value*, and *habit*. These constructs were added to the original UTAUT model to better capture the unique factors that influence consumer adoption of technology.

Most recently, Blut et al. (2022) proposed a "UTAUT synthesis of extensions" model, that integrates various UTAUT extensions to provide a comprehensive list of factors that influence technology acceptance. The new model was based on a meta-study of 1,935 independent samples and a total of 737,112 participants (Blut et al., 2022). The purpose of the "UTAUT synthesis of extensions" model was to expand the explanatory power of UTAUT and UTAUT2, as well as to construct a model that is applicable to both organisations and consumer markets. The new model introduces four new factors: *compatibility*, *education*, *personal inventiveness*, and *costs*. The definitions and TAM counterparts of all constructs are presented in Table 1.

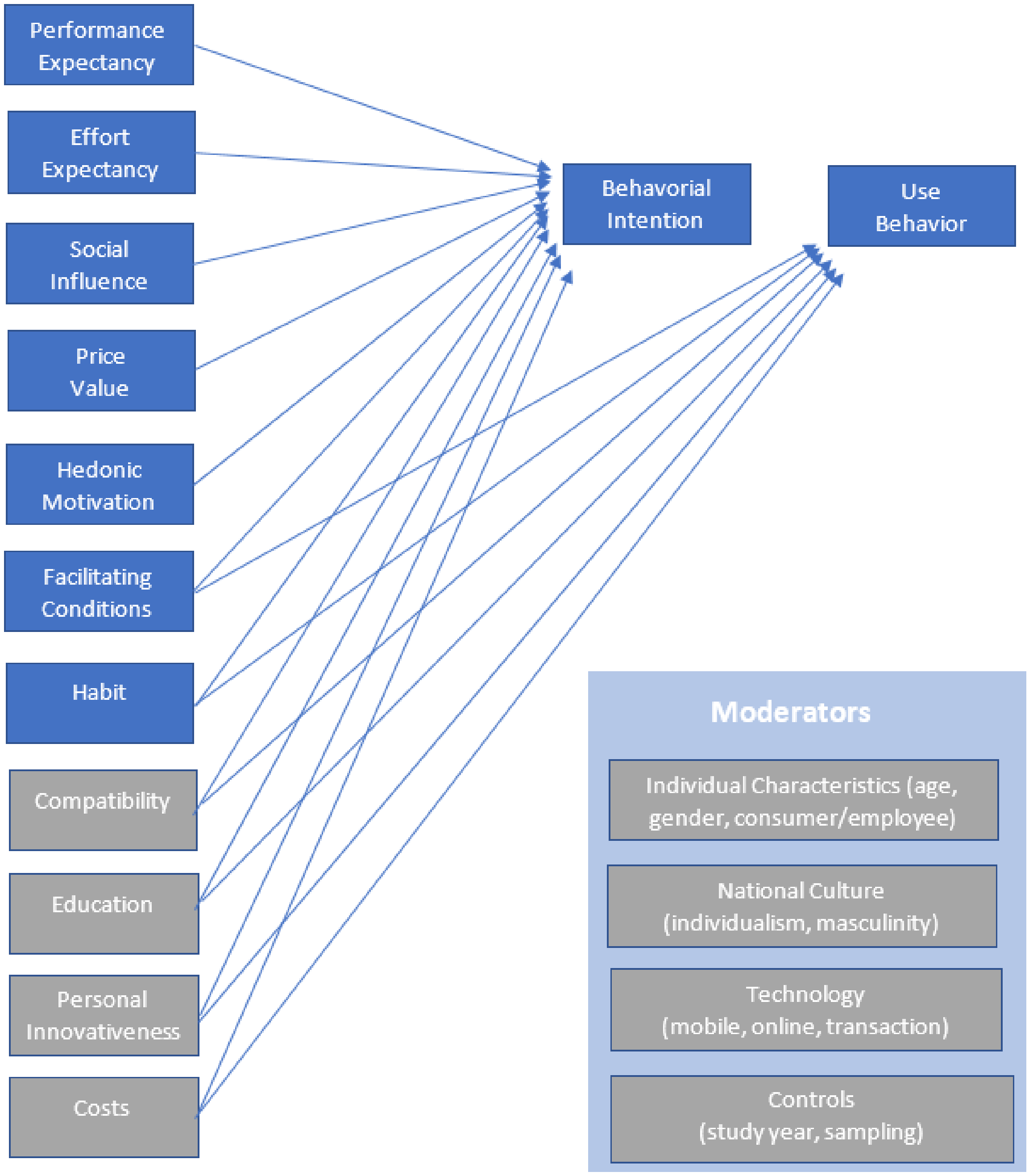

Figure 6. "UTAUT Synthesis of Extensions" model (Blut et al., 2022).

2.2.2. Predictive power and key constructs

The original UTAUT model was found to outperform most previous technology acceptance models (including TAM), explaining 69% of the variance in behavioural intention, and 40% of the variance in actual technology use (Venkatesh et al., 2003). The inclusion of the three additional constructs in UTAUT2 raised the model's predictive power, explaining 74% of the variance in intention to use, and 52% of the variance in actual technology use, suggesting that the model has high predictive validity when applied to the consumer market (Venkatesh et al., 2012). The most recent synthesis of extensions (Blut et al., 2022) showed similar predictive validity as UTAUT2, with the benefit of being applicable in both organisational and consumer settings.

In healthcare, UTAUT has been applied in various contexts, including electronic health records (EHRs) (Maillet et al., 2015), telemedicine (Cimperman et al., 2016), and mobile health (mHealth) applications (e.g., Dwivedi et al., 2019). However, the explanatory power of UTAUT within healthcare varies, with R^2 values for BI ranging from 42% to 68% (Dwivedi et al., 2019). UTAUT2 has been applied to healthcare contexts, such as patient portals (Hoque & Sorwar, 2017) and mHealth (Deng et al., 2019). However, the predictive power of UTAUT2 in healthcare remains inconsistent, with R^2 values for BI ranging from 43% to 71% (Deng et al., 2019).

In conclusion, UTAUT, UTAUT2, and “UTAUT Synthesis of Extensions” offer valuable insights into technology acceptance. However, their effectiveness is contingent upon the specific context and technology under investigation. Further research is required to establish the generalizability and robustness of these models within the healthcare domain.

2.2.3. Summary of UTAUT

The Unified Theory of Acceptance and Use of Technology (UTAUT) and its extensions, UTAUT2 and "UTAUT Synthesis of Extensions," present a holistic framework for understanding technology acceptance. These models emphasise core constructs such as performance expectancy, effort expectancy, social influence, and facilitating conditions, along with several context-specific factors included in the extensions. Their efficacy in predicting technology acceptance has been demonstrated across different contexts, including healthcare.

2.3. Limitations of the Theoretical Models and Challenges in their Application

This section provides an analysis of the inherent limitations of the TAM and UTAUT in the context of AI health chatbots. We will also address the challenges of applying these models to the healthcare domain

2.3.1. Inherent Limitations of TAM and UTAUT Models

While TAM and UTAUT models provide valuable insights into technology acceptance and use, it is crucial to recognise their inherent limitations, which include potential biases, constraints of the constructs, and issues of generalisability.

Research identifies the following limitations that are inherent to the two models:

Potential biases: The TAM and UTAUT models have been criticised for potential biases that may arise due to their reliance on self-reported data (Yousafzai et al., 2007; Dwivedi et al., 2017). These biases include social desirability bias, where respondents may provide answers that align with societal norms or expectations, and recall bias, where respondents may inaccurately remember past experiences or behaviours (Podsakoff et al., 2003). Such biases can lead to inaccurate estimations of the relationships between constructs, affecting the validity of the models.

Limits of the core constructs: The constructs of TAM and UTAUT models have been criticised for their limited scope and lack of comprehensiveness (Bagozzi, 2007; Venkatesh et al., 2012). For instance, TAM focuses primarily on PU and PEOU, neglecting other factors such as trust, privacy concerns, and social influence that may also impact technology acceptance (Gefen et al., 2003; Zhou, 2011). These overlooked factors might be especially relevant in a healthcare context, where trust and privacy are paramount. Similarly, UTAUT incorporates four core constructs (performance expectancy, effort expectancy, social influence, and facilitating conditions), but it does not account for factors such as individual differences, emotions, or cultural variations (Dwivedi et al., 2017).

Issues of generalisability: Both TAM and UTAUT models have been criticised for their limited generalisability across different contexts, populations, and technologies (Chuttur, 2009; Dwivedi et al., 2017). While these models have been widely applied in various domains, their applicability and validity in specific contexts, such as healthcare, may be subject to debate (Bagozzi, 2007). Furthermore, the rapid evolution of technology, particularly AI chatbots, may present new challenges and factors that have not been considered in the original models.

2.3.2. Challenges in Applying TAM and UTAUT Models to Healthcare Domain

Applying TAM and UTAUT to the healthcare domain and AI chatbots presents unique challenges. These challenges stem from the complexity of the healthcare domain, the novelty of AI chatbots, and methodological considerations.

Complexity of healthcare domain: The healthcare domain is characterised by its complexity, involving multiple stakeholders (e.g., patients, HCPs, administrators), strict regulations, and ethical considerations (Holden & Karsh, 2010). When applying TAM and UTAUT models to this context, many studies opt to adapt or extend the models to account for these complexities and the unique needs and concerns of healthcare stakeholders (Or & Karsh, 2009).

AI chatbots as emerging technology: AI chatbots represent an emerging technology that may introduce new factors influencing technology acceptance, which are not fully captured by the TAM and UTAUT models. For instance, the level of AI sophistication, the quality of human-chatbot interaction, and the potential risks associated with AI-driven decision-making may impact users' perceptions and acceptance of AI chatbots in healthcare (Laranjo et al., 2018).

Methodological issues: Most studies applying TAM and UTAUT models adopt a quantitative cross-sectional design, which may not capture the dynamic nature of technology acceptance and use over time (Chuttur, 2009; Venkatesh et al., 2012). Studies of qualitative and longitudinal designs could provide more robust insights into the factors influencing AI chatbot acceptance and use in healthcare, particularly as users gain more experience and familiarity with the technology (Holden & Karsh, 2010).

2.3.3. Summary of Limitations

Despite the widespread application of TAM and UTAUT models in understanding technology acceptance and use, it is important to consider their inherent limitations, as well as the challenges of applying the models within the healthcare domain.

2.4. Summary of Theoretical Background

This chapter has elucidated the TAM and UTAUT frameworks as key theoretical foundations underpinning this research. Both models, with their focus on user perceptions and behavioural intentions, offer valuable insights into the acceptance and use of AI chatbots in healthcare. Despite their widespread validation, there appear to be inherent limitations and challenges to the application of this study, including potential biases, construct constraints, and issues of generalisability, coupled with the unique complexities of the healthcare domain and novelty of AI chatbots. Nevertheless, rather than diminish their role, these limitations sever to inform the study's use of the two theoretical frameworks.

3. Literature Review

The purpose of this section is to review the published literature on patient and HCP attitudes towards AI-based health chatbots with three key objectives in mind. First, reading publications on the topic will improve the researcher's understanding of the subject prior to carrying out an investigation (Leavy, 2017). Second, reviewing the literature will also help identify research gaps and limitations that can be addressed in this study. Finally, such a review can provide insights into the methods and approaches used in previous studies, which can help inform the design of the new research (Leavy, 2017).

Two databases, PubMed and Scopus, were searched for relevant studies that explore the attitudes of patients and HCPs towards AI health chatbots. A detailed explanation of the methodology used to identify relevant studies is presented in Chapter 4.1. After filtering the studies based on relevance and exclusion criteria, a total of 16 studies were included in this literature review, combining a mixture of patient-only, practitioner-only, and multiple-user designs, as well as qualitative, quantitative, and mixed-method approaches.

This chapter is structured in the following way: Firstly, all findings extracted from the literature are separated by user type: either patient or HCP. Secondly, the findings within each user type are divided into themes. These key themes are then subjectively divided into positive and negative perceptions, which include the relevant attitudes.

3.1. Patient perspectives

The literature review uncovered a total of 11 papers focusing on patients as a study population, of which 8 were primary studies and 3 were scoping reviews. The primary studies were a relatively equal mixture of qualitative, quantitative and mixed-method studies. Only 3 of the studies recruited active inpatients as participants, and the remaining studies included members of the general public as subjects.

The systematic review of patient perspectives identified the following key themes: user experience and ease of use, trust and perceived usefulness, and privacy and data security. The literature on these themes reveals a complex and nuanced understanding of the potential advantages and drawbacks of AI health chatbots from the perspective of patients.

3.1.1. Theme 1: User Experience and Ease of Use

Relating to the research questions of the perceived usability of AI chatbots (RQ1b), the user experience and ease of use of the technology emerge as significant themes in previous research.

Positive perceptions:

Accessibility and convenience: AI health chatbots provide universal accessibility and convenience, a noted advantage in several studies (van Bussel et al., 2022; Nadarzynski et al., 2019). Cancer patients and UK users appreciate that these tools are always available, enabling general health information retrieval and administrative tasks. Systematic reviews affirm these findings, acknowledging AI's remote data collection capacity as a convenience factor (Ciecierski-Holmes et al., 2022; Chew & Achananuparp, 2022).

User-friendliness: Patients and users emphasise the importance of a user-friendly design as a key feature that makes AI-powered healthcare chatbots easy to use and, thereby, more likely to be accepted (van Bussel et al., 2022; Nadarzynski et al., 2019; Luca et al., 2023; Chew & Achananuparp, 2022). One study reports that 65% of subjects felt the AI medical interviewing system would be easy to learn (Hong et al., 2022).

Negative perceptions:

Lack of empathy: Patients frequently cite the lack of empathy and “human touch” in AI chatbots as a significant drawback (Luca et al., 2023; van Bussel et al., 2022; Nadarzynski et al., 2019; Koulouri et al., 2022). Past experiences with AI chatbots from other industries (e.g. e-commerce or virtual assistants like Alexa and Siri) lead to user frustration, and so does imperfect understanding during interactions. Patients also express concerns about the inability of chatbots to handle emotional responses triggered by unexpected medical information, such as when one becomes anxious after receiving bad medical news (Luca et al., 2023; Ciecierski-Holmes et al., 2022).

Resistance to change: One study identified patients' reluctance to change as an important barrier for AI health chatbot adoption (van Bussel et al., 2022). In this study, some interviewees shared a dislike for having to adopt novel systems and, whenever presented with a choice, said they would always opt for an interaction with a human. However, there is limited evidence from other research on the topic, which makes it challenging to draw conclusions about patient attitudes.

3.1.2. Theme 2: Trust and Perceived Usefulness

The theme of perceived usefulness relates to RQ1a of the research objective, while trust in AI may act as a motivator or barrier to adoption, thus relating to RQ4.

Positive perceptions:

Cost- and time-efficiency: AI health chatbots are viewed as a cheap and time-efficient alternative for non-serious medical queries (van Bussel et al., 2022; Nadarzynski et al., 2019; Ho et al., 2023; Biro et al., 2023). The convenience of not having to travel or queue to ask questions further enhances the patients’ positive perceptions of time-efficiency, by providing free 24/7 support in non-serious cases (Nadarzynski et al., 2019; Ciecierski-Holmes et al., 2022).

Negative perceptions:

Lack of trust in accuracy and credibility: There are significant concerns about the reliability of information provided by AI chatbots (Koulouri et al., 2022; Ho et al., 2023; van Bussel et al., 2022; Nadarzynski et al., 2019). Interviewees in one study said “I have to be able to trust the answers” and “I trust a machine less than a human” (van Bussel et al., 2022). Users are more likely to trust AI chatbots if they perceive them as competent, transparent, and consistent (van Bussel et al., 2022; Ciecierski-Holmes et al., 2022). Despite the acknowledged usefulness of AI chatbots, trust in their accuracy and reliability remains limited.

3.1.3. Theme 3: Privacy and Data Security

Understanding how privacy and data security concerns impact the acceptance and use of AI chatbots in healthcare is relevant to RQ4.

Positive perceptions:

Anonymity: Patients appreciate the anonymity that AI chatbots offer, especially when discussing stigmatized or embarrassing health issues (van Bussel et al., 2022). However, despite the perceived benefit of anonymity, GPs remain the preferred source of consultation, even for sensitive health conditions. In a study by Miles et al. (2021), which compared user attitudes towards AI medical chatbots, GPs, and GP-chatbot combinations as consultation sources, based on stigma (low vs. high) and condition severity (low vs. high), patients preferred GPs and GP-chatbot combinations over chatbots in cases of high stigma and both high and low severity.

Negative perceptions:

Concerns for data privacy and discrimination: Patients worry about the misuse of their sensitive personal health information, including fears of discrimination and higher healthcare insurance premiums (Luca et al., 2023; van Bussel et al., 2022; Nadarzynski et al., 2019; Koulouri et al., 2022; Ho et al., 2023). Although they acknowledge the potential for improved accuracy of AI tools with access to their data, the threat of cyberattacks and data leaks makes them hesitant to share personal information with AI chatbots (He et al., 2021; Ciecierski-Holmes et al., 2022).

3.1.4. Sub-conclusion

In conclusion, the examination of patient perspectives in current literature reveals a multifaceted understanding of the advantages and drawbacks of AI health chatbots. Patients appreciate the accessibility, convenience, and user-friendliness of AI chatbots and recognize their potential to save time and money in non-serious cases. However, concerns about the lack of empathy, resistance to change, trust in the accuracy and credibility of the chatbots, and privacy and data security issues remain prevalent.

While patients value the anonymity that AI chatbots can provide, particularly in the context of stigmatised health conditions, they also express apprehension about the potential misuse of their personal information and possible discrimination arising from data breaches. The mixed perceptions of patients highlight the importance of gaining a better understanding through further in-depth primary research of patient attitudes towards AI health chatbots.

3.2. HCP perspective

The literature review focused on two primary studies concerning HCPs' views on AI health chatbots (van Bussel et al., 2022; Moldt et al., 2022) and was expanded to incorporate four additional landmark studies on general AI attitudes among practitioners and medical students. These landmark studies, including two primary research papers and two systematic reviews, provided a quantitative and qualitative evaluation of HCP attitudes (Castagno & Khalifa, 2020; Blease et al., 2019).

This section distils HCPs' attitudes towards AI chatbots in healthcare into four key themes: efficiency, trust, professional impacts, and data privacy. While HCPs recognise AI chatbots' potential for improving diagnostic accuracy and reducing repetitive tasks, concerns persist regarding lengthy implementation, risk of misdiagnosis, lack of empathy, and data privacy. Through these themes, this section provides insights into factors influencing HCPs' acceptance of AI chatbots in healthcare.

3.2.1. Theme 1: Efficiency and Time Savings

This theme addresses the perceived usefulness of the technology, thus relating to RQ2a.

Positive perceptions:

Reducing simple or repetitive tasks: HCPs acknowledge AI chatbots' potential for routine tasks, such as arranging appointments and answering generic medical questions (van Bussel et al., 2022). Medical students also see the potential of chatbots in reducing administrative burdens and saving time and money (Moldt et al., 2022). In studies on general AI technologies, some practitioners even see AI tools as aiding in clinical examinations and other repetitive tasks, enhancing time savings and patient outcomes (Hogg et al., 2023; Blease et al., 2019; Castagno & Khalifa, 2020). The relevance of this theme is further confirmed by a systematic review of 60 studies and a cross-sectional survey across HCPs from 39 countries (Chen et al., 2022), suggesting that medical staff globally see AI technologies as beneficial for reducing simple or repetitive tasks.

Negative perceptions:

Challenging and time-demanding implementation: Despite these positive views, some HCPs express concerns about lengthy, resource-intensive implementation processes and resistance to change among patients (van Bussel et al., 2022). For example, in a 2022 study, medical students felt that chatbots were not yet sufficiently established and that long-term success had yet to materialise (81.8%) (Moldt et al., 2022). General AI studies also highlight concerns about the time- and resource-demanding implementation process (Hogg et al., 2023; Blease et al., 2019). Some HCPs worry about increased procedural time due to the need for human oversight of AI systems (Chen et al., 2022).

3.2.2. Theme 2: Accuracy and Trust

The theme of accuracy and trust may connect to potential motivators and barriers for acceptance, thus relating to RQ4.

Positive perceptions:

High perceived accuracy in standardised tasks: Doctors and medical students acknowledge AI chatbots' competence in answering standard medical questions and handling routine administrative tasks (van Bussel et al., 2022; Moldt et al., 2022). They also perceive AI systems as capable of capturing and analysing more information than humans, leading to faster and more accurate diagnoses. In general AI studies, GPs see AI advancements as helpful in managing workload issues (Blease et al., 2019), and a general consensus exists on AI improving workflow efficiency and standardisation of results (Hogg et al., 2023; Chen et al., 2022).

Negative perceptions:

Low perceived accuracy for complex or unusual tasks: Despite the aforementioned benefits, HCPs express concerns about AI chatbots' reliability in carrying complex tasks, such as concluding a diagnosis or choosing an appropriate treatment plan (van Bussel et al., 2022). There are also fears about potential misdiagnosis due to patients self-diagnosing more frequently (Moldt et al., 2022). General AI studies echo these concerns, with HCPs sharing sceptical views about AI's ability to inform complex clinical decisions and expressing preference for human checks on results (Hogg et al., 2023; Blease et al., 2019; Chen et al., 2022).

3.2.3. Theme 3: Impacts on Profession

This theme may be related to the perceived usefulness of AI chatbots by HCPs, thus relating to RQ1a, as well as connecting to a potential barrier to acceptance, relating to RQ4.

Positive perceptions:

Diagnosis and decision support: Some HCPs (e.g. radiologists and medical students) believe that AI chatbots can enhance diagnostic accuracy and decision-making support (van (Bussel et al., 2022; Moldt et al., 2022). Medical students believed that new technology, including AI chatbots, would be able to make diagnoses faster and more accurate in the future (Moldt et al., 2022). In general AI research, HCPs see AI technologies as potential tools for improving the quality of care by favouring evidence-based over eminence-based care and widening the scope of healthcare practice (Hogg et al., 2023). However, in one study from a systematic review, HCPs expressed concerns that AI training limitations may lead to potential inaccuracies in underrepresented populations (e.g. ethnic minorities, elderly, disadvantaged groups) (Chen et al., 2022).

Enabling professional autonomy: While not specifically about AI chatbots, research on general AI suggests HCPs view AI as a tool to assist the healthcare profession by fostering collaboration and levelling the professional hierarchy (Hogg et al., 2023; Blease et al., 2019; Chen et al., 2022). However, 68% of HCPs insist on the importance of AI serving as a complementary tool rather than a substitute for medical expertise (Hogg et al., 2023; Blease et al., 2019; Chen et al., 2022).

Negative perceptions:

Fear of job displacement: Concerns about AI replacing doctor jobs vary across studies, ranging from 6% to 78%, though three-quarters of the studies reported concern rates <50% (Chen et al., 2022). However, most studies on AI chatbots and other AI technologies report that HCPs are largely optimistic about AI's impact on their careers (Hogg et al., 2023; Blease et al., 2019; Castagno & Khalifa, 2020; Chen et al., 2022). For example, a survey of 98 UK HCPs reported that 72% of participants denied any worry that AI would replace them at their job (Castagno & Khalifa, 2020).

Lack of empathy and patient-centeredness: HCPs also worry about AI's inability to empathise and provide emotional support, believing this could have an impact on patient mental health, deteriorate doctor-patient relationships and ultimately hinder the quality of care patients receive (van Bussel et al., 2022; Moldt et al., 2022; Hogg et al., 2023; Blease et al., 2019; Chen et al., 2022). For example, in one study, 81.8% of students feared communication problems and 63.6% feared loss of personal contact with patients due to the lack of maturity of the technology (Moldt et al., 2022). This theme appears consistent in research on AI chatbots and general AI tools alike.

3.2.4. Theme 4: Data Privacy and Anonymity

The theme of data privacy may be connected to motivators, facilitators and barriers to HCP acceptance of AI chatbots, thus relating to RQ4.

Positive perceptions:

Patient anonymity and stigmatised health queries: Medical students see AI chatbots as therapy tools or interactive diaries for patients to be a good opportunity to improve confidentiality and reduce insecurity and shame about disclosing sensitive or stigmatised health information (Moldt et al., 2022). This subject is not addressed in studies on general AI tools, therefore it is difficult to draw conclusions due to limited literature.

Negative perceptions:

Lack of trust in data privacy: Medical students' trust in AI data privacy was initially low but improved after an educational course on chatbots and the future of healthcare (Moldt et al., 2022). However, as high as 80% of HCPs believe there are serious privacy risks associated with use of AI (Castagno & Khalifa, 2020). In a systematic review, four studies reported HCPs considering data security and the risks of data privacy disclosure as major challenges to clinical AI development and implementation (Chen et al., 2022). Issues relating to lack of trust in data privacy may be partially due to low understanding of AI and data security measures, as highlighted by the study on medical students (Moldt et al., 2022).

3.2.5. Sub-conclusion

The HCP perspectives on AI chatbots in healthcare are diverse and multifaceted. HCPs acknowledge the potential benefits of AI chatbots in terms of efficiency, time savings, and diagnostic support but have concerns about implementation, misdiagnosis, empathy, and data privacy. They prefer AI chatbots as supportive tools that enable professional autonomy, not replacements for their expertise. The level of trust in AI chatbots depends on the task performed, with more trust for simple and repetitive tasks over complex or unusual ones. Despite the limited literature on the topic of AI chatbots, this review offers insights into the factors affecting HCPs' acceptance of the technology, suggesting the need for further research to address concerns and facilitate successful integration in healthcare.

3.3. Summary of Literature Review

The literature review presented in this chapter aimed to provide a comprehensive understanding of patient and HCP perspectives on AI health chatbots. By examining the positive and negative perceptions across various themes, this review has highlighted the complex and nuanced attitudes held by both patients and HCPs towards AI chatbots in healthcare.

Patients appreciate the accessibility, convenience, and user-friendliness of AI chatbots and recognize their potential to save time and money in non-serious cases. However, concerns about the lack of empathy, resistance to change, trust in the accuracy and credibility of the chatbots, and privacy and data security issues remain prevalent. The mixed perceptions of patients emphasize the need for further in-depth primary research to explore patient attitudes towards AI health chatbots.

Studies on HCPs' attitudes towards AI chatbots are scarce. In research around practitioner attitudes towards general AI, HCPs acknowledge the potential benefits of AI chatbots in terms of efficiency, time savings, and diagnostic support, particularly for routine and standardized tasks. However, concerns persist regarding the implementation process, potential for misdiagnosis, lack of empathy, and data privacy issues. The literature suggests that HCPs are more inclined to accept AI chatbots as complementary tools that can support their professional autonomy and enhance patient care, rather than as a replacement for their expertise and decision-making capabilities.

In summary, this literature review has identified key themes and attitudes within the patient and HCP perspectives on AI health chatbots. The complex and multifaceted nature of these attitudes, as well as the general lack of research on the subject matter, underscore the need for further research to better understand the factors influencing the acceptance and adoption of AI chatbots in healthcare settings.

4. Methodology

4.1. Methods to the Literature Review

In order to hypothesise the research questions and provide contextual information regarding acceptance and attitudes towards AI health chatbots, a systematic literature review was conducted. The goal of the literature review was threefold: 1) to understand the general themes and attitudes of patients and doctors towards AI chatbots; 2) to identify relevant theoretical frameworks used in research; and 3) to inform on validated research methods and best practises in qualitative research design.

4.1.1. Identifying relevant studies

The literature search was performed on March 1, 2023, in the databases PubMed and Business Source Complete (EBSCO). These databases were chosen because of their extensive coverage of the fields of medicine and business, respectively, and their reputation for providing high-quality peer-reviewed research articles. The search strategy included keywords for the technology (i.e., "chatbot" or "conversational agent" and derivatives), the user type (i.e., "patient" or "doctor" and derivatives), and the studied subject (i.e., "attitude" or "acceptance" and derivatives). A comprehensive search strategy is presented in Appendix 1. The search yielded a total of 152 hits, of which 46 were in PubMed and 106 in EBSCO. Subsequently, the inclusion and exclusion criteria presented in Table 2 were applied.

Table 2. Inclusion and exclusion criteria to the Literature review.

Criteria	Details
Inclusion Criteria	
Full Text Availability	The study must be available as full text, either free of charge, or via the library of the Copenhagen Business School.
Type of Work	The work must be a finished study, report, book, or conference script.
Language	The text must be available in English.
Publication Date	The study must have been published within the last 10 years.
User Focus	The study must focus on attitudes or acceptance of either patients and/or doctors towards AI chatbots.
Exclusion Criteria	
Healthcare Context	Studies that are not in a healthcare context are excluded.
User Attitudes	Studies not studying user attitudes are excluded.
AI-Based Chatbots	Studies not based on AI-based chatbots are excluded.
Real-World Conditions	Studies investigating the feasibility of a specific product with limited user feedback and not under real-world conditions are excluded.

4.1.2. Study selection

The remaining 96 results had duplicates identified and removed, and were further screened for relevance by title, abstract, and full-text, while irrelevant studies were excluded (Figure 7). During screenings, articles were excluded if they were (1) not in a healthcare context, (2) not studying user attitudes, (3) not based on AI-based chatbots, or (4) investigating the feasibility of a specific product (except for studies that included user feedback). For instance, studies that collected general attitudes towards AI technologies, or that focused solely on the technical feasibility of chatbots, were among the articles excluded. Additionally, the discovery of connected literature and landmark studies was done via Litmaps, which is a software tool that allows for the identification of key papers and authors in a given field, based on citation networks and bibliometric analysis. This helped to ensure that the review included key landmark articles that were not discoverable via the keyword search strategy.

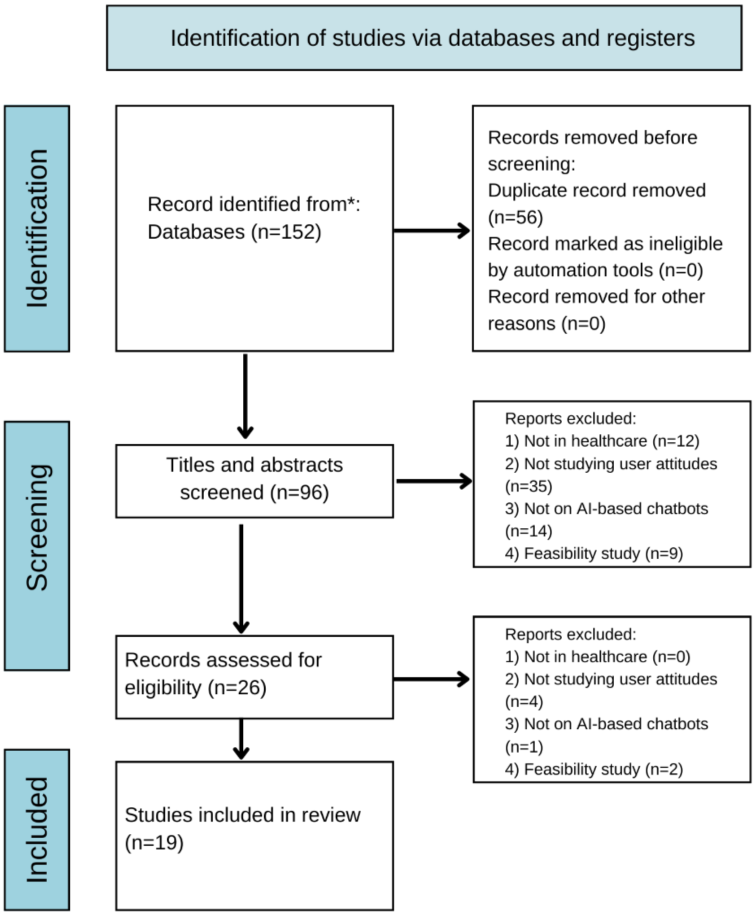

Figure 7. PRISMA flow diagram of the study seleciton process.

The literature search identified 19 relevant results, including 13 primary studies investigating patients and/or HCPs, and 6 literature reviews addressing the topic either entirely or partially. Most of the primary studies studied either active inpatients (4/13) or members of the general public (7/13), while only one study sampled only HCPs, and one sampled both patients and HCPs. The 13 primary and 6 review studies pooled participants from a variety of countries, including Canada, China, Ecuador, Germany, India, Japan, Korea, Malawi, Mexico, the Netherlands, Peru, Saudi Arabia, South Africa, Spain, UK, and USA. This review included diverse cultural contexts and a range of in-country economic conditions, providing a comprehensive understanding of global perspectives on the topic. It should be noted that studies on low- and middle-income countries were underrepresented, appearing in only one review paper, which is in line with other findings in health informatics research (Shumba & Lusambili, 2021), and underscores the need for further research in these areas to ensure a more complete understanding of attitudes and acceptance across diverse economic contexts.

4.1.3. Segmentation of results

The wide range of methodologies, contexts, and focuses among the selected studies necessitated a clear and organised presentation of the results to ensure that the differing perspectives and findings were accurately represented. Thus, the findings of the selected studies were grouped by the type of participant (patient or HCP) and then organised into themes grouped based on their connotation (either positive or negative). This segmentation was due to the heterogeneity of the studies included in the review, which allowed for a clearer and more organised presentation of the results. This approach also helped identify any potential differences or similarities between the different study designs.

Qualitative insights were further categorised into sub-themes, while quantitative insights were summarised and presented in narrative form. Findings from studies with mixed samples or mixed-method designs were allocated to relevant sections accordingly. Findings from all participants and both types of insights served as the foundation for setting the hypotheses for this study.

4.1.4. Identifying theoretical frameworks

In addition to providing a deep contextual understanding of the subject matter, the literature review also served as a review of the most commonly used theoretical frameworks for investigating user acceptance and attitudes in a healthcare setting. The two identified theories were the Technology Acceptance Model (TAM) and extensions, and the Unified Theory of Acceptance and Use of Technology (UTAUT) and extensions. The two theories and their extensions were deemed particularly fitting for this study due to their comprehensive approach to understanding user acceptance and attitudes towards technology. These frameworks guided the development of research questions and hypotheses for the study. Additionally, they provided a basis for selecting appropriate measures to assess user acceptance and attitudes towards the healthcare technology being studied.

4.1.5. Sub-conclusion

The systematic literature review served as a critical first step in framing the research questions and providing the necessary context for studying patient and HCP attitudes towards AI health chatbots. The review process, beginning with a comprehensive search of relevant databases, followed by careful screening and selection of articles, allowed for a well-rounded understanding of the topic. The chosen articles provided insights into the general attitudes and themes relating to the use of AI chatbots in healthcare. The segmentation of the results enabled a clearer and more organised presentation of these insights, which then informed the development of hypotheses for this study. By identifying the TAM and UTAUT as the key theoretical frameworks, the study was anchored in established theories of technology acceptance in a healthcare setting. The literature review thus provided a robust foundation for the qualitative research design adopted in this study. The next stage involves data collection and analysis, drawing on the insights and frameworks identified in the literature review.

4.2. Philosophical statement

This section lays out the philosophical underpinnings that guide the methodology of this study. It navigates through the layers of Saunders' “research onion”, explicating the research philosophy, approach, and research design adopted for this investigation on attitudes towards AI health chatbots among patients and HCPs.

Academic textbooks on research methodology refer to Saunders' “research onion” (Figure 8), which serves as a metaphorical illustration of the different elements that researchers must consider when designing and conducting a study (Saunders et al., 2019). The "research onion" is a model that demonstrates the steps involved in the formulation of an effective research strategy, starting from the outermost layer of philosophical considerations, and peeling through to the innermost layer of data collection and analysis techniques (Saunders et al., 2019). There are six layers: research philosophy, research approach, research strategy, research choices, time horizons, and data collection and analysis techniques. Each outer layer influences the subsequent inner layer, ultimately shaping the research design and methodology.

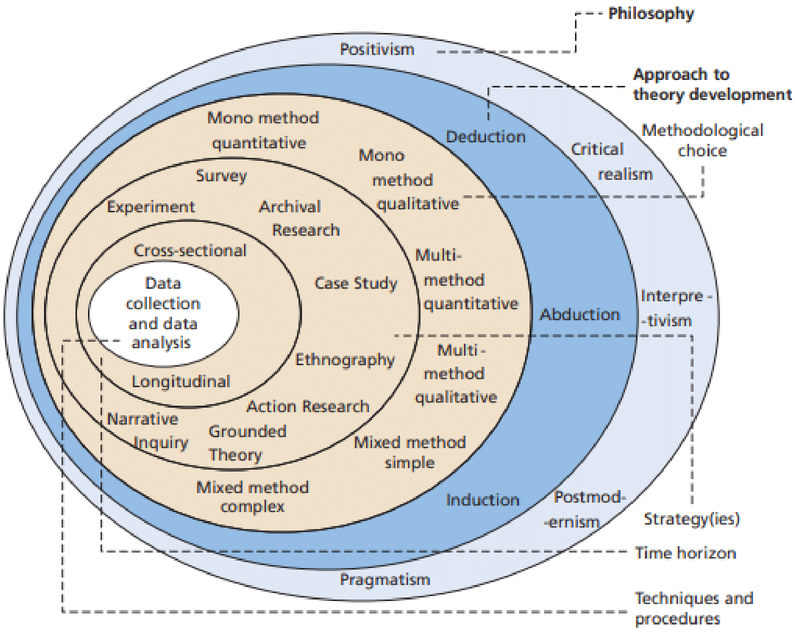

Figure 8. The "Research onion" (Saunders et al., 2019).

4.2.1. Research Philosophy

Research philosophy refers to the underlying assumptions, beliefs, or worldview guiding the researcher's approach to developing new knowledge (Leavy, 2017). There are four key research philosophies: positivism, realism, interpretivism, and pragmatism (Creswell & Poth, 2018).

An *interpretivist* research philosophy is adopted in this study. The interpretivist paradigm posits that reality is socially constructed, subjective, and context-dependent (Creswell & Poth, 2018). This research philosophy emphasises the significance of viewing humans as social actors rather than individual units, and thus aiming to understand the world from the standpoint of the individuals being studied (Creswell & Poth, 2018). In the context of this study, the interpretivist philosophy will facilitate a deep exploration of the attitudes, beliefs, and perceptions of patients and doctors regarding AI health chatbots. By adopting this philosophy, the researcher acknowledges the complexity and diversity of human attitudes and the importance of interpreting these attitudes in their specific context.

4.2.2. Research Approach

In alignment with interpretivist philosophy, this research will employ a combination of both deductive and inductive elements, known as an *abductive* approach, in order to produce a thorough and nuanced understanding of the research topic. Deductive research is characterised by starting with a theory or hypothesis and then testing it through the collection and analysis of data (Leavy, 2017). This approach allows for a more structured and systematic investigation of the research problem. On the other hand, the inductive approach enables the exploration of novel themes and patterns, and the generation of new insights and theories from the collected data (Bryman, 2015). The inductive approach allows for a flexible and open-ended research design, which is particularly suitable for exploring complex social phenomena such as technology adoption (Bryman, 2015). By employing an abductive approach, this study will first apply the TAM and UTAUT frameworks to the research (deductive), and then explore any additional themes that may arise during data collection and analysis (inductive) (Timmermans & Tavory, 2012; Klag & Langley, 2012), thus helping to achieve a more comprehensive understanding of the attitudes and acceptance of AI health chatbots among patients and HCPs.

4.2.3. Qualitative Research Design

The interpretivist philosophy adopted for this study aligns with and influences the choice of a qualitative research design. This study will adopt a qualitative research design to effectively capture attitudes towards AI health chatbots. In contrast to quantitative or mixed methods approaches, qualitative methods are well-suited for exploratory research seeking to understand complex attitudes, experiences, and perceptions (Creswell & Poth, 2018). They offer valuable insights into the complexities of human experiences, where qualitative data may not fully capture all nuances and subtleties (Bryman, 2015; Kvale & Brinkmann, 2014). This is especially important when studying sensitive topics such as one's health, or when there is limited information about the phenomenon being studied, such as the user's attitudes towards novel technology (Kvale & Brinkmann, 2014; Maxwell, 2012).

By leveraging the depth, flexibility, and context-sensitivity of qualitative interviews, this study aims to generate a comprehensive and nuanced understanding of patients' and doctors' attitudes towards AI health chatbots.

4.2.4. Sub-conclusion

In essence, the interpretivist philosophy adopted in this study leads to an abductive research approach, combining the rigour of deductive methods with the exploration of inductive research. This philosophy and approach are further reflected in the qualitative research design chosen, particularly in the use of in-depth, flexible, and context-sensitive qualitative interviews to understand the attitudes of patients and HCPs towards AI health chatbots.

4.3. Data Collection and Analysis

4.3.1. Interview Process

Interviewees were recruited through a combination of methods, including theoretical sampling, self-selection, accessibility, and snowball sampling (Kvale & Brinkmann, 2014; Leavy, 2017), in order to ensure a diverse and representative sample, while best utilising the researcher's limited resources and network. Study invitation messages to first- and second-degree connections were posted on the social media platform LinkedIn, as well as the work platform Microsoft Teams. Respondents who expressed interest in participating in the study booked their own interview time slot using a digital booking platform called “Calendly”. As part of the interview booking, participants had to complete a survey consisting of four demographics-related questions (age, gender, occupation, nationality) and two questions relating to their attitudes towards technology and AI chatbots. By scheduling an interview, participants also agreed to the informed consent statement. For a detailed explanation of the interview booking survey and consent statement, please see Appendix 2.

The interviews were then conducted online via video conferencing (Microsoft Teams) in order to enable the automatic recording and transcription of interviews. Conducting interviews via online video calls is a viable alternative to in-person qualitative interviewing (Krouwel et al., 2019) . The interviews were conducted in English or Bulgarian, depending on the participant’s choice. Transcripts in Bulgarian were translated into English using digital translating software (Google Translate and Deepl), and accuracy of the translation was manually validated.

4.3.2. Data Collection

A total of 7 HCPs and 12 patients expressed interest in participating in the study, of which 5 HCPs and 7 patients proceeded to schedule interviews, and all but 1 HCP attended the interviews. Recordings and transcripts of interviews were downloaded locally for up to 60 days after the submission of this study. To ensure participant anonymity, only the researcher had access to recordings and transcripts, and interviewees were assigned unique identification numbers, such as “P1” to “P7” and “HCP1” to “HCP4”. Transcripts were formatted using file editing and format conversion tools into workable and coherent text files. Finally, transcripts were also manually checked for accuracy compared to the recording by the researcher.

4.3.3. Data coding

To analyse the data collected from the qualitative interviews, text file transcripts were uploaded to NVivo, a research software recommended by the Copenhagen Business School (CBS) for managing and analysing qualitative data. A combination of deductive and inductive coding was employed in the data coding process. Deductive coding involves applying pre-established concepts or themes to the data, such as the general constructs of the TAM and UTAUT frameworks (Fereday & Muir-Cochrane, 2006). In contrast, inductive coding involves identifying emerging themes directly from the data without any preconceived notions, resulting in unique themes not appearing in the two frameworks (Fereday & Muir-Cochrane, 2006).

The coding process was carried in two stages. In the first stage of coding, descriptive and value coding were utilised. Descriptive coding involves assigning basic labels to the data that summarise the content in a word or a short phrase (Saldana, 2015). This allowed for the identification of general topics covered in the interviews. Values coding was also used to examine the participants' values, beliefs, and attitudes related to AI health chatbots (Saldana, 2015).

In the second stage, line-by-line coding was employed to further dissect the data and identify more specific patterns or themes (Charmaz, 2006). This involved examining each line of the transcript and assigning codes that represented the essence of the content. This process allowed for a deeper analysis of the data and facilitated the identification of emerging themes and subthemes that were not initially apparent during the first stage of coding.

4.3.4. Data analysis

For the data analysis, thematic analysis and grounded theory approaches were employed. Thematic analysis is a widely used qualitative research method that involves identifying, analysing, and reporting patterns (themes) within the data (Braun & Clarke, 2006). This approach allowed for the systematic identification of themes and subthemes that captured the participants' attitudes, perceptions, and experiences related to AI health chatbots.

The grounded theory approach was also employed to develop a theoretical understanding of the phenomenon under investigation (Charmaz, 2006). Grounded theory involves an iterative process of data collection, analysis, and constant comparison to generate new theoretical insights (Leavy, 2017). In this study, the grounded theory approach complemented thematic analysis by providing a systematic framework for developing a theory grounded in the participants' experiences with AI health chatbots.

Data analysis involved several steps, including:

1. **Familiarisation with the data:** The author carefully read and re-read the interview transcripts to become fully immersed in the data (Braun & Clarke, 2006).
2. **Generating initial codes:** The author applied the coding strategies mentioned in Section 5.3.3 to the transcripts and identified significant features of the data (Braun & Clarke, 2006).
3. **Searching for themes:** Codes were grouped into potential themes and subthemes, which were then reviewed and refined to ensure they accurately represented the data (Braun & Clarke, 2006).
4. **Reviewing and refining themes:** The identified themes were reviewed in relation to the coded data and the entire dataset to ensure their relevance and consistency (Braun & Clarke, 2006).
5. **Defining and naming themes:** Final themes and subthemes were defined and given concise, informative names that captured their essence (Braun & Clarke, 2006).
6. **Producing the report:** The author integrated the findings from the thematic analysis and grounded theory approaches to develop a coherent and insightful report that addressed the research questions and objectives (Braun & Clarke, 2006; Charmaz, 2006).

By employing a combined approach of thematic analysis and grounded theory, the researcher was able to effectively analyse the collected qualitative data and provide a comprehensive understanding of the participants' attitudes, beliefs, and perceptions regarding AI health chatbots. Moreover, the combination of deductive and inductive coding allowed the researcher to draw on established theories while remaining open to novel insights and perspectives. This enabled the capture of the complexity and diversity of the participants' experiences and attitudes towards AI health chatbots.

In conclusion, the study's process for analyzing data was both rigorous and versatile, ensuring that the results were reliable and pertinent to the study's objectives. The researcher was able to develop a comprehensive analysis of the key themes and factors in interviews by employing a combination of thematic analysis, grounded theory, and both deductive and inductive coding.

4.4. Limitations of the Methodology

Despite following a rigorous methodology process, there are several limitations in this study's research approach that should be acknowledged. These limitations relate to the literature review, the philosophical foundations, the research design, and the processes of data collection and analysis.

4.4.1. Limitations of the Literature Review

This section outlines the constraints encountered in the literature review phase, encompassing restrictions in database selection, language, recency of articles, and geographic representation.

Firstly, the literature review was limited to articles published in the databases PubMed and Business Source Complete (EBSCO), which may have led to the omission of relevant studies published in other databases or grey literature (Adams et al., 2017). However, it should be noted that the database Web of Science, which is also relevant, was screened and produced results which were largely falling outside the inclusion criteria, hence its screening was declined. In addition, the keyword search strategy was restricted to English-language papers, which may have excluded relevant studies in other languages. A multilingual search could have offered a more thorough view of global perspectives on the topic (Moher et al., 2015). However, conducting such a search was outside of the scope and available resources for this thesis.

Secondly, because the literature review was narrowed to studies published within the last 10 years, it may have missed some older, yet still relevant, papers. The rapid evolution of AI technologies and their applications in healthcare, however, justifies the focus on more recent literature to ensure the relevance and applicability of the findings to current AI chatbot technologies (Topol, 2019).

Lastly, the underrepresentation of low- and middle-income countries in the literature review may limit the generalisability of the findings to diverse economic contexts. Future research should aim to include more studies from these regions to ensure a more complete understanding of attitudes and acceptance across diverse economic settings (Shumba & Lusambili, 2021).

4.4.2. Limitations of the Philosophical Underpinnings

The interpretivist research philosophy adopted in this study acknowledges the complexity and diversity of human attitudes and the importance of interpreting these attitudes in their specific context. However, this approach may limit the generalisability of the findings, as they are context-dependent and may not be applicable to other settings or populations (Creswell & Poth, 2018). Furthermore, the abductive research approach, which combines deductive and inductive elements, may introduce researcher bias, as the researcher's preconceived notions and theoretical frameworks could influence the interpretation of the data (Leavy, 2017).

4.4.3. Limitations of the Research Design

The qualitative research design adopted in this study provides valuable insights into the complexities of human experiences, but it may not fully capture all nuances and subtleties of the participants' attitudes towards AI health chatbots (Kvale & Brinkmann, 2014). Ideally, a mixed-methods approach that combines qualitative and quantitative methods may have resulted in a more complete grasp of the studied topic (Creswell & Poth, 2018). However, due to constraints of time and financial resources, doing this was not feasible for the study.

Additionally, the small sample size of the study may limit the generalisability of the findings, as it may not be representative of the broader population. This is a standard limitation in qualitative research, particularly when it is carried out under time and financial constraints (Bryman, 2015). Despite these limitations, the chosen approach and sample size were considered the most appropriate given the available resources.

4.4.4. Limitations of the Data Collection and Analysis

Although a good substitute for in-person interviews, the use of online video conferencing for interviews may have reduced the depth and richness of the data collected, as it can potentially lose non-verbal cues and contextual information during the process (Krouwel et al., 2019). Moreover, the study’s dependence on self-selection, accessibility, and snowball sampling methods may have introduced sampling bias, as volunteers to the study may have had different perspectives and experiences than non-volunteers (Kvale & Brinkmann, 2014; Leavy, 2017).

The data analysis process, while rigorous and flexible, may have been influenced by the researcher's preconceptions and biases, particularly during the inductive coding and grounded theory development stages (Charmaz, 2006). To mitigate this limitation, the researcher could have engaged in reflexivity, by critically examining their own beliefs, assumptions, and biases throughout the research process (Creswell & Poth, 2018). Additionally, an external researcher may have been involved in the task of independently reviewing the codes and analysis (Leavy, 2017); however, this was deemed challenging due to financial and timely constraints of the thesis project.

4.4.5. Sub-conclusion

While this study pursued a rigorous methodology, it acknowledges several limitations spanning the literature review, philosophical underpinnings, research design, and data collection and analysis stages. Even with these constraints, the research provides valuable insights and a robust base for future explorations, with recommendations for these to address and overcome the outlined limitations.

4.5. Summary of Study Methodology

The methodology employed in this study, despite its limitations, provided valuable insights into the attitudes and acceptance of AI health chatbots among patients and healthcare professionals. The research process was designed to be comprehensive, involving a systematic literature review, adopting an interpretivist philosophy, using an abductive research approach, and implementing a qualitative research design. The literature review focused on recent studies published in PubMed and Business Source Complete, reflecting the fast-paced evolution of AI technologies in healthcare.

The interpretivist philosophy enabled a deep understanding of the diverse and complex human attitudes towards AI health chatbots. The abductive research approach allowed for a combination of deductive and inductive elements in the analysis, catering to both preconceived frameworks and novel insights. The qualitative research design, facilitated by video conferencing interviews and data analysis through NVivo software, provided rich data about participants' experiences and perspectives. Despite constraints such as time, resources, and sample size, this methodology yielded valuable findings about users' attitudes towards AI health chatbots, forming a solid foundation for future research. These findings will be explored in the following chapter.

5. Results

This chapter presents insights from interviews conducted with HCPs and patients, revealing the factors influencing their intentions to use AI health chatbots. This study, guided by the problem statement and research questions (Section 1.4), dives into perceptions and expectations of these groups and identifies factors impacting their willingness to use this technology. Through the thematic analysis, these factors are organised into themes. This research contributes to understanding the acceptance and adoption of AI chatbots in healthcare, aiding the development of user-centric healthcare solutions.

The chapter is divided into two sections, presenting attitudes of HCPs and patients, respectively. Chapter 5.1 discusses the results from HCP interviews and revealing themes, some of which match constructs of the TAM and UTAUT frameworks, some are unique findings, and some are potential moderators. Chapter 5.2 does the same for patient attitudes. Each section ends with a sub-conclusion, and the chapter wraps up with an overall summary.

5.1. Healthcare practitioners' attitudes

Four HCPs were interviewed, with backgrounds ranging from obstetrics and gynaecology to anaesthesiology, practising in Bulgaria, Denmark, and the UK. The age ranged from 28 to 61 years, with a mean age of 43.5 ± 14.4 years (confidence interval 95%). HCPs' self-reported attitudes towards technology were generally positive but cautious (n=2), very positive and open to new innovations (n=1) or sceptical or resistant (n=1). Lastly, based on self-reported experiences with AI chatbots, the HCPs self-identified as either non-users who are familiar with the technology (n=3) or occasional users out of interest (n=1). A detailed breakdown of the characteristics of all four HCP interviewees can be found in Appendix 3.

The thematic analysis revealed six key themes, including four theoretical constructs plus two unique ones, namely trust in AI, and legal and ethical responsibility. Figure 9 visualises the thematic map of HCP perspectives.

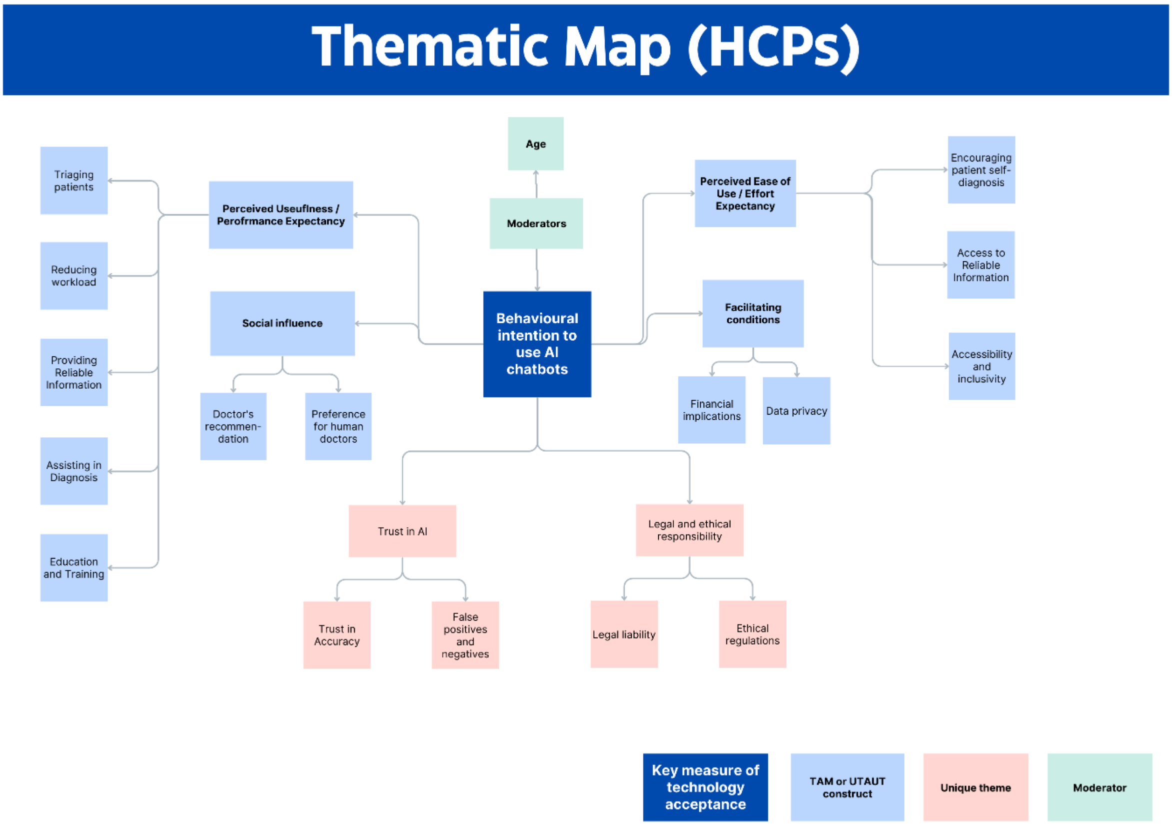

Figure 9. Thematic map of findings from HCP interviews.

5.1.1. Perceived Usefulness/Performance Expectancy

HCPs recognise the potential usefulness of AI health chatbots across several areas: triage, workload reduction, reliable information provision, assistance in diagnosis, and education and training. Despite their concerns, HCPs acknowledge the potential benefits of AI chatbots for enhancing healthcare services.

Triaging and streamlining patient care

Two of the four HCPs see chatbots as potential tools for triaging patients, assessing their medical concerns, and guiding them towards appropriate medical help, optimising healthcare resources. HCP3 also explains that triaging is currently carried out by hospital receptionists, who have limited medical knowledge: "*I don't see why not use AI chatbots instead. It would probably be even better.*"

Reducing Workload for Healthcare Professionals

All four HCPs believe that AI health chatbots can potentially lessen their workload by providing reassuring patients with minor issues and preventing unnecessary medical appointments. HCP3 notes that "*if patients don't present to their GP or to the hospital with this problem, this relieves a lot of the workload for us, so, it can definitely be very good*." This could lead to better resource allocation and improved patient care.

Providing Reliable Health Information

Opinions diverge on AI's information reliability. Three of the HCPs believe that AI chatbots can provide reliable and medically accurate information to patients, and will be a better alternative to patients seeking information on their own from potentially misleading sources. According to HCP3, "*If we can make that happen, it would definitely be better than patients simply Googling and interpreting their symptoms on their own.*" However, HCP4 expressed serious doubts about the reliability of AI chatbots in healthcare: "*This is a new technology, and we need to be very careful. I don't think I will ever trust it completely*."

Assisting in Diagnosis and Rare Conditions

Two HCPs suggest that AI chatbots could aid in the diagnosis process when used by the medical professional, rather than the patient. By having access to a wider range of medical knowledge and data, AI chatbots could help HCPs make more accurate diagnoses. As HCP1 notes, "*If it provides me with a breakdown of the likelihood of each suspected condition, it can help me make quicker and more accurate decisions*".

In addition, HCP2 believes that AI chatbots could be particularly useful in helping diagnose rare conditions. "*We currently do the same—we browse the internet for answers. The difference is that an AI chatbot can do the same [process] more quickly and read a wider range of articles, allowing us to reach a more accurate diagnosis in a shorter amount of time*." (HCP2)

Educating and Training Doctors

Two HCPs believe that AI chatbots can aid in doctor's education and training, particularly for junior doctors with little practical experience, and for doctors who are exploring a less familiar medical field. "*Experience is what you've learned as a result of your mistakes. With AI, you can learn from other [people's] mistakes as well*." (HCP2)

5.1.2. Perceived Ease of Use/Effort Expectancy

HCPs also recognise the low effort involved in using AI chatbots, though they share some concerns that this may encourage more patient self-diagnosis, highlighting the need to access reliable information, as well as accessibility and inclusivity.

Low Effort May Encourage Patient Self-Diagnosis

Due to the low effort of using the technology, all four HCPs expressed concerns about patients using the technology to self-diagnose. One HCP noted that patients may not be able to ask the correct questions or provide the necessary information for an accurate diagnosis through a chatbot. As HCP2 states, "*This process [anemnesis] is not something the patient can do on their own by using a chatbot*."

Access to Reliable Information

Three of the four HCPs suggest that AI chatbots should be designed to complement doctors, rather than replace them, in providing medical advice and diagnosis. Furthermore, one HCP (HCP1) argued that patients should have access to the original sources of information that the chatbot is using, so they can make informed decisions about their health.

Two of the HCPs also recognise that AI chatbots could be more reliable than patients searching for information online, if the chatbot is trained using trusted sources. HCP1 notes that they frequently forward patient queries to the FAQ page on the hospital's website, which can be used to train the model to answer patient queries.

Accessibility for People with Disabilities

Finally, HCP3 also addressed the need to adapt AI health chatbots for people with disabilities, accommodating people with visual, hearing, or mobility impairments, so that they can also benefit from the potential advantages of AI chatbots in healthcare.

5.1.3. Social Influence

The topic of social influence on patients' acceptance of AI medical chatbots also appeared in all four of the conversations. HCPs note that if they recommend the technology, their patients are more likely to try it, though most patients would strongly prefer human doctors over AI chatbots.

Doctor's Recommendation of AI Chatbots

Two HCPs acknowledge that a doctor's recommendation to use an AI chatbot would significantly encourage patients. HCP1 highlights the importance of the AI chatbot being safe and using reliable information: "*For the most part, it's going to matter that the doctor has prompted them to use it. He [the doctor] has assured them [the patient] that the app in question is safe, that is, it works according to the established guidelines out there, [and] it uses reliable databases*."

Preference for Human Doctors

Despite recognising the potential benefits, all four HCPs believe that patients will continue to prefer human doctors for their medical care. As HCP2 states, "*Patients will always prefer a doctor*." Other HCPs felt more strongly about this topic, such as HCP4, who states: "*It is important to remember that technology can never replace the human touch in healthcare. While AI, telemedicine, and other [digital tools] can be very helpful, they can never replace the empathy and understanding that come with a real doctor-patient relationship*."

5.1.4. Facilitating conditions

All four HCPs recognised that the technology is relatively easy to access through any internet-based device, however some HCPs express concerns about the financial implications, cost-effectiveness, and data privacy.

Financial Implications and Cost Effectiveness

Two of the four HCPs emphasise the importance of accurate and cost-effective recommendations from AI chatbots, as financial interests may influence the adoption of the technology. The two HCPs independently stated that if the AI technology provides recommendations to the patient that end up consuming additional healthcare resources (for example, by suggesting additional clinical tests), then it may not be cost-effective for the hospital and the healthcare system in the long run; "*However, if the system saves you money, for example, by reducing the number of clinical tests for a patient, then it will be liked and used.*" (HCP2).

Data Privacy

Two HCPs discuss data privacy, expressing varying concerns. HCP1 acknowledges that some patients may be reluctant to disclose confidential health information online but points out that many individuals already share similarly sensitive data on social media platforms. To address this issue, HCP1 suggests implementing appropriate privacy and confidentiality measures: "*Yeah, of course there should be some protections there for privacy, and there should be some confidentiality.*" On the other hand, HCP3 expresses more substantial concerns about data privacy and security, particularly when patients use AI chatbots outside of the healthcare system. Instead, HCP3 says they would feel more at ease if AI chatbots operated within the existing healthcare infrastructure, where data protection measures are already established.

5.1.5. Trust in AI

The first unique theme of this study, which fits outside of the TAM and UTAUT constructs, is trust in AI. The attitudes of HCPs are cautiously optimistic, with three of the HCPs recognising the potential benefits, but also acknowledging the need for caution.

Trust in Accuracy

HCPs believe that AI chatbots can be beneficial if trained on reliable data and providing medically accurate information. They consider chatbots a better alternative to patients searching for information on their own. One relevant quote from HCP3 is: "If we can make that happen, it would definitely be better than patients simply Googling and interpreting their symptoms on their own."

False positives and negatives

In line with trust in accuracy, three of the four HCPs express concerns about the potential risk of false positives and negatives when using AI health chatbots. HCP1 envisions a scenario where a patient with certain symptoms is advised by the chatbot that their condition is non-urgent, though in rare cases, undetected conditions can progress rapidly and become life-threatening, which may have been detected by a human doctor. HCP3 notes that false positives and negatives could lead to unnecessary investigations, extended hospital stays, or even unwarranted medical interventions. HCP4 echoes these concerns, stating that they will not trust the technology and would not recommend it to their patients, largely due to fear of misdiagnosis and the potential consequences.

5.1.6. Legal and Ethical Responsibility

Finally, the second unique theme of this study is the legal and ethical responsibility. Three of the four HCPs express concerns about the liability and ethics of using AI chatbots, highlighting the current absence of EU regulations when it comes to AI in healthcare.

Legal responsibility and liability

Three HCPs worry about the legal responsibility of incorrect or misleading information, questioning who would be held accountable in such situations. HCP1 asks: "*The question here is, with these applications, who will be liable in such situations? Is the patient responsible for making their own decision, or will the app in question also have some culpability?*" Similarly, HCP3 also points to the legal responsibility of medical errors.

Ethical considerations

Two HCPs emphasise the need for specific guidelines to ensure that the technology is used ethically and responsibly. HCP3 highlights the need for AI chatbots to be designed with the patient's best interests in mind: "*We need to make sure that the AI chatbot is not just built to make money, but also to improve [patient] outcomes*."

5.1.7. Moderators

Two of the four HCPs share views on practitioner age as a moderating factor of adoption, agreeing that older practitioners will be less likely to adopt.

Age

Two HCPs note that a doctor's age may be impact their intention to use AI chatbots, with older doctors often more sceptical. HCP1 points out that older doctors worry about chatbots replacing them or the legal implications of the technology. HCP4 also expresses caution towards the technology, indicating age might influence adoption: "*I think it's important to approach new medical technologies with caution, carefully examining effectiveness before implementation. I might be old, but I will be careful with this.*" The ages of HCP1 and HCP4, 30 and 55 respectively, imply that age may indeed be a factor in adopting AI health chatbots; however, the small sample does not allow for correlational or causational findings.

5.1.8. Behavioural intention to use

All four HCPs shared their intention to use the technology. Three HCPs indicate that they are conditionally open to using it, provided that the factors outlined in this section are met, such as high accuracy and high data security: "*I definitely feel comfortable using it as long as it's safe. Obviously, the concerns that we discussed need to be cleared before we implement it in any way*." (HCP3). In contrast, one HCP (HCP4) expressed a strong intention to not use the technology due to their lack of trust in its accuracy and other factors addressed in this section: "*I don't think I will ever trust it completely*".

5.1.9. Sub-conclusion of HCP attitudes

This section synthesises the findings from all four HCP interviews. The thematic analysis generated six key themes, four of which are part of the TAM and UTAUT frameworks: perceived usefulness, perceived ease of use, social influence, and facilitating conditions. Additionally, two unique themes emerged: trust in AI, and legal and ethical responsibility.

HCPs generally acknowledged the potential usefulness of AI health chatbots in various aspects of patient care and medical practise, such as triaging, workload reduction, and education. However, they also expressed concerns about the low effort involved in using AI chatbots, which may encourage patient self-diagnosis. HCPs believe patients are more likely to adopt after a doctor’s recommendation, but also emphasise the need for AI chatbots to complement, rather than replace, the role of HCPs in medical care. They also highlight the importance of cost-effectiveness in accepting AI chatbots.

HCPs voiced mixed attitudes about trust in AI, expressing concerns about data privacy, accuracy, and false positives/negatives. Legal and ethical responsibility was another unique theme, with HCPs worried about legal liability from incorrect information provided by AI chatbots and the need for ethical guidelines. Age was considered a moderating factor affecting adoption, though not statistically significant.

Overall, HCPs in this study showed a cautiously optimistic attitude towards AI health chatbots, recognising their potential benefits while also acknowledging the need for caution and careful consideration of their limitations.

5.2. Patient Attitudes

A total of 8 patients were interviewed in the study. 37.5% (n=3) of the patient interviewees were female, and the age ranged between 25 and 39, with a mean of 29.5 ± 3.1 years (±10.5%; confidence level 95%). Participant nationalities included Bulgarian (n=4), Danish (n=2), British (n=1) and Bahraini (n=1). 100% (n=8) of the participants were educated to a graduate level or higher. The participants worked in a variety of industries, including software, digital marketing, sustainability, education, engineering and manufacturing, and legal. Patients' self-reported attitudes towards technology were either very positive and open to new innovations (n=6) or generally positive but cautious (n=2). Lastly, based on self-reported experience with AI chatbots, the participants self-identified as either regular users of AI chatbots (n=5), occasional users out of interest (n=1) or non-users who are familiar with the technology (n=2). A detailed breakdown of the characteristics of all eight patient interviewees can be found in Appendix 3.

The thematic analysis of patient interviews generated key themes in their attitudes towards the use of AI chatbots in healthcare. Overall, the data analysis resulted in eight key themes, five of which are constructs of TAM and UTAUT: perceived usefulness, perceived ease of use, social influence, facilitating conditions, and perceived enjoyment. The analysis also generated two unique themes: perceived trust and legal and ethical responsibility. Lastly, the analysis identified three potential moderators, also from the TAM and UTAUT frameworks. Figure 10 visualises the general themes identified in patient interviews into a thematic map.

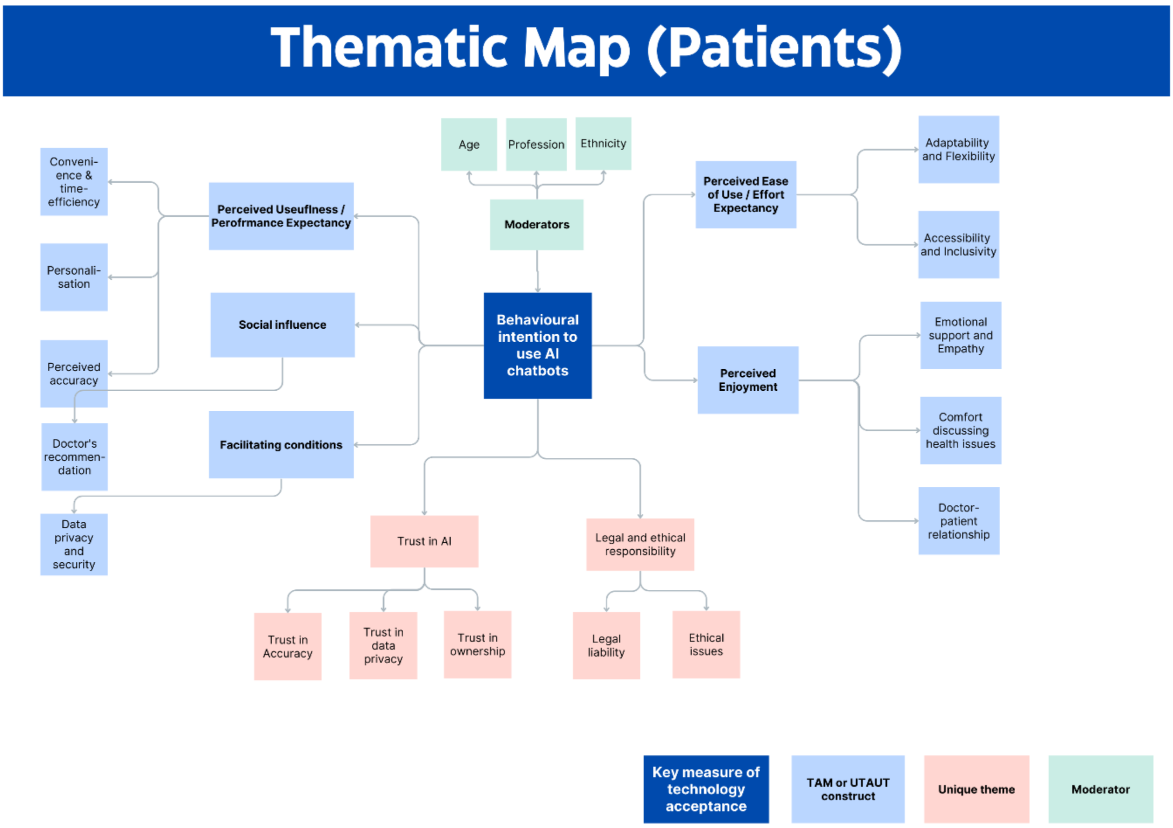

Figure 10. Thematic map of findings from patient interviews.

5.2.1. Perceived Usefulness / Performance Expectancy

All eight patients (P1-P8) share mixed opinions regarding the perceived usefulness of AI chatbots for providing health information, with some optimistic, some sceptical, and others conditionally optimistic. The three key themes of performance expectancy addressed in the patient interviews are: convenience and time efficiency, the ability to provide personalised information, and the perceived accuracy of the information.

Convenience and time-efficiency

Three of the eight patients shared views on the convenience of using AI health chatbots, particularly in the context of record-keeping and accessibility to medical information. P4 acknowledges the potential benefits of AI chatbots in maintaining and accessing medical records. Similarly, P5 valued the ability of chatbots to easily recall and store information, contrasting this with traditional doctor visits: "*That's a clear benefit. Having that sort of transcript*." Meanwhile, P8 sees chatbots as particularly useful in regions with limited access to medical care, especially in urgent situations.

Four patients valued the tool’s time efficiency, comparing its immediacy and accessibility to standard doctor appointments. P5 mentioned the potential time-saving benefits of chatbots, including reduced wait times at the doctor's office and the ability to provide information at their own pace. P7 echoed this sentiment, valuing the speed of chatbot responses in situations where immediate attention might be needed: "*The speed of how quickly it's available is probably the most* *important thing.*" However, P7 also argues that this perceived convenience can be quickly diminished if the chatbot takes too long to provide information or asks too many questions: "*I guess if it keeps asking too many questions, then I don't want to spend 20 minutes answering questions before I actually get information.*"

Personalization and customization

Three patients highlight access to personalised information as a key benefit of using AI chatbots for healthcare. They appreciate receiving tailored recommendations and advice based on their individual needs and medical history. P2 stated they are open to sharing data for personalization purposes, as long as they perceive the outcome to be positive. Similarly, P4 shared a preference for AI chatbots that provide personalised information over generic search engine results: "*It would make me want to use the AI chat...if it just said: "You have condition A. Your solution is B", rather than giving me A,B, C, and D.*" P6 suggested that AI chatbots should consider patients' psychological profiles when delivering information in order to avoid causing unnecessary distress.

However, all three patients also express concerns about the accuracy of the information provided by the chatbot and emphasise the importance of consulting with a doctor for more complex issues.

Perceived accuracy

Five patients discussed the perceived accuracy of the data provided by the AI chatbot, sharing contrasting views. P1 shares concerns about accuracy and misinformation, expressing doubts that the technology can be as accurate as a doctor's expertise: *They can be 100% wrong while being very confident*" and "*It may not be as accurate as a doctor. A doctor would be my preferred choice*." P7 notes that they would only trust the chatbot if the information came from reliable sources and if the people behind the chatbot had appropriate qualifications.

In contrast, two other patients shared excitement about the usefulness of AI chatbots for providing basic medical information. P6 believes that AI health chatbots have the potential to provide more accurate diagnoses due to their ability to process vast amounts of information and their lack of human biases. P2 expresses optimism about the accuracy of answers dependent on the amount of health data shared with the chatbot.

Finally, P3 expresses conditional optimism, noting that the quality of output is heavily dependent on the user's input, whereas in their opinion, patients are not always able to articulate their symptoms clearly: "*People aren't always clear about what they're feeling or what's happening*."

5.2.2. Perceived Ease of Use / Effort Expectancy

This section covers the perspectives of five of the eight patients on the perceived ease of use of AI health chatbots, focusing on two subthemes: adaptability and flexibility, and accessibility and inclusivity.

Adaptability and Flexibility

Four of the eight patients highlighted the importance of AI chatbot adaptability and flexibility, with contrasting views. P1 appreciated the chatbot's ability to understand the context of the conversation, as compared to search engines like Google, without requiring precise question formulation: "*You don't have to guess everything to ask your question the right way the first time.*"

In contrast, three patients believe that the technology is not yet adaptable enough and is still heavily dependent on the quality of input from the user. P2 emphasises the need for an easier-to-use system, without requiring extensive training to ask questions effectively: "*And so it requires a proper user, one who knows how to phrase questions and prompts*." Similarly, P4 felt that chatbots should adapt to individual needs rather than fitting users into a predefined structure. These insights underline the importance of adaptability and flexibility in AI health chatbots to better serve patients' needs.

Accessibility and Inclusivity

Two of the eight patients emphasised the importance of accessibility and inclusivity in the context of AI health chatbots. P3 states that AI chatbots should be free, easy to use, and ethically inclusive. P8 also addresses inclusivity, especially when it comes to people with disabilities. In the interview, they acknowledged that while they are comfortable using the chatbot on a computer, others may need the technology to be adapted to different platforms, including voice interactions or adaptations for people with different health conditions. P3 also expresses a desire for AI chatbots to be unbiased and inclusive, addressing issues like weight and gender bias: "*I would want to know that whatever programme I'm using is a lot more unbiased.”*

5.2.3. Social influence

Two patients state that their doctors’ recommendation may impact thier attitudes towards AI health chatbots.

Doctor's recommendation

Two of the eight patients emphasised the role of a doctor's recommendation in their willingness to use AI chatbots for healthcare, but also highlighted the value of direct consultation with a healthcare professional. P4 suggested that if a trusted doctor, especially one they have a history with or whose credentials are evident, recommends an AI chatbot, they would be more inclined to use it.

5.2.4. Facilitating Conditions

All eight patients addressed the topic of data privacy and security when discussing the use of AI chatbots in healthcare, sharing mixed opinions. Some patients express concerns about data privacy breaches, especially if the technology is owned by a private company. Others are more open to data sharing, provided that they see a positive outcome and ensure appropriate data protection. Some interviewees express a strong preference for their data to be government-managed to ensure that they are fair, transparent, and accountable.

Data privacy and security

The theme of data privacy and security was brought up in each of the eight interviews, with patients sharing mixed opinions. Three patients (P1, P3, and P6) voiced concerns about potential risks associated with data breaches or hacker attacks. For example, P1 mentions, "*The only problem [I see] is giving risk to some hacker attacks. If this chatbot stores my data on some server, then* *potentially they might get to know that, for example, I had chlamydia or something*." However, P1 also sees these risks as comparable to human interactions. P3 and P6 also express unease about sharing their medical information with the technology. P6 also expresses concerns about potential misuse of sensitive information by private companies: "*I'm more worried about which company [operates with] the data. […] Microsoft, for example, has a bad reputation for [managing data] well.”*

Three interviewees (P2, P5, and P8) appear to be generally open to sharing data for personalisation purposes, as long as they perceive the outcome to be positive and the data storage secure and encrypted: "*If I feel like there's a positive upside to me sharing data in that I get much more personalised questions and information, then I have no issue doing that at all*." (P2). "*As long as the firewalls and antiviruses and everything are put in place, I'm happy for that information to be shared.*" (P5)

Finally, P4 and P7 express a preference for AI chatbots provided by trusted, official entities, such as government-backed organisations, and they would be discouraged from using AI chatbots if they were owned by a company with a history of security breaches or data leaks.

5.2.5. Perceived Enjoyment

The perceived enjoyment of using AI chatbots for health information was addressed in six of the eight interviews. Three subthemes emerge from the interviews: emotional support and empathy, comfort discussing health problems, and the doctor-patient relationship.

Emotional support and empathy

Two patients (P2 and P6) mention the role of emotions and the need for empathy in their experiences with AI chatbots, sharing very differing perspectives. P2 expresses concerns about the inability of AI chatbots to understand nonverbal communication and empathise with their emotions. In contrast, P6 indicates that emotions do not play a significant role in their preference for receiving health information, as they are more concerned about the accuracy of the information provided.

Comfort with discussing health problems

Two patients (P1 and P2) share a high level of comfort with discussing sensitive health issues with AI chatbots, as long as this does not feel too intrusive: "*I don't find a difference. I even openly discuss it with people around me, so I will have no problem sharing it with the chatbot if I believe there will be some benefit.*" However, the patients also acknowledge that other people might prefer human contact for sensitive issues.

Doctor-patient relationship

Six of the eight patients address the theme of the doctor-patient relationship and how AI chatbots may affect it, with conflicting opinions. Three patients (P1, P5, and P6) are more comfortable with AI interaction and believe that the doctor-patient relationship may not be as essential in certain health situations, valuing accuracy over human touch: “*I think there are people who... want human contact at least at this stage... but I am rather not one of them*.” (P1)

In contrast, three patients (P2, P4, and P8) emphasise the importance of human interaction in healthcare and having a personal connection with your HCP. They believe that a doctor's personal connection allows for a more nuanced understanding of the patient's situation, mood, and emotions, which could lead to a more accurate diagnosis and treatment: "*They [doctors] can provide a more nuanced answer just because they have that personal connection, and the chatbot is still just a reflection of data points.*" (P2).

5.2.6. Perceived Trust

The first unique theme identified in the patient interviews is the topic of perceived trust in AI, emerging in four interviews. Three subthemes related to trust were identified: trust in accuracy, trust in data privacy, and trust in ownership (public vs. private), where patients expressed varying degrees of trust in AI chatbots.

Trust in accuracy

Five patients expressed conditional trust in the information that AI health chatbots provide, acknowledging the risks of inaccurate information. Three patients (P2, P4, and P7) explain that their level of trust in the information the AI provides depends on how accurate, in their opinion, its responses appear to be. Similarly, two patients (P3 and P8) note that their trust depends on whether the AI model is trained using reliable medical sources: "*I would trust in AI taught by medical universities for sure over any private company.*" (P3). However, P3 also expresses concerns about individuals trusting the technology too much and using it for self-diagnosis, potentially leading to misinformation and mistrust in human doctors.

Trust in data privacy

While most interviewees addressed the subject of data privacy and security (Section 5.2.4), only two of them (P4 and P7) express mistrust in how the company providing the AI chatbot handles their data. P4 explains that the appearance of reports of data mishandling will quickly discourage them from using AI chatbots again: "*If any reports come by on the news saying, "Oh, this chatbot got leaked of sensitive information", this would make me and anyone else not trust any chatbots for sure.*" (P4).

Trust in ownership: public vs. private

Finally, closely linked to trust in data privacy is the patients' trust in the ownership of AI health chatbots. Three of the eight patients (P4, P6 and P7) express a strong preference for such AI health chatbots to be government-owned rather than privately owned. P6 and P7 expressed a willingness to trust a private company, though strongly oppose the use of AI health chatbots for commercial purposes, such as advertising or targeted marketing.

5.2.7. Legal and ethical responsibility

The second unique theme identified in patient interviews relates to the legal and ethical responsibility of communicating with AI health chatbots. Two of the eight patients introduced this subject in their interview, highlighting important considerations about the ethical issues relating to drug prescription and the legal responsibility in cases of misdiagnosis or mistreatment.

Ethical issues of drug prescription

One patient (P7) raises concerns about potential conflicts of interest in drug prescription, wondering if AI health chatbots could be influenced by pharmaceutical companies to promote specific products. In such cases, they would question whether the AI chatbot provides the most applicable and reliable information, free from financial influence.

Legal responsibility for misdiagnosis and mistreatment

One patient (P8) expressed worries about the responsibility and accountability of AI chatbots in the event of a potential wrong diagnosis or treatment. In cases of such negative outcomes, they wonder whether the responsibility lies with the patient, the chatbot creators, the AI itself, or even the patient's doctor: "*Whose responsibility is it? It's mine for taking those steps […] I don't imagine someone else taking responsibility for my actions of taking the drug*." (P8).

5.2.8. Moderators

Despite the small sample size (n=8), the thematic analysis of patient interviews identified three weak moderators, namely age, education and profession, and cultural factors. In all three cases, patients do not view the factors as influencing their own behaviour but rather as moderating the adoption of AI chatbots for others in their social circle.

Age

One of the eight patients mentioned (P4) mentions age as a potential moderator in the adoption of AI medical chatbots, suggesting that younger individuals may be more willing to accept the technology, whereas older generations may require additional reassurance, such as an endorsement from a known doctor.

Education and profession

Interestingly, the two participants who addressed the legal and ethical responsibility of AI-based health chatbots (Chapter 5.2.7) both work in the legal industry. This may suggest that for people inclined to consider legal aspects due to their profession, these aspects may strongly influence their intention to adopt the technology.

Cultural factors

One of the eight patients mentioned (P4) explains that cultural preference can play a key moderator role in using the technology. The interviewee highlights that people in their region (the Middle East) may not trust AI chatbots as much as human interaction: "*From my region, people here would not trust the AI chatbots as much as a human interaction*." However, he explains that he sees the possibility for technology adoption, as many people from his country have embraced video consultations with doctors during the pandemic.

5.2.9. Behavioural intention to use

Six of the eight patients shared their intention to use the technology. Patients report being willing to try the technology or use it in the future, though they note that this willingness is dependent on the factors mentioned above in this section, as well as in specific situations. Patients also report that they are not keen on replacing doctors with AI chatbots, but rather see the technology as complementary to traditional health care.

Use in non-emergency situations

Three patients (P5, P7 and P8) are keen on using the technology in non-emergency situations. P7 and P8 intend to use AI chatbots in non-urgent situations, such as seeking advice on non-prescription medications or when waiting for a GP appointment. P5 shares excitement about trying AI health chatbots once they become readily available, especially for smaller queries such as rashes or pimples.

Use as complementary to doctors

Three patients (P1, P3, and P8) mention their interest in seeing the technology as complementary to standard health care, rather than replacing doctors. "*I wouldn't want AI to replace doctors. I would want AI to complement doctors.*" (P3). In addition, P8 acknowledges the potential for AI chatbots to be a helpful tool for doctors when diagnosing and providing care for patients.

5.2.10. Sub-conclusion of patient attitudes

In conclusion, patient interviews revealed diverse perspectives on the technology's usefulness, ease of use, social influence, facilitating conditions, and perceived enjoyment. The analysis also unearthed two unique themes: perceived trust and legal and ethical responsibility, as well as three potential moderators: age, education and profession, and cultural factors.

Patients' attitudes towards the perceived usefulness of AI health chatbots were mixed, with some being optimistic about its convenience and time-efficiency, while others expressing concerns about the accuracy of information and the potential risks of misinformation. The perceived ease of use was also a significant factor, with patients emphasising the importance of adaptability, flexibility, accessibility, and inclusivity.

Social influence played a role in patients' attitudes, with some stating that a doctor's recommendation would increase their trust in the technology. Facilitating conditions, such as data privacy and security, were crucial for patients, who expressed varying levels of trust in AI chatbots based on these factors. Perceived enjoyment was another theme that emerged, with patients discussing the importance of emotional support, empathy, and human interaction in healthcare settings.

The unique themes of perceived trust and legal and ethical responsibility also arose, highlighting important considerations for the implementation of AI health chatbots. Finally the potential moderators of age, education and profession, and cultural factors suggest that patients' adoption of AI health chatbots may be influenced by their demographic and cultural backgrounds.

Overall, this study provides valuable insights into patients' attitudes towards AI health chatbots, highlighting the importance of addressing concerns related to accuracy, personalization, data privacy, and ethical considerations in order to increase the technology's acceptance and adoption in healthcare settings.

5.3. Summary of Results

This Results chapter presented the findings from both HCP and patient interviews, offering insights into their perspectives on AI health chatbots. The thematic analysis of HCP interviews generated six key themes, including four from the TAM and UTAUT frameworks and two unique themes, with the addition of one potential moderator. The analysis of patient interviews also revealed eight key themes, five of which were from the TAM and UTAUT frameworks, with the addition of two unique themes and the identification of three potential moderators.

HCPs generally acknowledged the potential usefulness of AI health chatbots in various aspects of healthcare but expressed concerns about the low effort involved in using AI chatbots, which may encourage patient self-diagnosis. Trust in AI and legal and ethical responsibility emerged as significant themes, reflecting HCPs' concerns about the reliability and accuracy of information, data privacy, and the risk of false positives and negatives, as well as legal liability.

Similarly, patients expressed mixed attitudes towards the perceived usefulness of AI health chatbots and the importance of adaptability, flexibility, accessibility, and inclusivity in their use. Social influence, facilitating conditions, and perceived enjoyment also played a role in shaping patients' perspectives. Unique themes of perceived trust and legal and ethical responsibility highlighted the need to address concerns related to accuracy, personalization, data privacy, and ethical considerations.

The identified moderators of age, education and profession, and cultural factors suggest that the adoption of AI health chatbots may be influenced by demographic and cultural backgrounds for both HCPs and patients.

Overall, this study provides valuable insights into the attitudes of HCPs and patients towards AI health chatbots, emphasising the importance of addressing their concerns and expectations to ensure effective and user-centric implementation of this technology in healthcare settings. These findings will serve as the foundation for the Discussion chapter, where we will delve deeper into the implications of the results, compare them with existing literature, and explore recommendations for the design, implementation, and future research on AI health chatbots in healthcare settings.

6. Discussion

The objective of this study is to explore and understand the underlying themes in the attitudes of patients and HCPs towards AI health chatbots. Reiterating the problem statement and research questions, this study set out to:

- Discover the perceptions of usefulness and ease of use of patients (RQ1) and HCPs (RQ2).
- Compare the perceptions of both user groups and identify key similarities and differences (RQ3); and

- Identify crucial motivators, facilitators and barriers to the adoption of AI health chatbots (RQ4).

The Results chapter (Chapter 5) presented the key findings from interviews with patients (n=8) and doctors (n=4), which were systematised according to themes from the TAM and UTAUT frameworks, as well as unique themes appearing in this research. The purpose of the Discussion chapter is to delve into the importance and meaning of the findings which are presented in the Results chapter. This will be done by comparing them to the existing literature in the context of the research problem, questions and objectives. This way, the Discussion chapter will conclude implications of the study's findings, as well as their relevance to the healthcare system and the future of AI health chatbots. Additionally, this chapter will explore the limitations of the study and offer recommendations for future research.

This chapter is structured in the following way: first, it will address the attitudes towards AI chatbots of patients (Chapter 6.1) and HCPs (Chapter 6.2), diving into the perceptions of usefulness and usability for both; next, it will compare and contrast the views of both user groups (Chapter 6.3), before highlighting key motivators, facilitators and barriers that users identify as pertinent (Chapter 6.4); finally, we will present secondary outcomes related to moderators for adoption (Chapter 6.5) and the author's key reflections after conducting the study (Chapter 6.6), before summarising the entire section (Chapter 6.7).

6.1. Patient attitudes

In this section, we explore patient attitudes towards the use of AI chatbots in healthcare, focusing on their perceptions of usefulness and ease of use. We first discuss patients' performance expectations, highlighting their views on service quality, convenience, and accuracy concerns, before turning to their effort expectations, which encompass issues of user adaptability and inclusivity.

6.1.1. Perceived Usefulness and Performance Expectations

Exploring the performance expectations of patients towards AI chatbots introduced a number of interesting themes, some of which go along with previous studies, while others contradict past findings, and still others are entirely novel to the topic of patient attitudes towards AI chatbots. Overall, patients' views on AI chatbots largely revolve around service quality, convenience, and accuracy concerns.

Firstly, patients appreciate AI chatbots for their convenience, time efficiency, and ability to provide personalized information. In particular, they value the ability of AI chatbots to keep records and conversation transcripts, as well as time efficiency compared to traditional doctors' appointments, such as saving time on scheduling and travelling to appointments. These findings are in line with previous research, indicating that most patients perceive AI chatbots as beneficial for their convenience and time efficiency (van Bussel et al., 2022; Nadarzynski et al., 2019; Ho et al., 2023).

A novel finding is the value patients place on personalization and customisation, an aspect not covered in prior research. They expect the technology to adapt to their individual needs and medical backgrounds, offering a more reliable and efficient alternative to search engines. However, they also highlight the need to verify information accuracy with their healthcare providers until trust in the technology is established.

Finally, it appears that views on the accuracy of AI chatbots are mixed. While some express scepticism based on current experience with AI chatbots, others are conditionally optimistic, provided that there is proof that it is medically accurate. This finding aligns with previous research, where patients express scepticism towards the technology's reliability, especially if it relates to more serious medical conditions (Koulouri et al., 2022; Ho et al., 2023). It is interesting to observe that while patients from one past study state: "I trust a machine less than a human" (van Bussel et al., 2022), one of the participants in this study stated the opposite: “I'd rather trust AI.” (P2). These disparities could be due to sampling differences (Saunders et al., 2019), moderating factors like age or culture (Blut et al., 2022), or recent AI chatbot adoption trends. The accuracy perception of AI chatbot medical advice warrants future exploration.

Overall, the positive perception of AI chatbots by patients highlights their potential as a valuable tool in improving healthcare delivery and patient satisfaction.

6.1.2. Perceived Ease of Use / Effort Expectations

In terms of ease of use, patients emphasise the importance of user adaptability and inclusivity, expressing dissatisfaction with the current level of AI chatbot adaptability.

Firstly, patients are generally unhappy with the level of user adaptability that AI chatbots currently have. They find that the quality of the chatbot's output heavily depends on the user’s input, indicating the need for training in efficient question asking. However, some believe AI chatbots are more context-aware than current solutions. These views echo prior research emphasizing the importance of adaptability, user-friendliness, and ease of learning in AI chatbots (van Bussel et al., 2022; Nadarzynski et al., 2019; Hong et al., 2022).

In addition, patients also believe that AI chatbots should be free, easy to use, and inclusive of diverse populations, such as individuals with disabilities. This perspective aligns with previous research (van Bussel et al., 2022; Nadarzynski et al., 2019; Ciecierski-Holmes et al., 2022; Chew & Achananuparp, 2022). Furthermore, in one previous study (Chen et al., 2022), HCPs (rather than patients) noted the importance of AI chatbots being inclusive of under-represented populations, such as elderly people, rural communities, ethnic minorities, and other disadvantaged groups. Thus, it appears that several stakeholders view accessibility and inclusivity as pertinent to AI chatbots developed for healthcare services.

Finally, it should be noted that, as a crucial component in both TAM and UTAUT technology acceptance frameworks, the perceived ease of use of any technology is often strongly linked to its adoption rate (Venkatesh & Bala, 2008; Blut et al., 2022). As noted in one study, poor user interface design, such as one that is overly complex or unclear, can frustrate end users (both patients and practitioners), thereby limiting the beneficial effects of AI tools on healthcare services (Chew & Achananuparp, 2022). However, the perceived usefulness of the technology can still lead to acceptance even when user-friendliness is lacking, as noted by technology acceptance experts (Venkatesh & Bala, 2008).

6.1.1. Sub-conclusion

Overall, while patients appreciate AI chatbots' potential benefits, concerns about accuracy, adaptability, and inclusivity persist. These factors should be addressed to increase patient acceptance and satisfaction.

6.2. HCP attitudes

In this section, we delve into the attitudes of HCPs towards AI chatbots in healthcare, discussing their views on the usefulness and ease of use of these technologies. We explore how doctors perceive the potential impact of AI chatbots on their workload, decision-making processes, and professional development, as well as their apprehensions about patient self-diagnosis and the need for human oversight in healthcare delivery.

6.2.1. Perceived usefulness / Performance expectancy

HCP perceptions of the usefulness of AI chatbots appear to be generally positive, with users identifying potential benefits to workload reduction, diagnosis and decision support, and professional development.

Most notably, HCPs view AI chatbots as beneficial for reducing workload by automating tasks like patient triage and for supporting diagnosis and decision-making by analysing vast amounts of data. As concluded by findings in this paper and recent studies, this not only frees up time but also allows doctors to focus on more complex cases (van Bussel et al. 2022; Moldt et al. 2022). A unique example of usefulness that was identified in this study was using AI chatbots for diagnosing rare conditions. As the HCP notes, such rare diagnoses are challenging to conclude due to their infrequent and often under-researched nature; hence, AI's algorithms may be especially useful in such cases.

Finally, HCPs also see potential for professional development, using AI chatbots as educational and training tools. Once again, this finding is consistent both in the study results and previous literature (Hogg et al., 2023; Chen et al., 2022). However, this view is coupled with a somewhat prevalent fear of job displacement among medical staff, which is covered in Chapter 6.4.3. (Chen et al., 2022).

"*Experience is what you've learned as a result of your mistakes. With AI, you can learn from other [people's] mistakes as well.*" (HCP3)

In conclusion, despite some concerns about job displacement, HCPs largely endorse AI chatbots, viewing them as valuable tools for cost reduction and enhancing patient care quality. As the technology continues to evolve, HCPs will be considerate of how to integrate AI chatbots into their workflows effectively to balance benefits and potential challenges.

6.2.2. Perceived Ease of Use / Effort Expectancy

The perceived usability (i.e. ease of use) of AI chatbots is another aspect that draws the attention of HCPs. Generally, the study results indicate that users recognise the low effort involved in using AI chatbots, though they see this as both beneficial and potentially challenging.

On the one hand, the ease of use of AI chatbots allows users (both patients and HCPs) to access relevant information quickly and efficiently. Since most interviewed doctors believe the technology to be relatively accurate, they view AI chatbots as an easy and accessible way for patients to access reliable information, and a much better alternative to currently used search engines or hospital FAQ webpages.

On the other hand, however, the interviewed HCPs see the low effort involved as potentially dangerous, as it may encourage patient self-diagnosis, which they voice is already a problem. Instead, HCPs emphasise the importance of anamnesis and physical examination in the standard medical diagnosis process, which heavily depends on the medical training of the HCP, and therefore cannot be achieved through patient-chatbot interaction alone.

Interestingly, these findings are contrary to previous studies that suggest that HCPs see AI chatbot adoption as challenging and time-consuming (Moldt et al., 2022; Blease et al., 2019; Chen et al., 2022). While some studies note that the reason for these attitudes is patient resistance to change (van Bussel et al., 2022) and lack of healthcare resources allocated to implementation (Hogg et al., 2023), this study posits that this difference is possibly due to increased exposure and familiarity to AI chatbots (such as ChatGPT and Bard) in recent months.

Finally, it should be noted that despite their perceived usefulness and ease of use, doctors stress the need for AI chatbots to complement, rather than replace, the role of HCPs in medical advice and diagnosis. While AI chatbots may be a more reliable and user-friendly way for patients and doctors to receive medical information, HCPs note that the need for human oversight persists, at least in the near future.

6.2.3. Sub-conclusion

In summary, healthcare professionals generally view AI chatbots positively, appreciating their potential to reduce workload, support diagnosis, and facilitate professional development. However, they also emphasize the need for these technologies to complement rather than replace traditional medical practices, underscoring the critical role of human expertise in healthcare.

6.3. Comparing patient and HCP perspectives

In this section, we examine and compare patient and HCP perspectives on AI chatbots in healthcare. We explore their shared viewpoints on AI benefits, concerns about accuracy, and belief in human professionals' irreplaceable role. We also highlight divergences in their attitudes towards personalisation, trust in AI, professional development, and ease of use. The analysis concludes with implications of these findings for AI chatbot implementation strategies in healthcare.

6.3.1. Similarities

Both patients and HCPs perceive AI chatbots as potentially beneficial tools for improving healthcare delivery and efficiency. Both users appreciate the convenience and time-efficiency of AI chatbots (van Bussel et al., 2022; Nadarzynski et al., 2019; Ho et al., 2023), and both recognise its potential ability to reduce workload for HCPs by automating standardised tasks (van Bussel et al., 2022; Moldt et al., 2022). This shared recognition of convenience and time-efficiency underscores the universal appeal of AI chatbots' potential to streamline healthcare delivery.

With regards to limitations and negative perceptions, both patients and HCPs express concerns about the accuracy of information provided by AI chatbots, with some expressing scepticism based on their current experience with AI technology (Koulouri et al., 2022; Ho et al., 2023). Additionally, both groups emphasise the importance of accessibility, inclusivity, and user when it comes to using AI chatbots in healthcare (van Bussel et al., 2022; Nadarzynski et al., 2019; Hong et al., 2022; Chen et al., 2022). This shared concern raises critical questions about the reliability and robustness of AI technology in its current state, suggesting an area for further refinement and improvement.

Finally, both patients and HCPs acknowledge that while AI chatbots may be a valuable addition to healthcare services, they should not replace human medical professionals entirely. Instead, they should complement the role of HCPs in providing medical advice and diagnosis. This shared concern raises critical questions about the reliability and robustness of AI technology in its current state, suggesting an area for further refinement and improvement.

6.3.2. Differences

Despite these similarities, there are some notable differences between patient and HCP perspectives on AI chatbot use in healthcare, specifically around views on personalisation, accuracy and medical professional development.

Firstly, patients show a notable appreciation for the personalisation aspect of AI chatbots, valuing the ability to tailor their experience to specific needs. This theme is less prominent among HCPs' views, perhaps due to their broader focus on systemic efficiency and patient management rather than individual patient experiences (Chew & Achananuparp, 2022). This divergence may suggest a need for further exploration on how personalisation can benefit both patients and HCPs.

Secondly, while both groups express concerns about accuracy, there is a difference in their trust towards AI-generated medical information. Some patients, perhaps driven by positive experiences or convenience, appear more willing to trust AI over human doctors (e.g. P2). In contrast, most HCPs emphasize the indispensable role of human oversight in medical advice and diagnosis, highlighting the potential risks and limitations of AI technology. This disparity underscores the importance of managing patient expectations and ensuring robust checks and balances in AI-driven healthcare.

Lastly, while both groups acknowledge the potential of AI chatbots in supporting diagnostic and decision-making processes, a divergence emerges in terms of emphasis on professional development. HCPs place greater importance on the opportunities offered by integrating AI into their practice, viewing it as a tool for enhancing their skills and knowledge (Hogg et al., 2023; Chen et al., 2022). This contrast in opinions might indicate a need for greater patient awareness of the professional benefits that AI integration can bring, which in turn could influence their acceptance and trust in the technology.

6.3.3. Sub-conclusion

In conclusion, the insights derived from these comparative analyses of patient and HCP perspectives can serve as a valuable guide in formulating effective strategies for the implementation of AI chatbot technologies. They provide a nuanced understanding of the hopes, expectations, and concerns from both sides, which is crucial to ensure that the technology is designed and deployed in a way that meets the needs of all stakeholders, while also addressing potential reservations.

6.4. Motivators, facilitators, and barriers

Understanding these key elements that influence the acceptance of AI health chatbots by patients and HCPs – the motivators, facilitators, and barriers – is crucial to the successful implementation and utilisation of these technologies. It should be noted that each of these elements, although categorised separately, is interconnected and can either promote or inhibit adoption, depending on individual perceptions and experiences.

6.4.1. Motivators for adoption

The study identifies several factors that influence patients and HCPs to adopt AI health chatbots, based on the study findings and previous literature. These factors include social influence, financial incentives, the perceived enjoyment of using the technology, perceptions of trust in AI, and some factors of anonymity.

Firstly, a major motivator for many patients and HCPs is the perceived trustworthiness of the accuracy of AI chatbots. The study findings revealed a surprising contradiction to previous literature on this subject, which suggests a general lack of trust in AI chatbots (Koulouri et al., 2022; Ho et al., 2023; van Bussel et al., 2022; Chen et al., 2022). The discrepancy could be due to improvements in the technology itself, differences in the sample used in this study compared to previous ones, or caused by the complex nature of the concept of trust (van Bussel et al., 2022).

The anonymous nature of the technology is another key enabler for adoption. Patients generally express a high level of comfort in discussing high-stigma health conditions with AI chatbots, which underscores the significance of this factor (van Bussel et al., 2022; Moldt et al., 2022). However, it is important to note that while anonymity is viewed as a benefit, it should not replace the empathetic and emotionally supportive interactions that patients and HCPs also value (Luca et al., 2023).

The role of social influence, specifically the doctor's recommendation, emerged as another significant motivator for patient acceptance. This factor emphasizes the need for healthcare professionals to be well-informed and positive about AI technologies to encourage patient adoption. However, previous literature does not address this potential motivator, so while it is an interesting observation, this discovery in this paper is only suggestive, and thus, its influence on user acceptance should be validated in future research.

Lastly, the potential financial implications of AI chatbots in healthcare practice may motivate HCPs to adopt this technology. While doctors value AI chatbot accuracy, they state that such recommendations should not overconsume additional healthcare resources, such as requesting unnecessary clinical tests. This concern highlights the need for AI chatbots to balance cost-effectiveness with accuracy and reliability to ensure widespread adoption among both patients and HCPs. However, this study reveals a gap in the literature regarding this aspect, pointing to an area that needs further exploration.

The practical implications of these findings highlight the need for AI developers to enhance the accuracy and empathy of AI chatbots, and for HCPs to advocate for the benefits of these technologies. Moreover, understanding these motivators can guide the design and implementation strategies to ensure successful integration of AI chatbots into patient care.

6.4.2. Facilitators

Several facilitators, conditions or factors that encourage the acceptance and adoption of AI health chatbots, were identified in this study, including data privacy and security, trust in the owner company of the chatbot, and inclusivity for under-represented groups. These facilitators are consistent with and expand upon the existing literature.

Data privacy and security emerged as a crucial facilitator. Patients' mixed opinions highlight the complexity of this issue and the need for a balanced approach that ensures data protection without hindering the personalisation benefits of AI chatbots. Similarly, HCPs expressed varying levels of concern about data privacy, suggesting the need for robust and transparent data security measures in AI chatbot development and implementation. This aligns with previous findings of reluctance to share private data in both AI- and non AI-related health technologies (He et al., 2021; Ciecierski-Holmes et al., 2022; Dhagarra et al., 2020).

Trust in the owner company of the chatbot is another important facilitator. Patients' preference for government-owned AI chatbots or those with strong data security frameworks implies a critical trust factor that has not been directly addressed in previous literature, pointing to another area for future research.

Finally, inclusivity and adaptability also emerged as crucial facilitators (as addressed in Chapters 6.1.2. and 6.2.2.). Both patients and HCPs expect AI health chatbots to adapt to patients with disabilities and to include underrepresented populations, emphasising the importance of designing AI chatbots that can cater to a diversity of users (Luca et al., 2023).

In conclusion, the facilitators for the adoption of AI health chatbots identified in this study, such as data privacy and security, trust in the owner of the technology, and the preference for public or government-backed ownership, are essential aspects to consider when developing and implementing AI chatbots in healthcare. Recognising and addressing these facilitators can enhance user acceptance and promote the successful integration of AI chatbots into patient care. Further research should explore additional facilitators for adoption as well as potential strategies to address the barriers and challenges faced by patients and HCPs when using AI chatbots in healthcare settings.

6.4.3. Barriers

In addition to motivators and facilitators, this study identifies many key barriers to the acceptance of AI chatbots in healthcare, which include trust in AI accuracy, the need for contact with human doctors, and the lack of legal and ethical regulations. These barriers, prevalent among both patients and HCPs, align with the literature and underscore the challenges that must be addressed for successful AI chatbot implementation.

Trust in AI accuracy emerged as a significant barrier from both patient and HCP perspectives, hinging on the perceived accuracy of information provided and the reliability of the training data. This conclusion aligns with findings from previous studies, where patients and HCPs express scepticism regarding the accuracy and credibility of AI chatbots, especially for complex tasks, with some HCPs expressing concerns regarding the risks of false positives and negatives (Ho et al., 2023; van Bussel et al., 2022; Blease et al., 2019; Chen et al., 2022).

Interestingly, some authors attribute this lack of confidence in AI accuracy to the "black box" problem, which is especially pertinent to AI-based technologies (Chew & Achananuparp, 2022). The "black box" concept, introduced over 50 years ago in systems theory, depicts any physical open system that can be understood only in terms of its inputs and outputs, while the system's inner workings remain opaque ("black") to the observer (Bunge, 1963). Research demonstrates a prevalent lack of understanding among HCPs about the inner workings of AI algorithms (Romero-Brufau et al., 2020), resulting in a lack of trust among users towards the system and its outcomes (Cai et al., 2019; Drozdal et al., 2020). Thus, increasing trust in AI accuracy and facilitating adoption necessitates that AI chatbots be trained on reliable data and provide medically accurate information.

This study also reveals that both patients and HCPs foresee a significant role for AI chatbots in healthcare, but not as replacements for human doctors. While some patients comfortably rely on AI chatbots for health advice, others underscore the necessity of "human touch" with healthcare providers, even through virtual consultations, for more accurate diagnosis and treatment (Nadarzynski et al., 2019; Koulouri et al., 2022). This aligns with existing literature, showing HCPs' emphasis on the irreplaceable value of human communication in healthcare (van Bussel et al., 2022; Moldt et al., 2022; Blease et al., 2019; Chen et al., 2022).

Finally, both patients and HCPs express concerns about the legal and ethical implications of potential medical errors made by AI chatbots, such as misdiagnosis or misinformation. A key legal concern is the delineation of responsibility in the event of substandard patient care, especially when the AI chatbot is developed by an external company but operated by the hospital. Interestingly, some patients fear they may be held liable for following inaccurate medical advice provided by the chatbot, as one patient stated: "*[The responsibility] is mine for taking those steps, because if I hadn't used the bot, I wouldn't have gotten the wrong diagnosis.*" (P8). This underscores the pressing need for comprehensive legal regulations governing AI chatbots in healthcare.

To summarize, the highlighted key barriers to the adoption of AI health chatbots, including trust in AI accuracy, the irreplaceable role of human doctors, and the absence of robust legal and ethical frameworks. These findings echo previous literature and highlight areas that need urgent attention for successful AI chatbot integration in healthcare. Future research should focus on validating these barriers' impact on user intention and exploring additional obstacles and possible solutions to enhance AI chatbot integration into patient care and health outcomes.

6.4.4. Sub-conclusion

The exploration of motivators, facilitators, and barriers reveals key insights into the acceptance and adoption of AI health chatbots by patients and HCPs. Trust in AI, anonymity, social influence, and financial implications emerged as significant motivators, while data privacy, trust in chatbot ownership, and inclusivity were identified as major facilitators. Conversely, barriers like accuracy concerns, the need for human doctors, and lack of legal regulations present challenges to adoption.

These findings underline the nuanced and interconnected nature of these factors in shaping the perception and use of AI chatbots in healthcare. This understanding is vital to inform AI developers and healthcare professionals, guiding strategies for design and implementation to ensure successful integration. The insights also highlight areas for future research, particularly on potential motivators, facilitators, and barriers not yet fully explored in the literature. Addressing these factors is crucial to overcome challenges and enhance the adoption and effective use of AI chatbots in healthcare.

6.5. Secondary outcomes

Beyond the primary outcomes of this study, which focused on the factors influencing the adoption of AI chatbots by patients and HCPs, the analysis also identified several secondary outcomes related to potential moderators for adoption. These outcomes, while not directly answering the main research questions, are nonetheless valuable insights presented herein.

6.5.1. Demographic and cultural moderators

The analysis revealed potential adoption moderators including age, education, profession, and cultural factors. Although these moderating factors are quantitative and thus fall outside the Literature Review scope (Chapter 3), the study's heterogeneous sample enabled the identification of such moderators, warranting further examination in future quantitative research.

For patients, three weak moderators emerged: age, profession, and culture. Age, as suggested by one patient (P4), might affect willingness to try AI chatbots, with younger individuals more inclined and older ones needing additional reassurances (Wildenbos et al., 2018). Profession also emerged as a potential moderator, with those from the legal industry expressing concerns about AI's legal and ethical responsibility. Cultural factors, as mentioned by a patient (P4), may influence trust in AI chatbots, underlining the need for cultural considerations in healthcare technology implementation.

For HCPs, age was the predominant adoption moderator, aligning with existing research showing older HCPs' resistance to new technologies due to digital literacy concerns, professional role impacts, and potential legal implications (HCP1; HCP4; Gagnon et al., 2012; Najaftorkaman et al., 2014).

6.5.2. Sub-conclusion

The proposed moderators of age, profession and culture, while not directly addressing the main research questions, enrich our understanding of factors potentially influencing AI chatbot acceptance in healthcare. Further studies should delve into these moderators' predictive power and explore other impacting factors among different populations.

6.6. Key Reflections

Throughout the course of conducting this research, several key reflections have emerged that shaped my understanding and approach. One such realisation pertains to the literature search strategy. Initially, my search strategy was primarily based on generic terms such as "chatbot" and synonyms (see Appendix 1). However, I later found that the use of specific names of chatbots like “ChatGPT” and “Bard”, and language models like “GPT4” and “MedPaLM” revealed a more focused and richer dataset. The specificity of these terms led to more relevant results that could have potentially enriched the analysis, and this observation underlines the importance of precision in the search strategy (Booth, 2016).

In addition, by completing this research I recognised the dynamic nature of the AI field and the implications it has on the quality and timeliness of the data collected. The field of AI, including AI chatbots in healthcare, is rapidly evolving. Thus, rather than a one-and-done event, this research brought to light the importance of continual literature review and data collection to capture the most recent advances and trends (Leavy, 2017).

Another key learning emerged from the application of theories to the study, specifically the TAM and UTAUT frameworks. While these models provide a robust structure for understanding technology acceptance, their adaptation to the specifics of AI chatbots in healthcare proved challenging. The complexity of the models (as critiqued in Chapter 2.3) made it necessary to modify or remove certain factors and include new ones. Thus, this research project underscored the need for a more nuanced and flexible approach in applying these models to evolving technologies, potentially prompting the development of a new theoretical framework better suited to the unique characteristics of AI in healthcare.

Lastly, upon reflection, the entire research process shed light on the importance of adaptability in research design. The field of AI in healthcare is rapidly evolving, and new trends and technologies emerge regularly. If I were to conduct this study again or embark on a similar one in the future, I would adopt a more iterative approach, allowing for regular revisits and updates to the methodology based on emerging trends and data. This would also include more frequent pilot testing and revisions of the data collection tools to ensure they remain relevant and capable of capturing the most current and pertinent data (provided that there are sufficient resources for doing so).

In conclusion, these reflections provide valuable lessons that will guide my, and possibly others’, future research in the dynamic and complex field of AI in healthcare.

6.7. Summary of Discussion

This study has offered comprehensive insights into the perspectives of patients and healthcare professionals (HCPs) regarding AI chatbots' deployment in healthcare. Addressing RQ1, the patient attitudes towards these technologies highlighted potential benefits and persistent concerns about accuracy, adaptability, and inclusivity. On the other hand, answering RQ2, HCPs demonstrated a generally positive view, endorsing AI chatbots' potential to reduce workload and support decision-making, while stressing the continued necessity for human expertise in healthcare (Sections 6.1 and 6.2).

To address RQ3, a comparison of these perspectives revealed shared viewpoints on AI benefits and the irreplaceable role of human professionals but also unveiled divergences in attitudes towards personalisation, trust in AI, and professional development. These insights, collectively, provide a nuanced understanding of AI chatbot acceptance from both sides of the healthcare spectrum, which can help inform future adoption strategies that aim to meet all stakeholders' needs (Section 6.3).

Answering RQ4, an exploration of the motivators, facilitators, and barriers to AI chatbot acceptance discovered a complex and interconnected landscape of factors shaping AI chatbot perception and use. These include trust, data privacy, social influence, accuracy concerns, and regulatory issues, among others (Section 6.4).

Lastly, as secondary outcomes, the study identified potential moderators like age, profession, and culture that could influence AI chatbot acceptance in healthcare, albeit not directly answering the main research questions. Further exploration of these moderators' predictive power and other impacting factors among different populations is suggested for future research (Section 6.5).

7. Limitations and Future Research

This chapter discusses the limitations and potential areas for future research inherent in this study. We outline three principal limitations: methodological constraints, theoretical shortcomings, and the study's scope. For each, the text delineates the weakness and its practical or theoretical basis, considers how it may have influenced the research outcomes, and makes suggestions for future studies on the topic.

7.1. Methodological limitations

This study’s research methodology, while rigorous, was not without its limitations. One of the primary constraints was related to the qualitative research design – specifically, the reliance on a relatively small (n=12), purposefully selected sample for interviews (Bryman, 2015). Qualitative research design, with its emphasis on depth and context sensitivity, inherently limits the generalisability of the findings to broader populations (Creswell & Poth, 2018). This is further exacerbated by the absence of random sampling, which forced this research to adopt self-selection and snowball sampling methods, thereby introducing sampling bias (Kvale & Brinkmann, 2014; Leavy, 2017). Finally, the research could have adopted a mixed-methods approach in order to both identify and validate the acceptance factors, as was done in some previous studies (van Bussel et al., 2022). However, a mixed methods approach was not feasible due to time and resource constraints.

These limitations, while making this study's finding less generalisable, may act as opportunities for future research. The applicability of the results can be broadened by carrying a study that incorporates a larger, more diverse sample, and possibly a mixed-methods approach.

7.2. Theoretical limitations

The theoretical frameworks used in the study have some inherent weaknesses. While the TAM and UTAUT theories offer valuable insights into technology acceptance and use, they are not devoid of weaknesses, specifically by being overly complex and overlooking factors that are particularly pertinent to a healthcare context, such as trust and privacy (Venkatesh et al., 2012). Furthermore, the reliance on self-reported data and limited generalisability introduces potential biases and may constrain the validity of the research (Dwivedi et al., 2017).

Future research could enhance these models by adapting the constructs within the theories to address these limitations. It may be fruitful, for instance, to incorporate the notions of trust and data privacy into the models, given their significance in healthcare settings.

7.3. Limitations to the study scope

Lastly, the research included only patients who were able to schedule and attend video consultations, and therefore the perspectives of individuals unfamiliar with or uninterested in using technology were not captured. The study also intentionally did not consider the perspectives of other stakeholders in healthcare, such as policymakers and healthcare administrators. Finally, this study was also limited to its ability to allow interviewees to test and use AI chatbots for medical information, as such technologies are either costly or not yet available (such as Google's MedPaLM). This likely affects the findings of the study since users may build more appropriate perceptions of usefulness and ease of use by interacting with the technology.

Future research should focus on expanding upon the listed limitations, for example by interviewing underrepresented participants such as ethnic minorities, people with disabilities and those resistant to technology adoption. Further studies can also focus on expanding the stakeholder representation, including administrators and policy makers, as well as the geographical representation, including subjects from middle- and lower-income countries. Finally, future researchers may choose to wait until an appropriate AI health chatbot becomes freely available, in order to more accurately evaluate the attitudes and perceptions of key stakeholders.

8. Conclusion

In an era where artificial intelligence is revolutionising a number of sectors, its application in healthcare through AI chatbots is an emerging field of research. This study delved into the perceptions of patients and doctors towards AI chatbots, aiming to understand the complex factors influencing their acceptance and use. The study also examined the comparative perspectives of these two user groups and identified potential motivators, facilitators, and barriers to adoption. Finally, the research uncovered secondary factors that may further influence acceptance and outlined key areas for future exploration.

8.1. Key findings summary

Addressing the perceptions of patients and HCPs towards the usefulness and usability of AI chatbots (RQ1 and RQ2), the study showed that both user types appreciate the potential benefits of AI chatbots in healthcare, although with unique concerns. Patients expressed concerns about the accuracy, adaptability, and inclusivity of the chatbots when providing health information. In contrast, HCPs emphasised the importance of these technologies complementing, rather than replacing, the standard medical practice. Despite these concerns, the general outlook was positive, with the potential for AI chatbots to enhance service quality, convenience, and timeliness, and to support decision-making processes.

Answering the question of comparison between the attitudes of patients and HCPs (RQ3), a comparative analysis of both perspectives revealed some shared and some divergent viewpoints. Both groups agreed on the potential benefits of AI and the irreplaceable role of human professionals. However, they differed in attitudes towards personalisation, trust in AI, professional development, and ease of use. This analysis presents a nuanced understanding of both user types' hopes, expectations, and concerns, crucial for the successful integration of AI chatbots in healthcare.

Finally, discovering the unique motivators, facilitators and barriers to acceptance (RQ4) uncovered some unique perspectives. Trust, anonymity, and the recommendation by a doctor were identified as key motivators for patients, while for doctors a key one was the financial implications of using AI chatbots. Key facilitators for both users included data privacy, trust in chatbot ownership, and inclusivity of underrepresented populations. Barriers to adoption included accuracy concerns, the need for human contact and doctor-patient relationship, and the inadequate legal regulations of AI. These factors shed light on the complex landscape influencing the perception and use of AI chatbots in healthcare.

8.2. Contributions of the Study

This research offers an extensive review and analysis of patients' and HCPs' attitudes towards and acceptance of AI chatbots in healthcare. The findings contribute to the existing literature by providing a nuanced understanding of the motivators, facilitators, and barriers that influence AI chatbot acceptance, as well as studying a relatively underrepresented population in AI chatbot research. This study also introduced novel and unique themes underlying the perceptions of usefulness and usability of the technology, which have not been addressed in prior research.

8.3. Limitations of the Study

Despite its contributions, this study acknowledges its limitations, mainly related to its scope, methodology and chosen theories. These limitations are extensively covered in Chapter 7, as well as Chapters 2.3 and 4.4.

8.4. Closing statement

In closing, this study sets a bold course towards a future where AI chatbots are seamlessly integrated into healthcare, driven by an acute understanding of both patient and HCP perspectives.

It lights a spark of knowledge that may illuminate the pathway for future research, unlocking the vast potential of AI in healthcare to revolutionise patient care and transform the way health services are delivered. While I have made every effort to remain objective during this entire study, I cannot help but be excited to witness this transformation unravel over the next decades.

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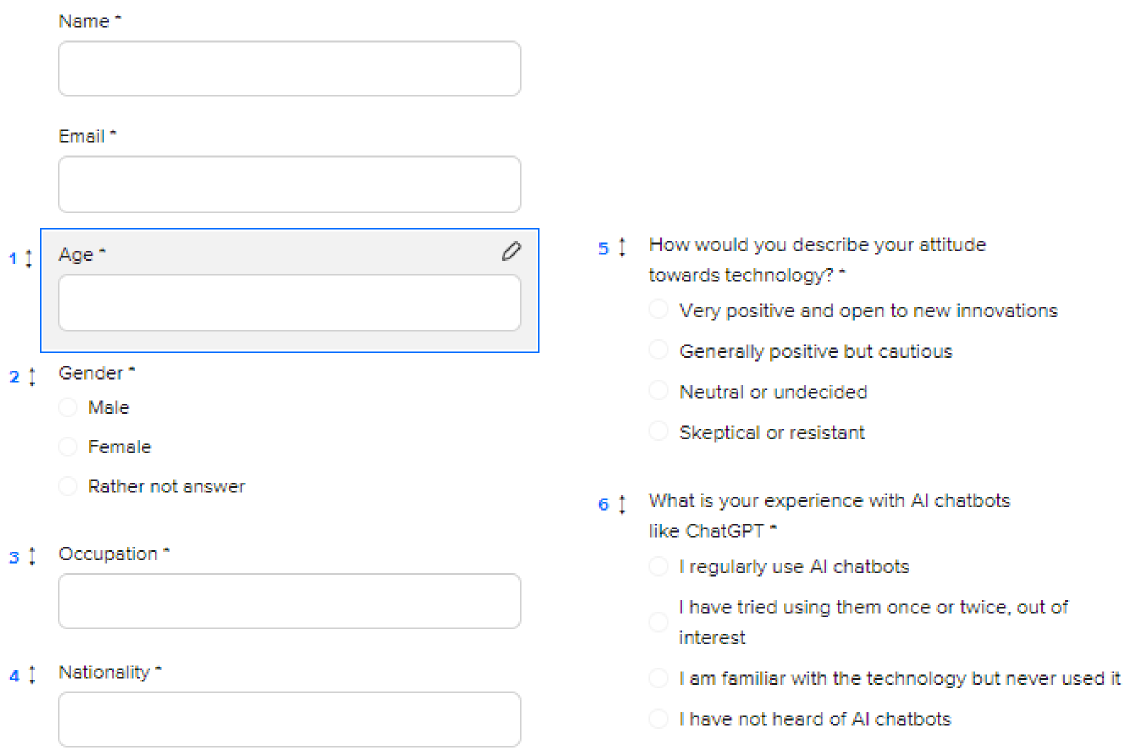
Appendices

Appendix 1: Literature review search strategy

Summary table of search keywords.

Categories	Search Keywords
Technology	chatbot*
	*bot
	"interactive agent"
	AI
	"artificial intelligence"
	robot*
User Type	healthcare
	medical
	doctor
	patient
	HCP
Studied Subject	attitude
	accept*
	adopt*
	perspective*
	opinion*
	diffusion

Appendix 2: Interview booking survey and infor med consent agreement



Name *

Email *

1 Age *

2 Gender *
- Male
- Female
- Rather not answer

3 Occupation *

4 Nationality *

5 How would you describe your attitude towards technology? *
- Very positive and open to new innovations
- Generally positive but cautious
- Neutral or undecided
- Skeptical or resistant

6 What is your experience with AI chatbots like ChatGPT *
- I regularly use AI chatbots
- I have tried using them once or twice, out of interest
- I am familiar with the technology but never used it
- I have not heard of AI chatbots

Description/Instructions:

Thanks for agreeing to participate in my study :)

Please find a 30-min time slot that suits you, then answer some questions to help with the interview.

Below is an explanation of the purpose of the study and what to expect from participating, followed by a statement of informed consent at the end.

Purpose of study:

This study aims to explore the views of patients and physicians with artificial intelligence chatbots.

What to expect from the interview:

The interviews will be confidential, lasting approximately 30-40 minutes, and conducted via Microsoft Teams. Please let me know if you prefer another video conferencing platform (e.g., Zoom or Google Meets).

The session will be recorded.

Informed consent:

Your participation in this study is completely voluntary. You can choose not to answer any questions or stop the interview at any time. All data collected, including your personal information and recordings/transcripts of the session, will be kept private and confidential, and will be used solely for research purposes. No personally identifying details will be included in any reports or publications from this research.

By participating in this study, you confirm that you provide your informed consent.

Appendix 3: Characteristics of HCP and patient interviewees

Table X. Detailed overview of characteristics of the individual interviewees (HCPs and patients)

Participant ID	Age	Gender	Occupation	Nationality	Attitude Towards Technology (1-4)	Experience with AI Chatbots (1-4)
P1	28	M	Software Developer	Bulgarian	1 - Very positive and open to new innovations	1 - I regularly use AI chatbots
P2	39	M	Senior Project Manager & Head of Digital B2B	Danish	1 - Very positive and open to new innovations	1 - I regularly use AI chatbots
P3	25	M	Consultant	Danish	1 - Very positive and open to new innovations	1 - I regularly use AI chatbots
P4	27	M	Training & Development Specialist	Bahraini	2 - Generally positive but cautious	3 - I am familiar with the technology but never used it
P5	29	F	CAD Draughtsman	British	1 - Very positive and open to new innovations	1 - I regularly use AI chatbots
P6	33	F	DevOps intern	Bulgarian	1 - Very positive and open to new innovations	1 - I regularly use AI chatbots
P7	27	F	Trainee solicitor	Bulgarian/ British	2 - Generally positive but cautious	2 - I have tried using them once or twice, out of interest
P8	28	M	Paralegal	Bulgarian/ British	1 - Very positive and open to new innovations	2 - I have tried using them once or twice, out of interest
HCP1	30	F	Paediatric surgeon	Bulgarian	2 - Generally positive but	2 - I have tried using them

					cautious	once or twice, out of interest
HCP2	61	M	Anaesthesiologist	Bulgarian	2 - Generally positive but cautious	2 - I have tried using them once or twice, out of interest
HCP3	28	F	ObGyn	Bulgarian/ British	1 - Very positive and open to new innovations	3 – I am familiar with the technology but have never used it
HCP4	55	F	ObGyn	Danish	4 – Skeptical or resistant	3 – I am familiar with the technology but have never used it

Appendix 4: Example of AI used in radiology for image recognition

Figure X provides a comparative analysis of a deep learning algorithm's performance against 15 physicians in the identification of lung tumours and pneumonia using chest x-ray images, as found by Hwang et al. (2019).

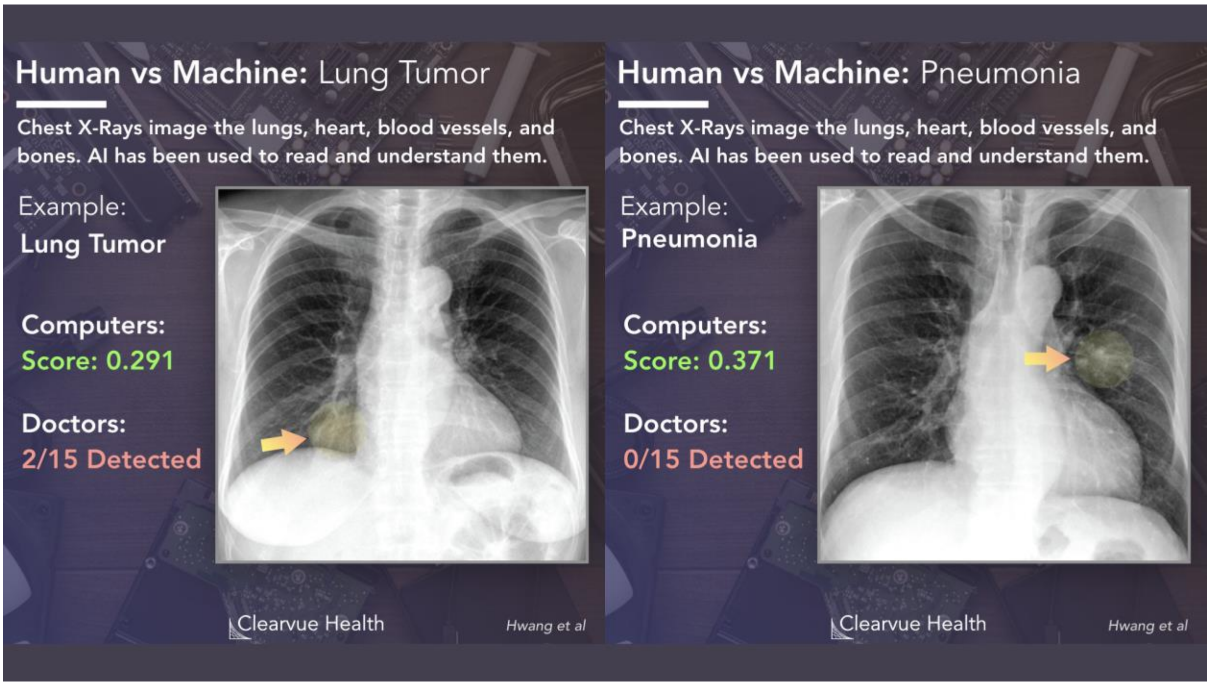


Figure X. AI vs. Doctor: lung tumour (left) and pneiumonia (right) recognition on a chest X-ray. A deep learning algorithm and 15 doctors were asked to read the above chest x-ray. "Score:" is the probability score as identified by the algorithm, whereas the 215 and 015 fractions indicate the number of doctors who identified the condition. (Hwang et al., 2019)