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The Impact and Acceptance of Large Language Models in Healthcare: A Perspective from China

Poh Soon JosephNg[1,*], Zhaoji Fu[2,3,4], Rui Zhang [4], Koo Yuen Phan[5]

1 Institute of Computer Science and Digital Innovation, UCSI University, 56000 Cheras Kuala Lumpur, Malaysia
2 School of Management, University of Science and Technology of China, Hefei 230000, China
3 HeartVoice Medical Technology, Hefei 230027, China
4 Division of Life Sciences and Medicine, University of Science and Technology of China, Hefei 230000, China
5 Faculty of Information and Communication Technology, Universiti Tunku Abdul Rahman, 31900 Kampar, Perak, Malaysia

ABSTRACT

This research explores the impact of Large Language Models like GPT on the healthcare industry, focusing on operational efficiency, patient experience, and cost structures to promote greater inclusive innovation. Employing a mixed-methods approach, this study integrates quantitative data from structured surveys with qualitative insights from interviews. Grounded in empirical evidence from 66 valid surveys conducted among healthcare professionals and patients in China, this study employs SmartPLS for robust statistical analysis. The findings suggest a significant potential of LLMs in enhancing healthcare delivery, marked by improvements in operational efficiency and patient experience. While LLMs are perceived to potentially lower costs, the study reveals that cost reduction alone does not significantly influence the acceptance of LLM-integrated healthcare solutions in the Chinese context. The high level of trust and acceptance in using LLMs for diagnosis and treatment planning among respondents underscores a shift towards prioritizing quality and effectiveness in healthcare over mere cost savings. This study contributes to the discourse on AI adoption in healthcare, challenging existing assumptions and indicating a future where quality and outcome improvements may be more significant factors for technology acceptance. The research advocates for a balanced approach to LLM integration, emphasizing the importance of both economic and qualitative benefits in enhancing healthcare practices.

Keywords:
Large language models; Healthcare industry; Operational efficiency; Patient experience; Cost structure; Mixed-methods approach; SmartPLS statistical analysis; Technology acceptance; AI adoption in healthcare; Healthcare delivery enhancement; Chinese healthcare; Trust in healthcare technology; Outcome improvements; Health technology integration

1. Introduction

1.1 Overview

The healthcare industry is undergoing a significant transformation, driven by the rapid advancements in artificial intelligence (AI), particularly in the realm of deep learning. Deep learning, a subset of machine learning, has emerged as a powerful tool for analysing complex medical data, leading to breakthroughs in predictive analytics, medical imaging, and personalized medicine [1]. The

* *Corresponding author.*
E-mail address: joseph.ng@ucsiuniversity.edu.my

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advent of Large Language Models (LLMs) like GPT represents a further evolution in this technological revolution, reshaping patient care, medical research, and health services administration through advanced natural language processing capabilities. The integration of LLMs into healthcare systems signifies a future where AI plays a pivotal role in diagnosing, treatment planning, and providing personalized patient care, marking a transformative era in health technology [2,3].

Operational efficiency, cost management, and improved patient experiences are pivotal in the evolving landscape of healthcare technology. Large Language Models (LLMs) present an opportunity to optimize healthcare processes, potentially lowering operational expenses while redistributing resources to where they are needed most. Concurrently, LLMs hold the promise of elevating the patient experience, delivering swift and precise health information, customizing interactions for individual needs, and demystifying medical terminology into comprehensible guidance.

The integration of LLMs into healthcare is not without its challenges. While there are ample opportunities for increased efficiency and improved patient engagement, there are also threats related to data privacy, the potential for misinformation, and the need for robust AI governance. The dynamic between these opportunities and threats will significantly influence the trajectory of LLM adoption in healthcare.

A brief review of the existing literature reveals a burgeoning interest in the intersection of AI and healthcare, with a growing body of work focusing on the practical applications and theoretical implications of LLMs. Studies have begun to highlight the benefits and drawbacks of these systems, although comprehensive research into their long-term impact remains nascent.

The research methodology for this study will utilize a mixed-methods approach, combining quantitative data gathered from surveys with qualitative insights from interviews. This dual approach aims to not only quantify the impact of LLMs on healthcare but also to understand the nuances behind their integration, as perceived by medical professionals and patients.

This research sets the stage for a detailed exploration of the role that LLMs could play in revolutionizing healthcare. Subsequent chapters will delve into the scope and depth of LLMs' impact, unravelling their significance and potential consequences for the industry. The ensuing discussion aims to weave a comprehensive narrative that not only examines the technological underpinnings of LLMs but also considers the broader implications of their integration into healthcare practices.

1.2 Background Studies

In the existing healthcare paradigm, much of the operations rely on expert interactions, where healthcare professionals such as doctors, nurses, and technicians play a crucial role in delivering health services. From diagnosis to treatment planning and patient engagement, these professionals utilize their extensive training and expertise to address patient needs. Furthermore, traditional healthcare delivery models also rely heavily on one-on-one, in-person interactions, involving activities such as physical examinations, consultations, and follow-up visits. (Bavafa *et al.,*; Santarossa *et al.,*)

This expert-dependent healthcare system has several strengths. It facilitates personalized care, as healthcare professionals can leverage their expertise to provide tailored medical advice. This system also allows for nuanced interpretation of patient symptoms, considering not just the physical but also the emotional and psychological aspects of patient health. However, the systemic weaknesses of the current healthcare industry are substantial and warrant serious attention (Haskell). Primarily, the expert-dependent system is inherently time-consuming due to the necessity of professional involvement at every stage, which often leads to longer response times. Accessibility to expert healthcare is another major concern, as it is often unevenly distributed across various regions, with rural and underprivileged areas facing more significant healthcare shortages. Moreover, the traditional model's effectiveness is intimately tied to the continual availability and capability of healthcare professionals. This reliance poses a significant challenge. From a scalability perspective, it becomes difficult to rapidly expand healthcare services to accommodate increasing demand because doing so would require an equivalent increase in skilled healthcare professionals. This is especially challenging given the time and resources required to train these professionals. In terms of adaptability, this model shows shortcomings as well. The healthcare landscape is continuously evolving with new diseases, treatments, and technologies. A system dependent on human professionals necessitates constant upskilling and training to keep up with these changes, which isn't always feasible or efficient. These factors contribute to the existing limitations in scalability and adaptability within the traditional, expert-dependent healthcare model (Ćwiklicki *et al.,*; Rangarajan *et al.,*). The rising global healthcare demands pose a challenge to this model, underscoring the urgent need for a more efficient and scalable approach.

The recent trend in healthcare technology is steering toward the adoption of Artificial Intelligence (AI), specifically Large Language Models (LLMs) (Shaheen). Large Language Models (LLMs) are advanced AI models, trained on extensive amounts of text data, that can generate and understand human-like text by learning patterns, nuances, and structures of language. These models, such as GPT-3 and GPT-4, can perform tasks like text generation, translation, summarization, and answering questions with a high degree of accuracy and fluency (Brown *et al.,*). These models, powered by the capacity to understand and generate human-like text, have shown immense potential in transforming the healthcare sector. LLMs can assist in automating routine tasks, interpreting patient symptoms, providing health information, and even predicting patient outcomes. Critically, LLMs can convert human medical cognition into healthcare services delivered directly through natural language interaction, presenting information in a manner that's easily understandable and accessible to patients. Importantly, these AI models offer scalability, cost efficiency, and round-the-clock availability, making them a valuable addition to the healthcare industry. As the healthcare sector continues to evolve, the integration of LLMs can potentially address the limitations of the current expert-dependent healthcare system and pave the way for a more efficient and accessible healthcare model (Esmaeilzadeh [43]).

1.3 Problem Statement

The role of artificial intelligence (AI), particularly large language models (LLMs), has garnered significant attention in recent years as a promising development within various sectors, including healthcare. This research focuses on the potential transformative impacts of LLMs on the healthcare industry. This investigation is crucial because, despite the healthcare sector's pivotal role in society and its widespread adoption of advanced technologies, it faces challenges that prevent it from delivering optimal outcomes. Notably, operational inefficiencies, variable patient experiences, and high costs are significant issues that warrant a forward-thinking solution.

Large Language Models offer a promising solution to these existing problems in healthcare. LLMs, powered by the capacity to understand and generate human-like text, have the potential to transform healthcare processes, patient interactions, and cost structures. Existing literature already points towards the significant benefits of LLMs in healthcare. For instance, [4] investigated the application of LLMs in healthcare, focusing on their ability to provide natural language responses to medical inquiries, generate discharge letters, and aid in diagnosis. [5] elaborates on the necessity and workflow of OpenAI's ChatGPT in healthcare, discusses its significance in applications such as chatbots and virtual assistants, and highlights challenges about medical ethics, data interpretation, accountability, and privacy.

Nonetheless, the existing body of literature also indicates limitations in the current application of LLMs in healthcare. Many of these studies have been conducted under controlled circumstances and have not yet fully navigated the challenges of real-world implementation. Additionally, the success of LLMs relies heavily on the quality and volume of data available, leading to critical concerns about patient privacy and data security. Another important consideration is the potential effect of LLMs on healthcare professionals' roles and the crucial patient-doctor relationship, which might be influenced as these models become more widespread.

This research endeavours to meticulously assess the impact of Large Language Models (LLMs) on the healthcare industry, addressing both the potential advantages and the challenges that accompany their integration. It specifically examines the effects of LLMs on enhancing operational efficiency, enriching patient experiences, and optimizing cost structures, while also scrutinizing how these advancements influence the acceptance of LLM-integrated healthcare among practitioners and patients. By exploring the operational mechanisms and patient-facing dynamics of LLMs, this study aims to contribute meaningful insights to the ongoing discourse on AI's role in healthcare. The objective is to articulate a vision for a healthcare system that is not only more efficient and patient-centric but also adaptive to the adoption of AI, thus paving the way for solutions that bolster acceptance of LLM-integrated healthcare practices and manage costs effectively.

1.4 Research Purpose

This section provides a summary of the research purpose, encompassing the research questions, objectives, and hypotheses designed to explore the integration and implications of Large Language Models (LLMs) within the healthcare industry.

Table 1
Triangulation research summary table

Research Questions	Research Objectives	Research Hypothesis
RQ1: How does the integration LLMs contribute to improving efficiency in healthcare industries?	RO1: To investigate the effects of integrating LLMs on efficiency in healthcare industries.	H1: The integration of LLMs will lead to improved efficiency in healthcare industries.
RQ2: What is the impact of LLMs on customer experience in healthcare industries?	RO2: To assess the impact of LLMs on customer experience in healthcare industries.	H2: The application of LLMs will enhance customer experience in healthcare industries.
RQ3: How does the use of LLMs affect the cost in healthcare industries?	RO3: To analyse the changes in cost resulting from the implementation of LLMs in healthcare industries.	H3: The implementation of LLMs in healthcare industries will lead to a reduction in overall cost.
RQ4: How does improved efficiency influence the acceptance of LLM-integrated healthcare?	RO4: To examine the effect of increased efficiency on the acceptance of LLM-integrated healthcare solutions.	H4: Enhanced efficiency will lead to higher acceptance of LLM-integrated healthcare.
RQ5: How does the customer experience affect the acceptance of LLM-integrated healthcare?	RO5: To investigate the impact of customer experience on the acceptance of LLM-integrated healthcare solutions.	H5: Improved customer experience will lead to higher acceptance of LLM-integrated healthcare.
RQ6: How does cost influence the acceptance of LLM-integrated healthcare?	RO6: To assess how cost considerations impact the levels of acceptance towards LLM-integrated healthcare.	H6: Lowering costs will increase the acceptance of LLM-integrated healthcare.

1.4.1 Research questions

i. RQ1: How does the integration of LLMs contribute to improving efficiency in healthcare industries?: Efficiency in the healthcare industry is a crucial aspect that impacts patient care, service delivery, and overall industry growth. By exploring this question, we aim to uncover the potential ways in which LLMs could streamline processes, reduce manual labour, increase speed of service, and improve productivity.
ii. RQ2: What is the impact of LLMs on customer experience in healthcare industries?: The customer experience is central to the healthcare industry, affecting patient satisfaction, treatment adherence, and health outcomes. With this question, we intend to scrutinize how LLMs could potentially enhance customer interactions, personalize services, and impact overall customer satisfaction in healthcare settings.
iii. RQ3: How does the use of LLMs affect the cost in healthcare industries?: Financial sustainability is a key concern for the healthcare sector. This question is formulated to dive deeper into the financial impacts of LLM implementation in healthcare. Specifically, we aim to evaluate how LLMs could affect both fixed costs, such as infrastructure and equipment investments, and variable costs, such as personnel and operational expenditures. Understanding the potential shift in these cost categories could shed light on the broader economic implications and the feasibility of LLM adoption in healthcare.
iv. RQ4: How does improved efficiency influence the acceptance of LLM-integrated healthcare?: This question seeks to understand the correlation between the efficiency gains attributed to LLM implementation and the subsequent acceptance of these technologies within the healthcare domain. It examines whether improvements in operational efficiency correlate with a greater willingness among healthcare providers and patients to adopt LLM-integrated solutions.
v. RQ5: How does the customer experience affect the acceptance of LLM-integrated healthcare?: We delve into the impact of customer experience improvements, driven by LLM deployment, on the acceptance of LLM-integrated healthcare. The inquiry focuses on the premise that superior patient engagement and satisfaction, achieved through LLMs, may foster a more favourable reception of such technologies in healthcare practices.
vi. RQ6: How does cost influence the acceptance of LLM-integrated healthcare?: This question addresses the influence of cost considerations on the acceptance of LLM-integrated healthcare models. It explores whether the potential for LLMs to lower healthcare costs contributes to higher acceptance among stakeholders, or if other factors play a more significant role in the integration of these technologies into healthcare systems.

1.4.2 Research objective

i. RO1: To investigate the effects of integrating LLMs on efficiency in healthcare industries: This objective focuses on providing empirical evidence to assess the potential of LLMs in boosting efficiency. By exploring various parameters such as time, resource allocation, and task completion rates, we aim to quantify the impact of LLMs on the efficiency of healthcare service delivery.
ii. RO2: To assess the impact of LLMs on customer experience in healthcare industries: In line with this objective, our research will delve into the various ways in which LLMs could reshape patient interactions, satisfaction levels, and overall experiences.

iii. RO3: To analyse the changes in cost resulting from the implementation of LLMs in healthcare industries: This objective aims to dissect the financial impact of LLMs by examining their influence on the cost structures of healthcare providers. The goal is to provide a detailed financial analysis that differentiates between the savings and expenditures attributable to LLMs, thereby offering a nuanced view of their economic viability within the healthcare sector.
iv. RO4: To examine the effect of increased efficiency on the acceptance of LLM-integrated healthcare solutions: This objective is to investigate whether improvements in operational efficiency, facilitated by LLMs, correlate with a greater degree of acceptance among healthcare professionals and patients. It seeks to establish a link between the benefits of efficiency gains and the willingness to adopt and endorse LLM-based healthcare solutions.
v. RO5: To investigate the impact of customer experience on the acceptance of LLM-integrated healthcare solutions: Under this objective, the research will probe into the relationship between the quality of customer experience enhanced by LLMs and the level of acceptance these technologies garner in healthcare practices. The aim is to determine how enhancements in personalized care and patient engagement influence the adoption of LLMs.
vi. RO6: To assess how cost considerations impact the levels of acceptance towards LLM-integrated healthcare: This purpose is to evaluate how the cost-related advantages or disadvantages perceived by integrating LLMs into healthcare services influence their broader acceptance. This involves understanding if cost reductions are a primary motivating factor for healthcare stakeholders when deciding to implement LLMs or if other factors take precedence in the decision-making process.

1.4.3 Research hypothesis

i. H1: The integration of LLMs will lead to improved efficiency in healthcare industries: Based on preliminary literature and the potential of LLMs, we hypothesize that integrating these models into healthcare systems could bring about notable efficiency improvements, thereby positively impacting patient care and service delivery.
ii. H2: The application of LLMs will enhance customer experience in healthcare industries: Building upon existing research and the capabilities of LLMs, we propose that the use of these models could significantly enhance the patient experience by providing more accessible, personalized, and effective communication.
iii. H3: The implementation of LLMs in healthcare industries will lead to reshaping the overall cost structure: Considering the potential for automation and scalability offered by LLMs, we hypothesize that their implementation could cause significant shifts in both fixed and variable costs within the healthcare industry. Such a shift in cost structure could potentially lead to considerable cost savings, creating a more economically sustainable healthcare system.
iv. H4: Enhanced efficiency will lead to higher acceptance of LLM-integrated healthcare: This hypothesis posits that efficiency gains provided by the integration of LLMs in healthcare workflows will correlate directly with increased acceptance among healthcare professionals and patients. The premise is that improvements in operational speed, reduction in administrative burdens, and enhanced data handling will encourage stakeholders to embrace LLM technologies more readily.

v. <u>H5: Improved customer experience will lead to higher acceptance of LLM-integrated healthcare:</u> The hypothesis here is that the deployment of LLMs within healthcare settings will result in a more tailored and responsive patient experience, which in turn will foster greater acceptance of such technologies. It is anticipated that the ability of LLMs to provide personalized communication and support will resonate positively with patients, leading to higher satisfaction and endorsement.

vi. <u>H6: Lowering costs will increase the acceptance of LLM-integrated healthcare:</u> The hypothesis suggests that cost reduction as a result of LLM integration into healthcare services will be a key driver of their acceptance. It is hypothesized that demonstrating cost-effectiveness, without compromising the quality of care, will not only appeal to healthcare administrators but also patients, thereby promoting a more favourable view of LLMs in healthcare.

1.5 Research Framework

The research framework established in this study provides a structured approach to investigating the multifaceted impact of Large Language Model (LLM) applications within the healthcare industry. It serves as a conceptual map to guide the exploration of how LLMs influence key areas such as operational efficiency, customer experience, and cost structure, and consequently, how these influences affect the acceptance of LLM-integrated healthcare solutions.

As depicted in Figure 1, the research framework is anchored around the central theme of LLM application trends in healthcare. It branches out into three main domains which are hypothesized to be directly impacted by the integration of LLMs: Operational Efficiency (H1), Customer Experience (H2), and Cost (H3).

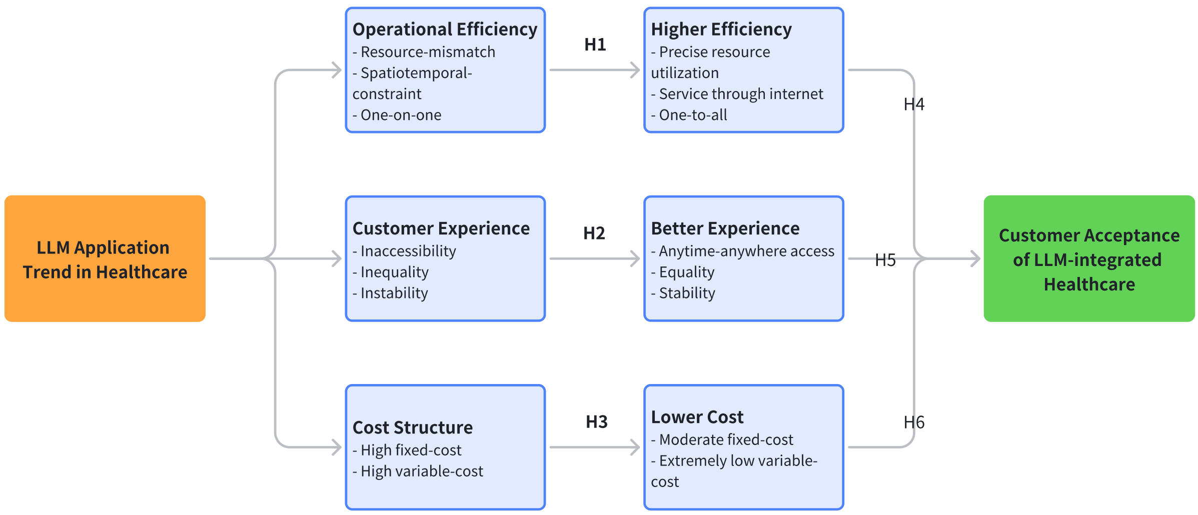

Fig. 1. Research framework

The framework further illustrates the interrelationships between these domains and the ultimate outcome of interest—Customer Acceptance of LLM-integrated Healthcare (H4, H5, H6). It posits that enhancements in efficiency (H4) and customer experience (H5) will positively influence customer acceptance. Conversely, it also proposes that a reduction in costs (H6) will have a direct positive impact on the acceptance and integration of LLM-based healthcare solutions.

This comprehensive framework underpins the study's research questions, objectives, and hypotheses, setting a clear direction for the subsequent analysis and interpretation of findings. It provides a coherent basis for understanding the complex interplay between technological innovation and its practical implications in the healthcare sector.

1.6 Scope

The scope of this research is delineated to provide clarity on the boundaries within which the study operates. It outlines the specific areas that the research will cover, acknowledges the limitations, and describes the sampling methodology used to gather data.

This research primarily focuses on the application and implications of Large Language Models (LLMs) in the healthcare industry. It covers the potential of LLMs to enhance operational efficiency, improve the customer experience, and alter the cost structure within healthcare settings. The study investigates these areas through a series of structured research questions, objectives, and hypotheses that guide the exploration of LLMs' impact on healthcare delivery and patient engagement. Additionally, the research examines the level of acceptance of LLM-integrated healthcare solutions by healthcare providers and patients, considering various factors such as cost-efficiency, operational improvements, and the quality of patient care.

The research does not extend to the technical development of LLMs or the detailed algorithmic analysis behind these models. It also excludes a broader examination of LLM applications outside the healthcare industry, such as their use in finance, education, or other fields. This study does not address the long-term societal and ethical implications of integrating AI in healthcare to a significant extent, nor does it cover the regulatory and policy aspects governing the use of LLMs in healthcare services.

The sampling for this study involves collecting data from healthcare professionals and patients who have interacted with or are aware of LLMs within healthcare contexts. The sample includes a diverse group of participants from various backgrounds, roles, and experiences in healthcare to ensure a comprehensive understanding of the perspectives on LLMs. Sampling techniques employed may include stratified sampling to ensure representation across different healthcare roles, as well as purposive sampling to include individuals with firsthand experience with LLMs in healthcare. The aim is to obtain a sample that is sufficiently large and diverse to support the reliability and validity of the research findings.

In summary, the scope of this research is focused on evaluating the functional impact of LLMs within the healthcare industry and understanding the factors influencing the acceptance of LLM-integrated healthcare. It is bound by the limitations of its focus on the healthcare industry and the parameters defined by the research questions and objectives.

1.7 Chapter Summary

In this initial chapter, we have established the context for our investigation into the impact of Large Language Models (LLMs) in healthcare. We have identified key trends and challenges in the industry, proposed our research questions, objectives, and hypotheses, and set out a clear framework to guide our analysis.

We have also outlined the scope of our study, explaining what will and will not be covered, and given an overview of our research methodology which incorporates both surveys and interviews.

Moving forward, Chapter 2 will delve into the existing body of literature, situating our study within the broader academic discourse on LLMs and healthcare. Chapter 3 will describe our research methodology in detail, explaining how we will collect and analyse our data. Chapter 4 will present our findings and discuss their implications, and finally, Chapter 5 will conclude our research, highlighting its contributions to the field and suggesting avenues for future study.

2. Literature Review

2.1 Introduction

The advent of Artificial Intelligence (AI) and Large Language Models (LLMs) has ushered in a new era of possibilities across various sectors. These advancements have revolutionized how we interact with technology, solve complex problems, and enhance human life. This chapter aims to offer a comprehensive overview of the development, applications, and impact of AI and LLMs, with a particular focus on their role in service operations and healthcare.

The objectives of this chapter are manifold. First, it seeks to provide an understanding of the history and current state of AI and LLM technologies. Second, it aims to evaluate their application and impact on service operations. Finally, it delves deeply into the specialized field of healthcare, exploring the roles and implications of AI and LLMs across various sub-sectors, such as education, personalized medicine, and public health.

The significance of this chapter is twofold. On one hand, it serves as a comprehensive guide to the capabilities and potential of AI and LLMs. On the other, it scrutinizes their real-world applications, particularly in healthcare—a sector where the use of such technology can make a life-altering difference.

While the chapter is rich in its scope, it's important to note some limitations. The focus is primarily on the applications and implications of AI and LLMs in service operations and healthcare, without delving into the technical details of these technologies. The aim is to offer a high-level overview that captures the essence and impact of these tools in the selected sectors.

The chapter is organized as follows: the development of AI and LLMs is covered in Section 2.2, breaking it down into its historical context and current state-of-the-art. Section 2.3 discusses their applications in service operations, illustrating how they've optimized various aspects of service delivery. Section 2.4 zeroes in on healthcare, providing a detailed exploration of how AI and LLMs have made strides in education, personalized medicine, public health, and customer acceptance. Section 2.5 will synthesize all these findings into a conclusion, focusing primarily on healthcare due to its unique challenges and opportunities.

By navigating through these segments, the chapter aims to furnish readers with a well-rounded perspective on the transformative capabilities and limitations of AI and LLMs in both general service operations and the specialized field of healthcare.

2.2 The Development of Artificial Intelligence and Large Language Models

In the annals of technological development, few advancements have held as much promise or provoked as much debate as artificial intelligence (AI). Since its inception, AI has taken myriad forms, reflecting our evolving understanding of what it means for a machine to be "intelligent." From solving intricate mathematical equations to interpreting natural human language, AI has steadily expanded its capabilities, prompting us to continually reassess the boundaries between human and artificial intelligence.

A significant offshoot of these developments in AI has been the rise of Large Language Models (LLMs). These machine learning-based systems, capable of generating human-like text, represent a significant leap in AI's ability to interact naturally with humans. Yet, like AI in general, they also raise questions about their capabilities, limitations, and broader societal impacts.

In the following sections, we will delve into the development of AI and LLMs, examining their historical progression, current state of the art, and the challenges and opportunities that they present.

2.2.1 History and evolution of Artificial Intelligence (AI)

Artificial Intelligence (AI) has held a steadfast allure for scientists and engineers for over 65 years, a testament to the continued human endeavour to push the boundaries of what machines can accomplish [6]. The crux of AI research and development lies in the belief that human-made machines can transcend rudimentary, labour-intensive tasks and exhibit intelligence that echoes human cognitive abilities [6,7]. This belief has fuelled innovations that have inserted AI into our daily lives, impacting a multitude of sectors, from industry and healthcare to transportation and education [8].

AI's journey has been marked by seasons of growth and plateaus, aptly characterized as AI 'summers' and 'winters'. The summers of AI represent periods of rapid advancements and profound influence, spurred by heightened societal interest, bountiful funding, and surmountable technical challenges [7]. However, such periods also beget lofty expectations that, when unmet, usher in winters of stagnation or even decline [7].

AI has notably evolved from its inception, with its timeline punctuated by significant milestones. These include the creation of symbolic AI in the mid-20th century, the rise of machine learning in the 1990s, the advent of deep learning in the 2000s, and most recently, the focus on creating human-level AI. These landmarks represent leaps in AI's capabilities, achieved through increasingly complex algorithms and computational power, enabling AI to surpass human performance in tasks like computer vision and speech recognition [7].

The path AI has traversed, however, has not followed a simple upward trajectory. Instead, its history is rich with instances of exponential growth and regression, punctuated by drastic shifts in research priorities. The prophecy of Samuel Butler in his 1863 essay "Darwin Among the Machines," where he contemplated machines gradually gaining an upper hand over us, rings true today [9]. We've become increasingly dependent on AI, dedicating significant resources to its evolution, an insight that continues to shape the course of AI research and its applications.

The current state of AI, while promising, heralds a set of unique challenges. Foremost among these are ethical considerations around AI-enhanced human intelligence and the potential security threats that unrestricted AI might pose [10]. The speed at which AI is progressing further amplifies these issues, necessitating a robust legal and regulatory framework that could potentially mitigate associated risks. The creation and implementation of such a framework is a complex endeavour, mainly due to the fast-paced evolution of AI and the widespread lack of understanding of its underlying mechanics [10].

In a separate but closely related discussion, the AI-enhanced future also carries philosophical implications. It forces us to contemplate the nature of intelligence, consciousness, and what it means to be human in a world where machines can mimic, and sometimes outdo human cognitive abilities. These existential questions underlie the technical considerations and elevate the conversation from mere practicalities to deeper, human-centred concerns [10].

To encapsulate, the journey of AI has been a winding road of remarkable advancements interspersed with periods of stagnation. These historical ebbs and flows have shaped the AI we see today, setting the stage for its ever-increasing role in various sectors. It also raises profound questions about the future implications of this technology and its interaction with society [6,7,9,10].

In the next section, we shift our focus to Large Language Models (LLMs), a subfield of AI that has come into the limelight due to its remarkable capabilities and potential implications.

2.2.2 The state of the art in large language models

Advancements in large language models (LLMs) have fundamentally redefined our understanding of machine learning capabilities, particularly concerning the emergence of novel abilities and reasoning strategies. However, it is imperative to underscore their inherent limitations.

i. Emergent Abilities and Scaling Effects: Recent advancements in LLMs have been characterized by the development of emergent abilities – capabilities that are not observable in smaller models but become apparent as the model size increases [11]. For instance, research has revealed that large-scale models have developed multistep reasoning abilities [12]. Such findings underscore the inherent unpredictability of emergent abilities, making it critical to investigate their origins, properties, and potential implications for future research in Natural Language Processing (NLP).
ii. Chain-of-Thought Prompting: A Method for Eliciting Reasoning: The practice of chain-of-thought prompting has been identified as a potent tool for enhancing the performance of LLMs in multistep reasoning tasks [12]. This technique, which simulates the human reasoning process, represents an intriguing new frontier in our ongoing attempts to optimize LLMs' performance. This raises compelling questions about how far we can push these reasoning abilities with further model scale-ups and how different prompting methods could potentially expand the scope of tasks LLMs can accomplish.
iii. Limitations and Interpretations of LLMs: Despite these promising advances, it is vital to acknowledge the limitations of LLMs. Studies have found that LLMs, including models like GPT, often stumble with certain types of questions and are not inherently designed to pass tests based on mathematical, semantic, and ethical principles [13]. Therefore, viewing LLMs as an emerging form of general artificial intelligence remains speculative at this stage.

In response to these limitations, there have been calls for the implementation of strategies to optimize the effective utilization of LLMs. Recommendations include developing a system of checks and balances to moderate AI's impact, improving our understanding of their behaviour, and fostering the responsible use of AI technology [14]. Emphasizing the importance of responsible AI stewardship, these suggestions aim to maximize the benefits of LLMs while mitigating their potential drawbacks.

In conclusion, state-of-the-art research in LLMs presents a vibrant field marked by significant achievements and unexplored potential. However, as we continue to develop this technology, we must keep sight of its limitations and ensure a commitment to its responsible use and continued ethical development.

2.3 Application and Impact of AI and LLMs in Service Operations

The application of Artificial Intelligence (AI) in the domain of service operations has been a subject of keen interest and development. AI has brought about transformative changes, enhancing operational efficiency, redefining service delivery, and offering new value propositions. However, the integration of AI into service operations also comes with its share of challenges.

i. Operational Efficiency and Service Level Agreements (SLAs): One of the most intricate facets of incorporating AI into service operations is the management of Service Level Agreements (SLAs). Engel *et al.,* [15] delve into the complexity that arises from SLAs, particularly in AI-enabled service chains. These chains often involve multiple organizations and require deep integration of information systems for efficient operations. Furthermore, individual engagements often involve bespoke, highly customized SLAs that differ significantly from general Key Performance Indicators (KPIs). Managing such an array of unique SLAs becomes increasingly challenging as organizations grow in size. Engel *et al.,* [15] argue that 'siloed' approaches to managing SLAs hinder the simultaneous optimization of global operational efficiency and engagement-specific SLA compliance. They propose an AI-supported approach to managing SLAs that is deeply integrated into the core workflows of enterprises [15].

ii. Broad Implications for Operations Management: Fosso Wamba *et al.,* [16] provide an overview of how AI technologies are impacting the broader field of Operations Management (OM). They point out that AI has been successfully applied across diverse operational contexts, from healthcare operations to inventory management and transportation. The authors note that recent advancements in computing power and internet diffusion have led to a significant uptick in the adoption of AI in OM [16].

iii. Task-Level Replacement and Human Job Impacts: AI's impact on job replacement within service operations should not be ignored. Huang and Rust propose a theory of AI job replacement that categorizes the kinds of intelligence required for service tasks. These include mechanical, analytical, intuitive, and empathetic intelligence. They highlight that AI is replacing humans primarily at the task level, beginning with tasks requiring 'lower' forms of intelligence and progressing to those that require 'higher' forms of intelligence. For service employees, this shift implies that while analytical skills are becoming less important due to AI, softer skills such as empathy and intuition are gaining more significance (Huang & Rust).

iv. Customer Engagement and Strategy: Service operations are also seeing a strategic shift due to AI, specifically in the domain of customer engagement. Huang and Rust lay out guidelines for how to effectively use AI for engaging customers across different stages of service delivery. According to their framework, the nature of the service task, offering, and strategy should dictate the type of AI that should be employed. For instance, mechanical AI should be used for standardization, thinking AI for personalization, and feeling AI for relationalization [17].

v. Organizational and Customer Impact: Lastly, Paluch and Wirtz discuss the organizational challenges and opportunities arising due to the integration of AI and robots in service operations. They emphasize the importance of understanding the potential impact of AI not just for organizational success but also for the well-being of employees and customer satisfaction. Future research needs to focus on understanding these dimensions more comprehensively [18].

vi. Business Value in IT Service Operations: Vijayakumar (2023) specifically explores the business value impact of AI in IT Service Operations, termed as AIServiceOps. He notes that AI has brought about significant efficiency and resilience in operations, liberating IT staff from low-level, repetitive work. His research aims to fill the literature gap concerning the business value impact of AI in IT service operations [19].

In summary, the application and impact of AI in service operations are multifaceted, offering a plethora of opportunities but also presenting significant challenges. Whether it's the nuanced management of SLAs, the transformation of job roles, or the strategic deployment for customer engagement, AI is significantly altering the landscape of service operations.

2.4 Application and Impact of AI and LLMs in Healthcare

The application of artificial intelligence (AI) technologies in healthcare is a subject of growing importance and complexity. The use of large language models (LLMs) like ChatGPT in healthcare settings is still in its infancy but holds significant promise for the future of patient care, medical practice, and public health. This section aims to offer an overview of how LLMs are influencing different facets of healthcare, from diagnostics to patient engagement and cybersecurity.

ChatGPT, developed by OpenAI, has already garnered attention for its potential applications in healthcare. In the field of nursing, for example, it has been viewed as a tool that could provide insights into future trends and developments, such as the growing role of technology, AI, and robotics in patient care [20]. The model's potential for simplifying medical jargon is particularly noteworthy. A study on simplified radiology reports showed that ChatGPT could be used to make these reports more understandable for patients, although the quality of these simplified reports still requires validation [21].

Moreover, the double-edged sword of LLMs in healthcare is particularly palpable in radiology, where their application could either enable or endanger clinical procedures [22]. ChatGPT's capability of generating human-like text has also sparked conversations about its role in cybersecurity, especially concerning the protection of medical information [23]. With more patient data being digitized, the importance of cybersecurity in healthcare cannot be overstated.

Discharge summaries are a crucial element of healthcare administration, often requiring a significant time investment from healthcare providers. ChatGPT has been suggested as a tool to aid in the speedy and efficient creation of these summaries, although there are hurdles to its full-scale deployment in a clinical setting [24]. While LLMs like ChatGPT offer significant benefits, such as time-saving and perhaps even enhanced quality, their implementation should not compromise data governance or patient safety.

There is also speculation about the broader influence of AI in healthcare, transcending beyond ChatGPT to encompass biotechnology and translational medicine [25,26]. These interdisciplinary applications of AI suggest that LLMs could eventually find applications in diverse sectors, such as drug discovery [27].

In summary, the role of ChatGPT and other LLMs in healthcare is an evolving narrative with a wide array of applications, benefits, and concerns. Ensuring the responsible use of this technology while maximizing its potential will require ongoing dialogue among medical professionals, AI researchers, and policymakers.

Given the breadth of applications and concerns, the subsequent sections will delve deeper into specific domains to understand how ChatGPT and other LLMs are reshaping healthcare:

i. 2.4.1 Application and Impact of AI and LLMs in Healthcare Education
ii. 2.4.2 Application and Impact of AI and LLMs in Personalized and Precision Medicine
iii. 2.4.3 Application and Impact of AI and LLMs in Public Health
iv. 2.4.4 Customer Acceptance of AI and LLMs in Healthcare

Through this focused exploration, we aim to provide a nuanced view of the opportunities and challenges presented by LLMs in healthcare.

2.4.1 Application and impact of AI and LLMs in healthcare education

i. Reshaping Medical Education: Artificial intelligence (AI), particularly Large Language Models (LLMs) like ChatGPT, is no longer confined to the realms of science fiction but is becoming increasingly integrated into medical education. Khan *et al.,* [28] have discussed the gradual but steady intrusion of ChatGPT into the educational landscape, providing an avenue for enhanced learning and clinical management training. The study underscores the necessity for careful consideration in employing this technology, citing both its potential benefits and pitfalls [28].
ii. Creating and Revising Clinical Scenarios: One of the key contributions of AI and LLMs like ChatGPT in healthcare education lies in their ability to produce and modify clinical vignettes. According to Benoit, ChatGPT demonstrated a unique competency in swiftly generating, rewriting, and evaluating sets of clinical vignettes, particularly focusing on common childhood illnesses. The technology showcased its proficiency in adhering to the guidelines for vignette creation, which can offer medical students and professionals an invaluable resource for studying a wide range of cases [29].
iii. Bridging the Gap in Academic Writing: ChatGPT has shown promise as a tool for academic writing in the biomedical sciences, despite its limitations. HS Kumar found that the model could generate text responses that were systematic, precise, and original but lacked the depth and quality associated with academic writing. Nevertheless, when utilized under proper academic mentorship, the tool has the potential to serve as a training and upskilling resource for writing in healthcare education [30].
iv. Supplementary Resource for Life Support Training: While LLMs like ChatGPT are not yet ready to replace conventional training methods in life support, they offer some intriguing possibilities. Fijačko *et al.,* conducted a study that revealed ChatGPT's moderate performance on American Heart Association Basic Life Support (BLS) and Advanced Cardiovascular Life Support (ACLS) exams. Although it failed to meet the passing criteria, the tool showed promise as a supplementary educational resource [31].

The advent of AI and LLMs in healthcare education has opened up avenues for innovative learning and skills development. Whether in enhancing traditional educational approaches, contributing to scenario-based learning, or offering supplementary support in academic writing and exam preparation, these technologies are showing potential to reshape healthcare education for the better. However, the unanimous recommendation from existing research is for cautious and responsible implementation [28-31].

2.4.2 Application and impact of AI and LLMs in personalized and precision medicine

Artificial Intelligence (AI) and Large Language Models (LLMs) like ChatGPT are revolutionizing personalized and precision medicine, shaping a more nuanced and effective healthcare system. These technologies are expanding the boundaries of clinical practice, incorporating the understanding of individual variability into patient care and decision-making.

i. Personalized Diagnostics and Treatments: One of the most promising applications of AI and LLMs is in facilitating personalized diagnostics and treatments. AI's ability to integrate and analyse complex genomic and nongenomic data enables a more targeted approach to patient care [32,33]. For instance, AI can work in tandem with precision medicine methods to identify less common phenotypes of patients, thereby tailoring treatments to individuals based on their unique healthcare needs [32,34].

ii. Bridging the Gap between Research and Application: AI technologies are rapidly moving from the research stage to real-world application. The gap between medical research and practical deployment is narrowing, especially in fields like medical imaging [35]. This not only enhances the accuracy of diagnostics but also makes healthcare more efficient and universally accessible.
iii. Cybersecurity and Data Protection: With the increasing application of AI and LLMs in healthcare, issues surrounding data protection and cybersecurity have come to the forefront. Given the sensitivity of medical data, robust cybersecurity measures are essential [23].
iv. Role in Life Sciences and Biotechnology: AI and LLMs are not limited to direct patient care; they have broad applications in life sciences and biotechnology [25]. Whether it's drug discovery, genomics, or other areas of biotechnology, AI helps in data analytics, natural language processing, and decision support, among other applications.
v. Ethical and Technical Challenges: While AI and LLMs hold significant promise, they also bring a host of ethical and technical challenges, including data scarcity and racial bias [35]. These challenges need to be thoughtfully addressed to fully realize the potential of these technologies in healthcare.

In conclusion, the integration of AI and LLMs in healthcare promises to address some of the most pressing challenges in personalized and precision medicine. However, a balanced approach that considers the ethical and technical implications is crucial for the widespread adoption of these technologies.

2.4.3 Application and impact of AI and LLMs in public health

Artificial Intelligence (AI) and Large Language Models (LLMs) like ChatGPT have started to make significant inroads in public health, displaying utility in multiple dimensions, including patient education, medical decision-making, and research.

i. Medical Decision Support and Patient Education: One of the most crucial aspects where LLMs could make a difference is in patient education and decision-making support. ChatGPT can provide tailored responses to specific medical questions, such as those related to cardiopulmonary resuscitation (CPR) [36]. This is highly relevant as public health guidelines like those of CPR are not always easily comprehensible for individuals without specialized training. Hence, LLMs offer an avenue for quickly receiving accurate and tailored information, thus mitigating the risk posed by unreliable sources found during web surfing [36]. Such educational potential is not just limited to emergency procedures. LLMs like ChatGPT can also support medical education at a professional level. For instance, it has been evaluated in the context of the United States Medical Licensing Exam (USMLE) and found to perform at or near passing thresholds [37]. This suggests that AI could potentially aid medical students and even professionals by providing reliable information and decision support, contributing to improved healthcare outcomes [37].
ii. Emotional and Psychological Support: ChatGPT has also shown promise in offering emotional and psychological support, especially in the domain of chronic conditions like cirrhosis and hepatocellular carcinoma (HCC) [38]. While it might not replace human

expertise in these complex domains, it can serve as an adjunct tool that offers practical and emotional support to patients and caregivers, thereby potentially improving patient outcomes [38].

iii. Enhancements in Research and Data Collection: AI has been increasingly recognized for its role in enhancing research in the medical field. ChatGPT has showcased its utility in research conceptualization and even in creating primary research documents [39]. Its ability to help in both patient care and research sets the stage for an integrated AI-enabled healthcare ecosystem that not only addresses current care but also facilitates future advancements.

iv. Limitations and Ethical Considerations: However, despite these potential benefits, there are significant limitations and challenges. For instance, LLMs like ChatGPT have not yet demonstrated significant superiority in terms of accuracy over human responses, especially in high-stakes clinical settings [40]. Furthermore, it is essential to recognize that while AI holds potential to enhance public health, it must be applied thoughtfully, considering social determinants and ethical guidelines [41,42].

In conclusion, AI and LLMs are showing remarkable promise in the field of public health, from patient education to professional medical training and research. As these technologies continue to evolve, their integration into public health systems seems not just plausible but highly advantageous. Nonetheless, to maximize their potential, it is vital to address their current limitations and to apply them in an ethically and socially responsible manner.

2.4.4 Customer acceptance of AI and LLMs in healthcare

The burgeoning integration of Artificial Intelligence (AI) and Language Learning Models (LLMs) like ChatGPT in healthcare has become a focal point of discussion among researchers, clinicians, and policymakers alike. While the technical capabilities of these systems are frequently explored, understanding the human factor—specifically, how patients and healthcare consumers perceive and accept these technologies—remains critical for their successful implementation. Customer acceptance isn't just a matter of technological feasibility; it also encompasses ethical, regulatory, and psychological dimensions. This section delves into various studies that investigate customer perceptions, trust factors, and the overall acceptance of AI and LLMs in healthcare.

i. Perceived Benefits and Risks: Esmaeilzadeh (2020) and Esmaeilzadeh *et al.,* focus on examining the perceived benefits and risks of using AI in clinical settings from the consumers' perspective. According to their studies, patients are largely optimistic about the potential of AI to improve healthcare outcomes but are also cautious about the risks involved. Technological concerns, including performance and communication features, are the most significant predictors of perceived risks [43]. Factors such as privacy concerns, trust issues, and regulatory standards also significantly influence consumer perceptions [44].

ii. Trust in AI Technologies: The issue of trust is critical when it comes to the acceptance of AI in healthcare. A five-country study by Gillespie *et al.,* [45] indicates that citizens' trust varies across countries and domains. Their findings emphasize the need for an evidence-based pathway to strengthen trust and acceptance of AI systems in healthcare among different populations.

iii. Factors Contributing to Acceptance: Kelly *et al.,* conducted a systematic review identifying that perceived usefulness, performance expectancy, attitudes, and trust significantly and positively predicted the behavioural intention to use AI. Despite the promising potential, the need for human contact remains irreplaceable in some cultural scenarios [46].
iv. Cognitive Engagement and Value Creation: Kumar *et al.,* found that cognitive engagement with AI-enabled technologies significantly impacts customer benefits and value creation in healthcare. They suggest that understanding the dynamics of patient engagement with AI can lead to a more nuanced approach to implementing these technologies [47].
v. Personalization and Privacy Concerns: Liu & Tao extended the Technology Acceptance Model to include AI-specific characteristics like personalization, loss of privacy, and anthropomorphism. Their study found these characteristics to be key determinants, fully or partially mediated by trust, in public acceptance of smart healthcare services [48].
vi. Role of ChatGPT in Healthcare: Shahsavar & Choudhury specifically addresses the use of ChatGPT for self-diagnosis. They found that performance expectancy and risk-reward appraisals are significant factors influencing users' intentions to use ChatGPT for healthcare purposes [49].

In summary, customer acceptance of AI and LLMs in healthcare is influenced by a complex interplay of factors including perceived risks and benefits, trust, cognitive engagement, and cultural values. For the successful integration of these technologies, healthcare institutions and regulatory agencies must address these factors through guidelines, audits, and continuous monitoring [43-49].

2.5 Conclusion

In this chapter, we traversed the broad landscape of Artificial Intelligence (AI) and Large Language Models (LLMs), beginning with their developmental trajectory and concluding with a deep dive into their applications in service operations and healthcare. While the utility of AI and LLMs in services at large is noteworthy, their transformative potential within the healthcare sector warrants special attention for multiple reasons.

i. Revisiting The Evolutionary Journey: Section 2.2 helped establish the historical and current contexts of AI and LLMs. The journey from simple, rule-based algorithms to sophisticated models capable of human-like text generation has been meteoric, laying the groundwork for the revolution we witness in various domains today, including service operations and healthcare.
ii. AI and LLMs in Service Operations: The third section (2.3) revealed how AI and LLMs have significantly optimized customer experience and operational efficiency in general service sectors. These technologies have made services more accessible, reliable, and customizable, heralding a new age in the service industry.
iii. The Singular Importance of Healthcare: Our discussions in Section 2.4, however, spotlight the unique and profound implications of AI and LLMs in healthcare. Each subsection outlined a specific arena—be it healthcare education, personalized medicine, public health, or customer acceptance—where AI and LLMs have either already demonstrated impact or hold enormous future potential.
    - 2.4.1 discussed the potential of AI and LLMs in healthcare education, where they can tailor learning experiences for medical professionals and contribute to simulation-based training.

- 2.4.2 elaborated on how personalized and precision medicine could be revolutionized, making healthcare more effective and tailored to individual needs.
- 2.4.3 addressed the broader scope of AI and LLMs in public health initiatives, from predictive modelling of epidemics to public awareness campaigns.
- 2.4.4 focused on customer acceptance, reminding us that despite its promise, the integration of AI into healthcare faces the hurdle of public trust, compounded by ethical and regulatory considerations.

iv. <u>Interconnected Threads: Services and Healthcare:</u> While healthcare is undeniably a specialized form of service, it shares with general services the core objective of fulfilling human needs effectively and efficiently. The commonalities and differences highlighted between sections 2.3 and 2.4 affirm that while healthcare is a form of service, it is unique in its ethical and human implications.

v. <u>Future Outlook:</u> Given the compelling evidence of AI and LLMs' transformative capabilities, future developments will undoubtedly further embed these technologies in our societal fabric. Yet, healthcare will remain the litmus test for these technologies, requiring a harmonious blend of innovation, ethics, and human-centred design.

In conclusion, as AI and LLMs continue to evolve, their increasing significance in service operations and especially in healthcare is unmistakable. However, for their full potential to be realized, especially in healthcare, interdisciplinary collaboration and rigorous ethical frameworks will be essential.

Table 2
Framework literature summary

Framework	Problem Statement	Objective	Methodology	Contribution	Limitation	Perspective
AI on Service Operations Huang, M.-H., & Rust, R. T. (2021). Engaged to a Robot? The Role of AI in Service. Journal of Service Research, 24(1), 30–41.	1. Inadequate understanding of how AI can substitute or replace humans in different service tasks. 2. Absence of a clear roadmap outlining AI's role in taking over tasks requiring diverse intelligence. 3. Limited guidance on optimizing AI's use in service tasks and on the skill, adjustments needed by workers.	1. To develop an understanding of AI's role in various service tasks. 2. To provide a roadmap for AI's advancement and task takeover. 3. To identify the four necessary intelligences for service tasks. 4. To guide firms on choosing between humans and AI for service tasks. 5. To raise awareness of AI's impact on service jobs. 6. To highlight the ethical and social implications of AI in service work.	The main research methodology is a conceptual analysis of AI and service work. Reviewed and synthesized existing research and develop a theoretical framework for understandin g the impact of AI on service operations.	Theoretical: Crafting a framework to assess AI's effects on service jobs. Defining the four intelligences service tasks require. Outlining AI’s role in services and skill adaptation for a human-machine synergy. Managerial: Advising companies on human vs. machine task	1. Unclear task allocation between humans and AI in services. 2. Limited study on customer preferences for service delivery by humans vs. AI. 3. No specific guidance on optimizing processes for human and AI service agents. 4. Inadequate methods for achieving service automation and	What Is Going to Happen to Service Jobs? What Skills Will Become More Important for Humans in Service Industries?

	4. Lack of firm-level direction on deciding between humans and AI for service task completion. 6. Low awareness of the broader implications of AI on service jobs and the need for workers' skill transition. 7. Underexplored ethical and social implications of deploying AI in service work.			allocation. Exploring innovative human-AI service collaborations. Societal: Highlighting AI's influence on service jobs and the need for skill evolution. Emphasizing the ethical and societal facets of AI in services.	enhancing human-AI cooperation. 5. No defined strategies for fostering human-AI collective intelligence. 6. Lack of analysis on job shifts and the future shape of the service economy due to AI. 7. No concrete plans for upskilling workers and students for an AI-integrated service sector.	
LLMs on Healthcare Shen, Y.; Heacock, L.; Elias, J.; Hentel, K.D.; Reig, B.; Shih, G.; Moy, L. ChatGPT and Other Large Language Models Are Double-edged Swords. Radiology 2023, 230163.	The healthcare industry is grappling with issues like inefficiency in clinical workflows and the high burden of documentation. These problems often lead to elevated costs and a decline in service quality.	To evaluate the potential of LLMs in enhancing healthcare operations. This encompasses improving discharge summaries, optimizing diagnostics, predicting disease risk and outcomes, and advancing drug discovery.	These studies typically involved a comparative analysis, benchmarking the effectiveness of LLMs against conventional healthcare procedures and processes.	Theoretical: These studies enrich our understanding of AI, specifically LLMs, in healthcare, opening new research avenues. Managerial: The findings offer healthcare decision-makers practical insights into using LLMs for efficiency and innovation in operations. Societal: LLM applications may improve patient outcomes, reduce	Ethical issues include the risk of bias and transparency. Inaccurate content generation, and justification for incorrect decisions are needed. the issues of interpretability, reproducibility, and the handling of uncertainty.	The application of LLMs to advance healthcare should be carried out ethically and responsibly, taking into account the potential risks and concerns it entails

				healthcare costs, and enhance the quality of service, contributing to public health advancements.		
LLMs on Healthcare Education Khan, A.; Jawaid, M.; Khan, A.; Sajjad, M. ChatGPT-Reshaping medical education and clinical management. Pak. J. Med. Sci. 2023, 39, 605–607.	Tailored education has always been an aspiration in the education sector, yet the scarcity of educational resources makes its widespread implementation challenging. High-quality instructional content has always been both valuable and scarce.	1. To investigate the capacity of LLMs to provide personalized learning experiences within the healthcare education sector. 2. To assess the utility of LLMs in creating cost-effective, diverse, and rich medical teaching content.	The studies utilized a mixed-methods approach, where qualitative and quantitative data were gathered to evaluate the performance of ChatGPT in health care education. Feedback was obtained from healthcare learners to measure the impact of ChatGPT on self-learning and group learning experiences. A separate experiment involved the creation of medical teaching content using ChatGPT, and its effectiveness was evaluated in terms of cost, diversity, and quality.	Theoretical contributions detail AI's enhancement of healthcare education through LLMs like ChatGPT, highlighting personalized learning and cost-effective content creation. Managerially, the research guides healthcare education leaders on leveraging AI for improved self-learning and content generation. Societally, it underscores LLMs' role in making healthcare education more accessible, potentially elevating healthcare quality and patient care.	1. Predominant focus on ChatGPT, overlooking other potential LLMs. 2. Lack of consideration for further development of specialized tools based on LLM capabilities. 3. Issues related to the quality and bias of training datasets, leading to potentially inaccurate information. 4. Limitation of ChatGPT's knowledge of pre-2021 information. 5. Current inability of ChatGPT to handle images. 6. Low performance of ChatGPT in certain topics, as evidenced by failure in a parasitology exam.	More studies are needed to evaluate the potential impact of LLMs on the quality and efficiency of both educational content and assessment tools. LLMs' utility to help in refining communication skills among healthcare students is another aspect that should be further explored as well as the applications of LLMs in the better achievement of the intended learning outcomes through personalized and instantaneous feedback for the students.
LLMs on	The societal	To leverage LLMs	Employing	Theoretical:	1. AI models	1. Active

Personalized and Precision Medicine Johnson, K.B.; Wei, W.Q.; Weeraratne, D.; Frisse, M.E.; Misulis, K.; Rhee, K.; Zhao, J.; Snowdon, J.L. Precision Medicine, AI, and the Future of Personalized Health Care. Clin. Transl. Sci. 2021, 14, 86–93.	demand for personalized medicine is growing, driven by the aspiration for treatments tailored to individual patient characteristics, improving efficacy and minimizing side effects. The most difficult challenges facing personalized diagnosis and prognostication include combining nongenomic and genomic determinants with information from patient symptoms, clinical history, and lifestyles.	for enhancing personalized diagnosis and prognostication by effectively processing multimodal personalized data.	deep learning methodologies for multi-dimensional complex data machine learning training, to generate models that can facilitate personalized and precision medicine.	These studies expand the theoretical understanding of AI and LLMs in personalized medicine, revealing AI's potential for enhancing disease prediction, and diagnosis and aiding in therapy planning. Managerial: These studies shed light on the use of AI and LLMs in personalizing medical data analysis and precision in healthcare decision-making, fostering operational excellence in health management. Societal: At a societal level, they underscore the transformative potential of AI in personalizing patient care and precision medicine, leading to improved health outcomes and reduced healthcare disparities, which can significantly contribute to	may reflect inherent biases in health data, potentially leading to unfair treatment outcomes and affecting clinical validity. 2. The deployment environment and workflows influence AI performance and its clinical effectiveness. 3. As AI use in precision medicine grows, so do concerns about data privacy and the security of personal health information.	research with LLMs envisions enhancing health-related tasks via personalized medical information. 2. LLM integration in personalized healthcare aims for early disease prevention and detection, potentially reducing disease burden and healthcare costs. 3. Building a well-regulated ecosystem for data management is crucial, necessitating new technologies, collaborations, regulations, and business models.

				societal health and well-being.		
LLMs on Public Health Biswas, S. S. (2023). Role of Chat GPT in Public Health. Annals of Biomedical Engineering, 51(5), 868–869.	The low level of health literacy among the public poses a significant challenge in the field of public health.	To provide easily accessible and understandable health information to the general public through LLMs.	Quantitative Analysis Comparative Analysis	Theoretical: Method of emulation on empathetic responses Managerial: Increased efficiency among health providers; Societal: Improved health literacy with better patient outcomes; free availability.	Sometimes non-comprehensive responses; the limited knowledge up to 2021(GPT-4); responses can be limited and not tailored to a specific country or region; legal issues	LLMs have the potential to play a role in public health. Legal and regulation issues should be investigated.
Customer Acceptance of AI in Healthcare Liu, K., & Tao, D. (2022). The roles of trust, personalization, loss of privacy, and anthropomorphism in public acceptance of smart healthcare services. Computers in Human Behaviour, 127, 107026.	Public acceptance of AI healthcare services is crucial for their successful implementation. However, there is limited research on the factors that influence public acceptance of AI-based healthcare services.	1. To examine how AI-specific characteristics (personalization, loss of privacy, and anthropomorphism) are associated with public acceptance of smart healthcare services and how these effects are mediated by trust. 2. To explore whether paths in the proposed research model differ across participants' gender, age, and usage experience.	- The proposed research model was tested using a professional web-based survey company in China. - 769 valid samples were obtained from both users and non-users of smart healthcare services. - Theoretical basis: Technology Acceptance Model (TAM) - Data analysis: Partial Least Squares Structural Equation Modelling (PLS-SEM)	Theoretical: - The study provides empirical evidence on the factors that influence public acceptance of AI-based healthcare services. - The study extends the Technology Acceptance Model (TAM) by incorporating AI-specific characteristics and trust as mediators. Managerial: The study provides insights for healthcare providers and policymakers on how to design and promote smart	- The study was conducted in China, which may limit the generalizability of the findings to other cultural contexts. - The study relied on self-reported data, which may be subject to social desirability bias.	1. Future research could explore the factors that influence public acceptance of AI-based healthcare services in other cultural contexts. 2. Future research could use experimental designs to test the causal relationships between the variables in the proposed research model.

	healthcare services that are more acceptable to the public. Societal: The study contributes to the development of AI-based healthcare services that can improve the quality and accessibility of healthcare for the general public.	

3. Research Method

3.1 Overview

The essence of this research revolves around understanding the implications, effects, and outcomes of integrating Large Language Models (LLMs) within healthcare industries. This chapter elucidates the methodologies employed to accomplish the research objectives and address the questions formulated. The foundation of this methodology is built on:

i. The Aim of this Research: The primary aim of this research is to explore the multifaceted impact of Large Language Models (LLMs) within the healthcare sector. This includes examining their contributions to operational efficiency, the enhancement of patient experience, and their influence on cost structures. Additionally, the study seeks to understand the factors that drive the acceptance and trust in LLM-integrated healthcare, investigating how improvements in efficiency and customer experience, as well as cost considerations, affect stakeholders' willingness to adopt these advanced AI technologies.
ii. Research Questions: The pivotal inquiries this study seeks to answer are:
   - RQ1: How does the integration of LLMs contribute to efficiency in healthcare industries?
   - RQ2: What is the impact of LLMs on customer experience in healthcare industries?
   - RQ3: How does the use of LLMs affect the cost in healthcare industries?
   - RQ4: How does improved efficiency influence the acceptance of LLM-integrated healthcare?
   - RQ5: How does customer experience affect the acceptance of LLM-integrated healthcare?
   - RQ6: How does cost influence the acceptance of LLM-integrated healthcare?
iii. Data Collection & Analysis: The methodology leans on a mixed-mode approach, amalgamating both quantitative and qualitative techniques. The quantitative dimension will involve a survey employing Structure Equation Modelling to derive tangible statistical

insights. In contrast, the qualitative facet will encompass interviews that will undergo thematic analysis to derive deeper, nuanced understandings. For managing missing data, we'll use multiple imputations for random gaps and sensitivity analysis for non-random ones to ensure data robustness. Outliers, defined as data points more than 3 standard deviations from the mean, will be evaluated individually using the Z-score method to maintain analytical accuracy.

iv. Sampling: In this research, while acknowledging the practical constraints of time and resources, we aim to balance the efficiency of convenient sampling with the rigor of stratified random sampling to ensure a representative sample across diverse demographics, professional backgrounds, and geographic locations within China's healthcare sector. Initially, we will employ a convenient sampling approach to quickly engage accessible participants from our targeted demographic within the healthcare sector. Subsequently, to ensure the representativeness of our sample, we will categorize these participants into strata based on key demographic variables such as age, gender, professional role, and geographic location (urban vs. rural). From each stratum, we will then randomly select participants for inclusion in the study. This hybrid sampling strategy allows us to efficiently manage research constraints while ensuring our sample accurately reflects the diversity and complexity of China's healthcare environment.

v. Instrumentation: Established questionnaires will be consulted and possibly modified to align with our research scope. Furthermore, inspiration will be drawn from related academic articles to craft bespoke questionnaires.

This chapter possesses a coherent understanding of the methodological scaffolding that supports this research, ensuring its robustness, relevance, and potential contribution to academic and practical realms.

3.2 Research Design

The purpose of the research design is to provide a structured approach to answer the research questions. This study will use a mixed-method design to ensure a comprehensive understanding of the impact of LLMs on healthcare industries.

3.2.1 Method

The choice of a mixed-method research design is motivated by the need to capture both quantitative and qualitative insights. Quantitative data will provide measurable data related to the integration of LLMs, efficiency improvements, customer experience, and cost structure. In contrast, qualitative data will offer a deeper understanding of patient experiences, perceptions, and nuances that might not be captured by quantitative measures alone.

Quantitative Research:

Method: Survey

Aim: To gather measurable data from a large sample of healthcare professionals and patients to answer the research questions.

Instrument: Structure Equation Modelling will be used to analyse the survey data, primarily to understand the relationships and impacts.

Qualitative Research:

Method: Interview

Aim: To gain in-depth insights into the experiences and opinions of healthcare professionals and patients concerning the integration and use of LLMs.

Instrument: Thematic Analysis will be employed to interpret the qualitative data collected from the interviews, focusing on identifying patterns or themes.

3.2.2 Sampling and instrument

This survey targets a diverse group with an interest in the healthcare industry's future and current state, especially in the context of technological advancements such as LLMs. The participants range from healthcare consumers to professionals and IT specialists involved in health-related technological solutions. Non-probabilistic convenient sampling is utilized, inviting respondents to participate voluntarily, thus simplifying the data collection process and ensuring a sample that accurately reflects willing participants' views. Employing "Questionnaire Star," a leading online survey tool in China, the study capitalizes on its expansive reach through WeChat to distribute the questionnaire effectively.

The instrument for data collection, the questionnaire, is meticulously crafted to encompass a variety of question types to extract a rich data set. It includes single-choice questions for straightforward demographic data, 7-point Likert scale items for nuanced attitudes and perceptions, and open-ended questions to capture more complex, qualitative responses.

To accommodate the diversity of data, interval scales are employed for Likert-scale questions, providing a spectrum of response intensity. This enables the utilization of a wide array of descriptive statistics to portray the respondents' sentiments. Open-ended questions offer respondents the opportunity to share personal insights and experiences, adding a qualitative dimension to the data set. Microsoft Excel is the tool of choice for analysis, offering robust functionalities to manage, analyse, and visualize the collected data for a more comprehensive interpretation of the results.

3.2.3 Data collection

"Questionnaire Star" is pivotal in this study for creating, disseminating, and collecting the survey. The platform's adaptability facilitates a customized approach to questionnaire design, tailored to elicit detailed information relevant to the research objectives.

Data collection relies mainly on the "Questionnaire Star" platform, with the survey designed to require approximately 10 minutes of participant engagement. This duration is deliberate to accommodate the mixed-mode nature of the survey, seeking both qualitative depth and quantitative breadth in its inquiries.

The survey is structured into six parts, starting with demographic questions in a single-choice format to streamline the data collection process. The core of the survey probes into the key research areas—trend, efficiency, cost, experience, and acceptance of LLMs in healthcare—through Likert-scale questions and concludes with open-ended questions. This design enables a multifaceted analysis of attitudes and experiences related to LLM applications in healthcare.

In crafting the survey, particular attention is given to the flow and clarity of questions to encourage thoughtful and considered responses, thereby ensuring the collection of high-quality data. The open-ended questions provide space for participants to express their opinions and experiences, granting valuable insights beyond quantitative measures. This blend of question types is essential for a well-rounded understanding of the research topic. The questionnaire is as follows:

Table 3
Questionnaire question sheet

Demographic Question				
Gender		What is your gender?		
Age		What is your age?		
Education		What is your education level?		
Tech Awareness Status		Have you heard of Large Language Models (like ChatGPT, Bard, etc.)?		
Research Variables	Survey Question		Interview Question	
TREND: Emerging Trend of LLM Integration in Healthcare	SQ1	To what extent do you think LLMs could contribute to the healthcare industry?	SI1	What role do you think LLMs will play in the healthcare industry?
	SQ2	Would you be willing to consult medical and health issues with an LLM chatbot, such as ChatGPT?		
	SQ3	Can LLM help accelerate medical research?		
EFFICIENCY: LLM-Related Operational Efficiency Changes in Healthcare	SQ4	Can LLM help doctors complete their work more quickly?	SI2	Medical resources are always scarce. How to efficiently use scarce resources is an unremitting pursuit in the healthcare industry. In this regard, what role do you think LLM will play?
	SQ5	Can LLM speed up the examination and judgment of patient conditions?		
	SQ6	How do you perceive the future accuracy of LLM in disease diagnosis?		
EXPERIENCE: Experience Enhancements Linked to LLM Deployment in Healthcare	SQ7	Does LLM contribute to providing more personalized care and services for patients?	SI3	In the current medical experience, what aspects displease you? What improvements in experience do you think LLMs could bring?
	SQ8	Can LLM help patients more clearly understand their medical information and health conditions?		
	SQ9	Can LLM assist you in better managing your health?		
COST: Cost Dynamics Associated with LLM Application in Healthcare	SQ 10	Can the use of LLM in hospitals reduce the cost of each medical visit?	SI4	What cost increases and decreases do you think would result if a medical institution were to use LLMs?
	SQ 11	Can the use of LLM in health check-up facilities reduce the cost of each check-up?		
ACCEPTANCE: Public Acceptance of LLM-Integrated Healthcare Solutions	SQ 12	To what extent would you accept and trust the diagnosis and treatment plans provided by LLM?	SI5	What factors would encourage you to trust and use LLM-supported medical services? What factors would lead you to distrust and not use them?
	SQ 13	To what extent would you accept and trust the health management advice provided by LLM?		

3.2.4 Data analysis techniques
3.2.4.1 Unit of measurement

In this study, the 7-point Likert scale is employed extensively throughout the questionnaire to measure respondents' attitudes and perceptions towards various aspects of LLMs in healthcare. This scale is a psychometric response scale predominantly utilized in questionnaires, and it is instrumental in the fields of psychological research and social sciences. A 7-point Likert scale offers a series of statements that respondents may evaluate, providing more granularity than the commonly used 5-point scale. This finer scale can potentially reveal more subtle shifts in opinion or perception, as it offers options ranging from "strongly disagree" to "strongly agree," typically anchored by integers from 1 to 7. Utilizing a 7-point scale enables participants to express a neutral stance or varying degrees of agreement or disagreement, contributing to a more nuanced understanding of their stances on the issues presented. The key advantage of this scale lies in its ability to transform subjective attitudes and opinions into quantifiable data, thereby facilitating an in-depth analysis of complex sentiments and trends.

3.2.4.2 Data preprocessing

Data preprocessing is a critical step before conducting any statistical analysis. It involves ensuring data quality by checking for and addressing missing values, outliers, and duplicate records. Strategies for managing missing data include imputation, deletion, or employing algorithms that can handle such discrepancies. Outliers, identified through statistical tests or data visualization, may need adjustments or removal to maintain data integrity. Duplicate entries must be identified and resolved to avoid skewed results. This process is vital for maintaining the robustness and accuracy of the subsequent analysis.

3.2.4.3 Statistical analysis tools

For the statistical analysis of the data gathered from the 7-point Likert scale and other question types, SmartPLS software is utilized for structural equation modelling (SEM). SEM is a comprehensive statistical analysis technique that allows for the assessment and modelling of complex relationships between observed and latent variables. It is particularly suitable for exploratory studies like this one, where the relationships between the constructs of LLM integration, efficiency, cost, experience, and acceptance are multifaceted and hypothesized based on theoretical underpinnings.

SmartPLS is especially advantageous for its user-friendly interface, making it accessible to researchers from various disciplines, including those with limited statistical backgrounds. It offers an intuitive graphical representation of models and easy-to-interpret outputs, such as path coefficients, loading values, and R-squared values, which help in articulating the strength and significance of the relationships between variables. The SEM approach using SmartPLS is particularly fitting for this study as it can handle the complex model structures and data types, including the interval data from the Likert-scale responses, providing a robust framework for the investigation of the hypothesized relationships.

3.3 Chapter Summary

This chapter has systematically outlined the research design of the study, focusing on the methodologies employed to investigate the impact of Large Language Models (LLMs) on the healthcare industry. By employing a structured questionnaire disseminated through the Questionnaire Star platform via WeChat, the study captured diverse perspectives from participants with varying degrees of involvement in healthcare, ranging from consumers to professionals and IT experts.

The questionnaire, the primary instrument for data collection, was carefully developed to incorporate various question types, including single-choice, 7-point Likert scale, and open-ended questions. This mix aimed to extract both quantitative and qualitative data, allowing for a more robust analysis of the LLMs' impact on healthcare. The 7-point Likert scale, in particular, facilitated a more nuanced capture of participants' attitudes and perceptions, providing a rich dataset for subsequent analysis.

In terms of data collection, the Questionnaire Star platform's compatibility with WeChat significantly enhanced the reach and convenience of the survey, resulting in the successful collection of 66 complete responses. The data collection was designed to be succinct yet comprehensive, respecting the participants' time while ensuring the depth of information collected was sufficient for the study's needs.

The chapter also detailed the data preprocessing steps and the analytical tools utilized. SmartPLS emerged as the chosen software for statistical analysis due to its efficacy in structural equation modelling—essential for validating the research hypotheses. This choice reflected a commitment to employing rigorous and sophisticated analytical techniques to ensure the reliability and validity of the findings.

In summary, this chapter has provided a transparent and detailed account of the research design, data collection, and analysis methods. It sets the stage for a comprehensive understanding of the subsequent chapters, which will delve into the findings and discuss the implications of LLMs in healthcare, guided by the structured approach outlined herein. The groundwork laid in this chapter is critical for the credibility of the research and the actionable insights it aims to provide.

4. Findings and Discussions

This chapter presents the findings from a systematic analysis of survey data concerning the role of Large Language Models (LLMs) in healthcare. It outlines the contributions of LLMs across various facets of healthcare delivery and management, as perceived by the survey respondents. Through statistical validation and direct feedback from the field, this study uncovers the potential of LLMs to revolutionize the healthcare industry by enhancing efficiency, improving patient experience, and even reducing costs, despite a nuanced understanding of cost implications on technology acceptance.

For ease of reference in the following table, the questionnaire items will be referred to by their abbreviated labels as presented in Table .

Table 4
Questionnaire questions and short name relationship

Questionnaire Question	Short Name
To what extent do you think LLMs could contribute to the healthcare industry?	Trend 1
Would you be willing to consult medical and health issues with an LLM chatbot, such as ChatGPT?	Trend 2
Can LLM help accelerate medical research?	Trend 3
Can LLM help doctors complete their work more quickly?	Efficiency1
Can LLM speed up the examination and judgment of patient conditions?	Efficiency2
How do you perceive the future accuracy of LLM in disease diagnosis?	Efficiency3
Does LLM contribute to providing more personalized care and services for patients?	Experience1
Can LLM help patients more clearly understand their medical information and health conditions?	Experience2
Can LLM assist you in better managing your health?	Experience3
Can the use of LLM in hospitals reduce the cost of each medical visit?	Cost 1
Can the use of LLM in health check-up facilities reduce the cost of each check-up?	Cost 2
To what extent would you accept and trust the diagnosis and treatment plans provided by LLM?	Acceptance1
To what extent would you accept and trust the health management advice provided by LLM?	Acceptance2

4.1 Statistical Analysis of Data
4.1.1 Theoretical framework

In our theoretical framework within SmartPLS depicted in Figure 2, we posit that the trend in the adoption of Large Language Models (LLMs) in healthcare (LLM Healthcare Trend) impacts Operational Efficiency, Customer Experience, and Cost. These three dimensions are critical determinants of LLM Healthcare Acceptance. The model suggests that as healthcare industries increasingly integrate LLMs, we anticipate improvements in efficiency and customer experience, along with cost modifications. These changes, in turn, are expected to influence the acceptance of LLM technologies within the healthcare domain. This cascade effect, from LLM Healthcare Trend through to Operational Efficiency, Customer Experience, and Cost, ultimately culminates in the level of acceptance by healthcare professionals and patients.

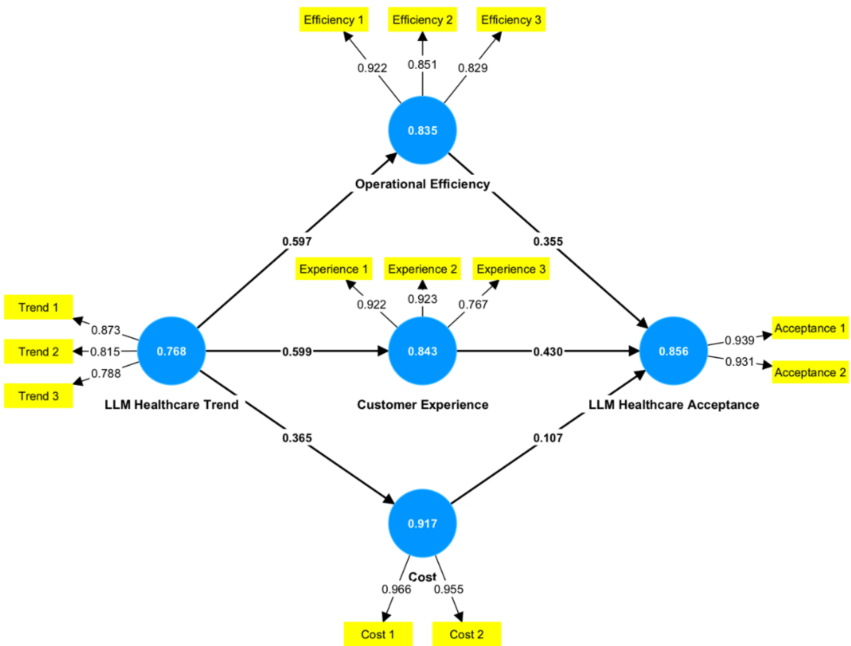

Fig. 2. Theoretical framework

4.1.2 Cronbach's Alpha

Cronbach's Alpha is a measure of internal consistency, commonly utilized to assess the coherence and reliability of items within a questionnaire or scale. It is derived from the inter-item correlations and is indicative of the extent to which all the items in a test measure the same concept or construct. The Alpha coefficient ranges from 0 to 1, with values closer to 1 suggesting a high level of internal consistency among the items within the scale [50].

In the context of survey research, a Cronbach's Alpha value exceeding 0.7 is generally considered acceptable, reflecting adequate reliability for the data obtained from the questionnaire [51]. As depicted in Table , all Cronbach's Alpha values surpass the 0.7 threshold, affirming the reliability of the data collected through this survey instrument [52].

The verification of data reliability through Cronbach's Alpha enables researchers to proceed with a greater degree of confidence in subsequent data analyses. This confidence stems from the assurance that the scale or questionnaire used is a consistent measure of the construct it purports to assess, which in turn supports the derivation of sound and reliable research conclusions.

Table 5
Convergent validity and construct reliability

Latent Construct		Loadings	Standard Deviation	Cronbach's Alpha	Composite Reliability		Average Variance Extracted (AVE)
					Rho_a	rho_c	
Trend	Trend 1	0.873	0.852	0.768	0.774	0.866	0.683
	Trend 2	0.815	0.791				
	Trend 3	0.788	0.933				
Efficiency	Efficiency 1	0.922	0.686	0.835	0.835	0.901	0.753
	Efficiency 2	0.851	0.814				
	Efficiency 3	0.829	0.913				
Experience	Experience 1	0.922	0.969	0.843	0.866	0.906	0.764
	Experience 2	0.923	0.853				
	Experience 3	0.767	0.712				
Cost	Cost 1	0.966	1.141	0.917	0.929	0.960	0.923
	Cost 2	0.955	1.062				
Acceptance	Acceptance1	0.939	0.974	0.856	0.858	0.933	0.874
	Acceptance2	0.931	0.901				

4.1.3 Average Variance Extracted (AVE)

Average Variance Extracted (AVE) serves as a key indicator of construct validity within the framework of structural equation modelling (SEM) [53]. This metric quantifies the level of variance captured by a construct through its indicators relative to the variance due to measurement error. Essentially, it calculates the proportion of total variance that is attributed to the construct in comparison to the error variance.

To compute AVE, one sums up the squared loadings of the indicators associated with the construct and then divides this total by the number of indicators. AVE values range from 0 to 1, where a higher AVE signifies that a greater proportion of variance in the indicators is accounted for by the latent construct, thus implying robust construct validity [54]. A threshold of 0.5 or above is commonly accepted as satisfactory, indicating that the construct explains more than half of the variance of its indicators.

As presented in Table , the AVE values exceed the 0.5 benchmark, suggesting that the constructs in question offer a substantial explanatory capacity for the variances in their associated indicators. This degree of explanatory power corroborates the soundness of the measurement model, confirming that the constructs are reliable and effective in capturing the intended concepts.

The substantial AVE values suggest that the measures designed in the survey are closely representative of the underlying constructs and are not unduly influenced by measurement error or extraneous variables. Consequently, the data derived from such a measurement model can be deemed more credible, bolstering the confidence with which one can interpret the survey findings. Researchers, thus, can proceed with greater assurance when utilizing these data in further statistical analyses and inferences, leading to more grounded and valid research outcomes [55].

4.1.4 Loadings

In the context of structural equation modelling (SEM), loadings are critical indicators that measure the strength and nature of the association between latent constructs and their observable indicators. Loadings, therefore, play a pivotal role in assessing the extent to which individual indicators represent a latent construct. These loadings are expressed numerically, typically ranging between -1 and +1, with values closer to these extremes indicating a stronger correlation. A positive loading signifies a direct relationship, whereas a negative loading indicates an inverse relationship between the construct and its indicators.

The magnitude of these loadings is crucial for establishing the validity of each observed indicator within the model. Specifically, a loading value above the threshold of 0.708 is generally considered to indicate a robust and reliable measure, suggesting that the observed indicator is a good representative of the underlying latent construct [56]. This threshold ensures that the majority of the variance in the indicator can be accounted for by the latent variable it is intended to measure.

In practical terms, when evaluating the loadings within an SEM, a higher value signifies that an indicator has a strong and significant role in defining the construct, providing a substantial contribution to its conceptual essence. It reflects that the indicator shares a substantial proportion of variance with the construct, thereby reinforcing the construct's validity within the model [57].

Upon reviewing the loadings presented in Table , it's evident that all values surpass the 0.708 benchmark. This outcome not only underlines the strength of the relationships between the constructs and their respective indicators but also reinforces the construct validity within the model. Consequently, this high level of loadings offers a robust foundation for subsequent analysis, providing confidence in the structural model's capacity to reflect the theoretical framework accurately and effectively.

4.1.5 Cross-loading

The concept of cross-loading in structural equation modelling (SEM) involves comparing the loading of each indicator on its assigned construct with its loading on all other constructs in the model. This comparison is crucial for establishing discriminant validity, which assures that each indicator most strongly represents its intended construct rather than others [58].

Upon examining Table , it is evident that the cross-loading condition has been satisfactorily achieved. Each indicator's primary loading on its construct exceeds its cross-loadings with other constructs, confirming that the indicators are distinct and measure their respective constructs effectively [59]. This demonstrates that each construct is well-defined and captured by its indicators.

For instance, "Trend1" has a strong primary loading of 0.860 on its construct, while its cross-loadings on "Efficiency," "Experience," "Cost," and "Acceptance" are significantly lower. This pattern holds for all indicators across the board, suggesting a clear and strong relationship between the indicators and their respective latent variables.

The fulfilment of this criterion within the measurement model ensures that the indicators are not misrepresentative of other constructs, thus reinforcing the model's structural integrity [60]. Such clear demarcation between constructs due to well-satisfied cross-loading conditions solidifies the foundation for subsequent model interpretations and theoretical conclusions drawn from the SEM analysis.

Table 6
Hetero mono trait

		Trend	Efficiency	Experience	Cost	Acceptance
Trend	Trend1	0.873	0.505	0.554	0.320	0.436
	Trend2	0.815	0.433	0.441	0.249	0.394
	Trend3	0.788	0.532	0.479	0.328	0.261
Efficiency	Efficiency1	0.497	0.922	0.486	0.373	0.584
	Efficiency2	0.586	0.851	0.597	0.364	0.564
	Efficiency3	0.466	0.829	0.583	0.486	0.624
Experience	Experience1	0.516	0.666	0.922	0.496	0.704
	Experience2	0.619	0.525	0.923	0.454	0.628
	Experience3	0.420	0.484	0.767	0.400	0.526
Cost	Cost1	0.365	0.451	0.544	0.966	0.514
	Cost2	0.335	0.453	0.443	0.955	0.435
Acceptance	Acceptance1	0.420	0.697	0.661	0.430	0.939
	Acceptance2	0.401	0.573	0.673	0.501	0.931

4.1.6 Hypothetical structure model

In the Hypothetical Structure Model, the Standard Deviation (STDEV) is employed to gauge the variability or dispersion around the mean (average) of each construct's indicators. It essentially quantifies how much the indicators deviate from the expected value, providing insights into the measurement's precision. According to the study by Zeng *et al.,* [61], the standard deviation should be below 0.168 to ensure the stability and reliability of the measurement. As indicated in Table, all measured values fall beneath this threshold, thereby meeting the stipulated criteria.

The T Statistics (IO/STDEV), also known as the T-value, is the test statistic for the t-test, calculated as the ratio of the path coefficient (Indicator Original) to its standard deviation. This statistic assesses the significance of the relationship between the constructs in the model. A higher T-value typically indicates a more significant relationship.

The P Values in Table represent the probability that the observed data would occur if the null hypothesis were true. A P Value below a commonly accepted threshold (usually 0.05) suggests that the observed data are unlikely under the null hypothesis, leading to its rejection. This indicates that the path coefficients are statistically significant and not due to random chance.

In this specific model, the path coefficients are considered significant as their associated P Values are below the 0.05 threshold. The results suggest that the relationships hypothesized in H1, H2, H3, H4, and H5 are statistically significant and support the proposed theory. For instance, the positive and significant path coefficients in H1, H2, and H3 suggest that the LLM Healthcare Trend positively influences Efficiency, Experience, and Cost constructs, respectively.

However, H6 shows a P-value above the threshold of 0.05, which means the relationship between Cost Reduction and LLM Healthcare Acceptance is not statistically significant. The negative sign in the confidence interval also indicates a negative or inverse relationship, though not significant in this context. This could reflect the complex nature of healthcare decision-making, where cost may not be as decisive a factor in the acceptance of LLMs as efficiency or user experience. It underscores that the healthcare industry might consider emphasizing the value and quality of LLM-enabled services, rather than competing on price alone. Furthermore, healthcare providers could focus on educating patients about the non-monetary benefits of LLM, such as improved access to care and personalized treatment plans. The application of digital health technologies heralds transformative progress in individual and population health management, allowing for the integrated generation of new knowledge and insights [62]. Such technologies also enhance the public's accessibility and flexibility of healthcare [63], and the recent pandemic has underscored the importance of digital health in transforming care delivery and outcomes [64].

In summary, the model's path coefficients, T-values, and P-values provide a robust framework for validating the proposed hypotheses. The significant paths reinforce the theory that LLMs can positively influence efficiency, experience, and cost aspects within the healthcare industry, contributing to the overall acceptance of LLM healthcare. Conversely, the non-significant result in H6 warrants further investigation, potentially because individuals may not regard cost considerations as critical in matters of life and health as they do in other areas.

Table 7
Hypothetical structure mode

Hypo	PLS Paths	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (IO/ STDEV)	2.5%	97.5%	P Values	Hypothesis Accepted
H1	LLM Healthcare Trend → Efficiency	0.597	0.608	0.098	6.086	0.411	0.790	0.000	Yes
H2	LLM Healthcare Trend → Experience	0.599	0.602	0.086	6.942	0.410	0.748	0.000	Yes
H3	LLM Healthcare Trend → Cost	0.365	0.367	0.119	3.064	0.119	0.585	0.002	Yes
H4	Efficiency → LLM Healthcare Acceptance	0.355	0.361	0.136	2.613	0.098	0.640	0.009	Yes
H5	Experience → LLM Healthcare Acceptance	0.430	0.418	0.118	3.631	0.168	0.638	0.000	Yes
H6	Cost → LLM Healthcare Acceptance	0.107	0.108	0.111	0.965	- 0.100	0.331	0.335	No

4.2 Analysis of Investigation Result
4.2.1 Demographic profile of respondents

The demographic breakdown of the respondents provides critical insights into the composition of the study sample, laying the groundwork for a nuanced understanding of the survey results. In total, 66 individuals participated in the survey, offering a diverse cross-section of views that enriched the data analysis.

4.2.1.1 Gender

i. Quantitative Analysis: Gender representation in the survey was nearly balanced, with females accounting for 48.48% (32 out of 66) and males making up 51.52% (34 out of 66) of the respondents, showcasing a diverse range of perspectives in the responses collected.
ii. Qualitative Analysis Discussion: The nearly equal gender distribution in this survey underscores the inclusive nature of the study and ensures that the findings are not overly skewed by a single-gender perspective. The balanced viewpoints between female and male participants may reflect the general gender dynamics within the healthcare sector and the broader societal engagement with LLMs. This diversity is beneficial, as gender can influence the perception and utilization of healthcare technology, potentially affecting the acceptance and adoption of LLMs. For instance, females may have different healthcare needs and technology interactions compared to males, which could influence their assessment of LLMs in healthcare. By capturing a nearly equal gender representation, the study is well-positioned to explore these nuanced differences and their implications on the technology's acceptance.

4.2.1.2 Age

i. Quantitative Analysis: The survey participants displayed a diverse range of ages. The majority of the respondents, representing 36.36% (24 individuals), were under the age of 30. This suggests a significant engagement with the younger demographic, possibly reflecting their openness to new technologies like LLMs. Those aged between 30 to 35 years made up 22.73% (15 individuals) of the respondents, indicating a substantial representation of early to mid-career professionals who may have practical experience with the application of LLMs in their work. The 36 to 40 age group constituted 30.30% (20 individuals) of the sample, reflecting a cohort that likely brings a mix of experience and adaptability to technological advancements in healthcare. Respondents over the age of 40 were the least represented in the survey, comprising 10.61% (7 individuals), which may suggest varying degrees of familiarity with or access to LLM technology among this group.
ii. Qualitative Analysis Discussion: The age distribution of respondents is indicative of the generational differences in technology adoption and perception. The significant representation of the younger demographic, those under 30, may point to a greater propensity for embracing innovative technologies, which is crucial for the adoption of new tools like LLMs. This age group is often more tech-savvy and may have fewer reservations about integrating new technologies into their healthcare experiences. The representation of individuals between 30 to 35 years reflects a segment that is likely to be at the forefront of implementing LLMs in practical healthcare settings, providing valuable insights into the applicability and usability of these models in real-world scenarios. The cohort aged 36 to 40 adds to the survey's depth by bringing a likely blend of technological adaptability and healthcare system understanding. Their perspectives can offer a bridge between innovative applications and established healthcare practices. The smaller proportion of participants over 40 could signal a gap in exposure or a slower adoption rate of new technologies such as LLMs within this age group, which may highlight the need for targeted educational and engagement strategies to increase familiarity and trust in LLMs.

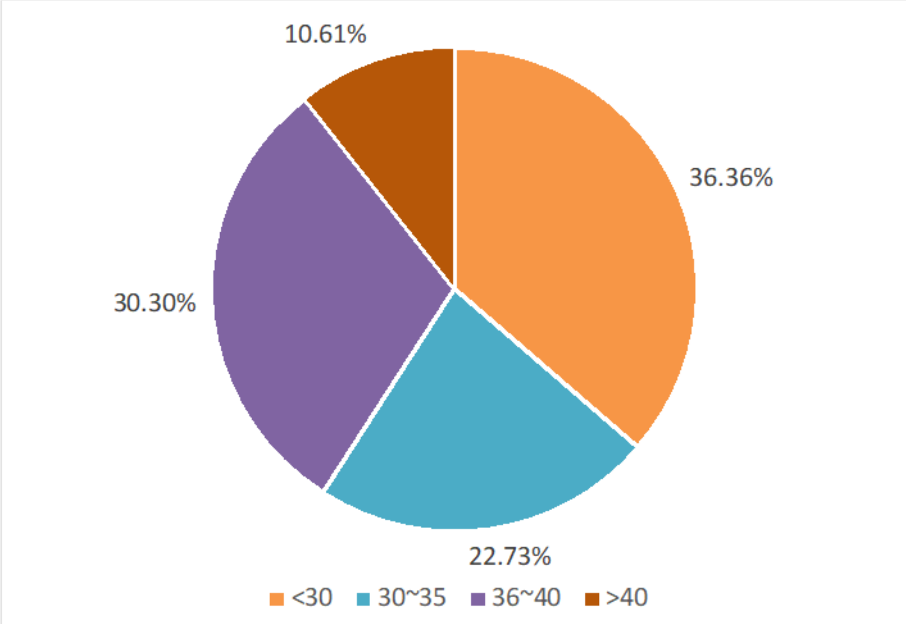

Fig. 1. Age distribution

4.2.1.3 Educational background

i. Quantitative Analysis: The educational qualifications of respondents present a critical dimension to the survey, offering insight into the academic diversity within the group. From the total of 66 participants:
   - Bachelor's Degree: A significant 42.42% (28 individuals) reported holding a bachelor's degree, indicating a solid foundational level of tertiary education within the sample.
   - Master's Degree: Individuals with master's degrees comprised 24.24% (16 participants), reflecting a substantial representation of advanced academic achievement.
   - Doctoral Degree: Respondents with the highest level of academic attainment, a doctorate, constituted another 24.24% (16 participants) of the sample, indicating a highly educated cohort reflective of the survey's target demographic.
   - High School and Others: A smaller proportion, 9.09% (6 individuals), reported a high school education or other forms of non-traditional or vocational training as their highest attained level of education. This category encapsulates a diverse set of educational experiences outside the conventional academic path, highlighting the inclusion of varied perspectives in the survey population.

ii. Qualitative Analysis Discussion: The distribution of educational backgrounds among the survey respondents is indicative of a sample with a strong academic foundation, which may influence their perceptions and interactions with technology like Large Language Models (LLMs) in healthcare.

The prevalence of bachelor's degree holders in the survey suggests that a significant portion of participants have a foundational understanding of higher education concepts, which may include exposure to technological advancements and critical thinking skills relevant to evaluating new healthcare tools. This level of education could correspond with an openness to adopting new technologies, as well as an ability to critically assess their practical applications in healthcare settings.

The substantial representation of individuals with master's degrees points to an advanced understanding of specialized academic knowledge, which likely includes familiarity with research methodology and analytical skills. These competencies are essential for comprehending the complexities and potential of LLMs in healthcare and may predispose this group to appreciate the nuances of such technologies.

The cohort with doctoral degrees, representing an equal proportion of master's degree holders, brings the highest level of academic achievement into the mix. This group's presence is significant, as they can offer deep insights into the theoretical underpinnings and potential research applications of LLMs. Their critical and research-oriented approach could provide a sophisticated level of scrutiny to the acceptance and implementation of LLMs in healthcare.

Lastly, those with high school education or other forms of training contribute diversity to the survey, potentially reflecting a more practical and experiential viewpoint. This group may prioritize different factors when evaluating healthcare technologies, such as ease of use and immediate applicability, which can be crucial for broad-based technology acceptance and user satisfaction.

In summary, the educational background of the respondents provides a multidimensional view of the potential reception and evaluation of LLMs in healthcare. The higher educational attainment of most participants could correlate with greater receptivity to complex innovations, while the inclusion of those with high school and vocational training ensures that practical and varied perspectives are also considered. This blend of educational experiences enriches the understanding of how different demographic groups might perceive and interact with LLMs in the healthcare sector.

4.2.1.4 Awareness of Large Language Models (LLMs)

The survey's findings indicate a significant awareness of Large Language Models (LLMs) like ChatGPT among the participants. An overwhelming 89.39% (59 out of 66) acknowledged familiarity with these advanced AI systems. This substantial recognition reflects the growing penetration and discourse surrounding LLMs in contemporary society. The high level of awareness also suggests that LLMs have not only piqued public interest but have also become a topic of widespread conversation, likely due to their potential impact across various sectors, including healthcare.

The pronounced awareness among respondents underscores the relevance of LLMs as a technological phenomenon that is increasingly becoming part of the collective consciousness. It is indicative of a trend where cutting-edge technologies, especially those that promise to revolutionize communication and information processing, quickly capture the attention of both professionals and the general public [65]. This heightened level of awareness is a testament to the rapid advancements in the field of AI and a populace that is keeping abreast with these changes, recognizing the implications they hold for future developments in healthcare and beyond.

Collectively, the demographic data underscore the depth and breadth of the respondent pool, highlighting the survey's capacity to capture a wide array of insights on the perception and acceptance of LLMs in the healthcare industry.

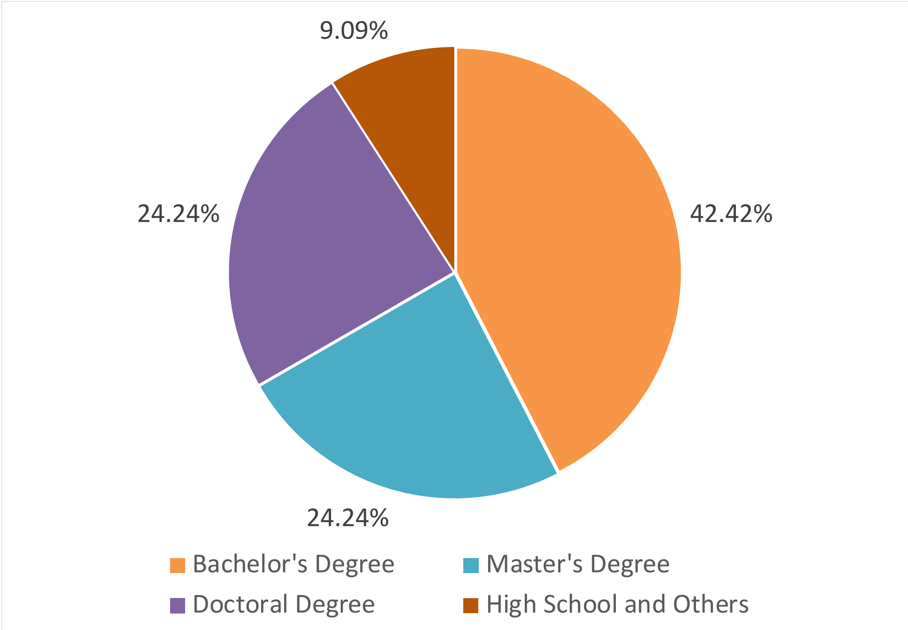

Fig. 2. Statistics of educational background

4.2.2 To what extent do you think LLMs could contribute to the healthcare industry?

The graphic distribution of responses reveals a compelling consensus on the significance of LLMs in healthcare, with a majority of 53.03% of participants acknowledging the 'very important' role of LLMs. This majority suggests that LLMs are widely recognized for their potential to revolutionize various facets of healthcare, from patient engagement to clinical decision-making.

An additional 25.76% of respondents rated the contribution of LLMs as 'important', reinforcing the sentiment that LLMs are more than just a technological novelty; they are increasingly seen as an integral component that can drive significant improvements within the sector.

A smaller segment of the sample, 16.67%, deemed LLMs' role as 'slightly important', which may reflect a cautious optimism about these technologies. These respondents might acknowledge the benefits of LLMs while also recognizing the complexities and challenges inherent in integrating advanced AI within healthcare systems.

Neutral views constitute 4.55% of responses, indicating a reserved judgment or a lack of sufficient information to assess the impact of LLMs.

Interestingly, the survey revealed that none of the respondents consider LLMs unimportant for healthcare, indicating a universal acknowledgment of their potential value in the industry. This consensus underscores the growing trend toward embracing LLMs as a significant role in healthcare.

This data underscores a broad-based acknowledgment of the transformative potential of LLMs in healthcare, aligning with the global trend towards digitalization and the growing incorporation of AI in medical practices. The overarching sentiment from the respondents points to an expectation that LLMs will contribute significantly to enhancing healthcare delivery, suggesting a readiness among healthcare professionals and stakeholders to embrace and integrate these advanced technologies for improved patient outcomes and operational efficiency.

4.2.3 Can LLM help doctors complete their work more quickly?

Fig. **4** illustrates a strong consensus among respondents regarding the capacity of Large Language Models (LLMs) to expedite doctors' tasks. A substantial 54.55% of participants strongly agree that LLMs can enhance the speed at which medical professionals complete their work. When combined with those who agree (28.79%), it becomes evident that a significant majority (83.34%) support the notion that LLMs could be a catalyst for increased efficiency in medical practice. This sentiment is indicative of the growing confidence in LLMs' ability to streamline workflows, possibly by automating administrative tasks or by providing quicker access to medical literature and patient data.

It's noteworthy that a minor segment, amounting to 13.64%, somewhat agree, while an even smaller fraction of 3.03% remains neutral, neither agreeing nor disagreeing with the statement. The percentage of those who disagree (0%) or strongly disagree (0%) is non-existent, underscoring a nearly unanimous belief in the benefits of LLMs in the medical field.

This data suggests that the medical community is optimistic about the integration of LLMs into their work environment, recognizing the potential for these models to significantly reduce the time spent on routine tasks. The absence of dissenting opinions further reinforces the idea that LLMs are not viewed as a threat to professional expertise but rather as a valuable tool to complement and enhance the capabilities of healthcare providers.

Fig. **4** shows the distribution of responses, reflecting the medical community's readiness to adopt innovative AI solutions like LLMs to meet the demands of a rapidly evolving healthcare landscape.

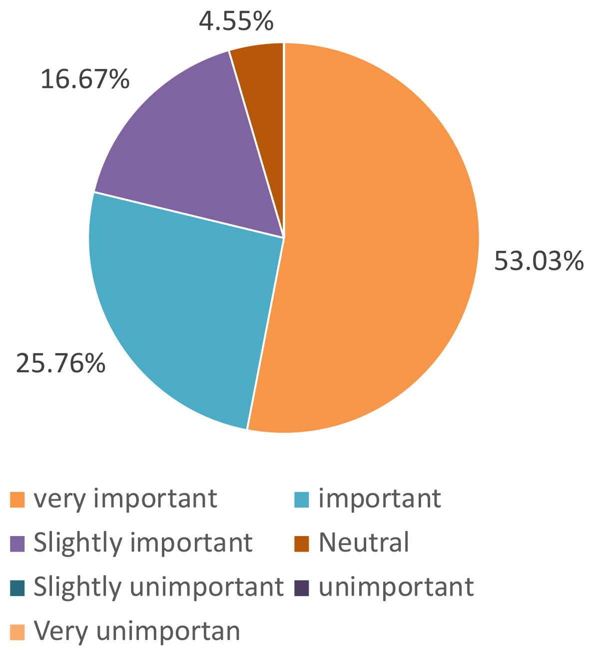

Fig. 3. Statistics of “To what extent do you think LLMs could contribute to the healthcare industry?”

4.2.4 Does LLM contribute to providing more personalized care and services for patients?

The survey data, as depicted in Fig. **5**, suggests a prevailing belief among respondents that Large Language Models (LLMs) contribute substantially to providing more personalized care and services for patients. A significant 34.85% of the participants 'Strongly agree' with this statement, indicating a high level of conviction in the potential of LLMs to tailor medical services to individual patient needs.

Furthermore, when we add the 40.91% of respondents who 'Agree', it becomes clear that the majority, representing 75.76%, are in favour of the idea that LLMs can enhance personalization in healthcare. This is a telling indicator of the perceived capacity of LLMs to refine and customize patient interactions, likely by leveraging vast datasets to inform and direct care more effectively.

Conversely, 'Somewhat agree' was selected by 15.15%, demonstrating a cautious optimism towards the potential benefits of LLMs in personalizing care. A small fraction, 7.58%, neither agree nor disagree, which might reflect a wait-and-see attitude or a request for more evidence of LLMs' effectiveness in this domain.

Notably, the percentages of respondents who 'Disagree' (1.52%) or 'Strongly disagree' (0%) are minimal, further solidifying the overall positive reception towards LLMs in enhancing patient-centric care.

This data illustrates a strong inclination towards embracing LLMs as a means to improve the patient care experience by offering services that are more aligned with individual health profiles and preferences. It highlights the healthcare sector's readiness to integrate advanced AI tools like LLMs in a bid to deliver more attentive and customized care solutions.

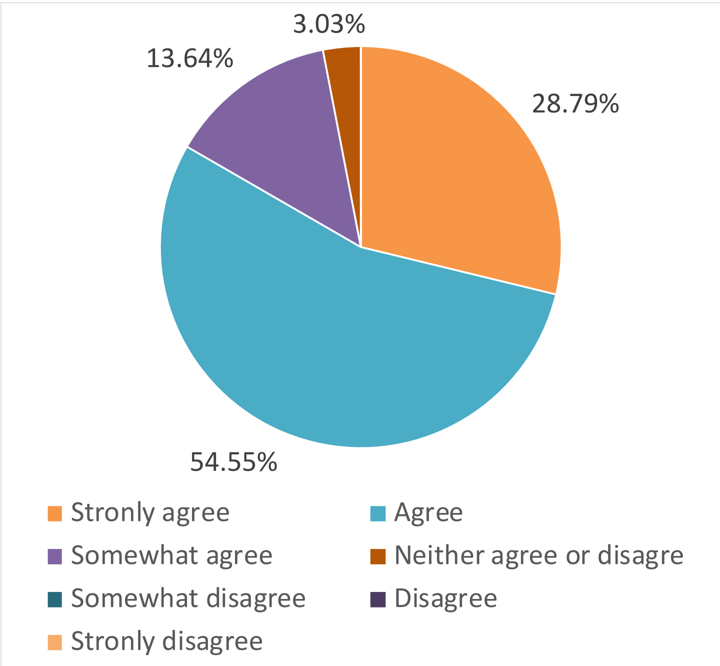

Fig. 4. Statistics of “Can LLM help doctors complete their work more quickly?”

4.2.5 Can the use of LLM in hospitals reduce the cost of each medical visit?

The gathered data, as shown in Fig, reveals a compelling consensus among the respondents about the cost-effectiveness of implementing Large Language Models (LLMs) in hospital settings. A substantial 40.91% of respondents 'Agree' that LLMs can play a pivotal role in reducing the costs associated with each medical visit, suggesting an appreciation for the economic benefits of integrating these advanced AI systems into healthcare operations.

Moreover, the 'Strongly agree' cohort, comprising 19.70% of participants, underscores a segment of the survey population that is highly confident in the potential of LLMs to streamline processes and cut down on expenses, thereby making healthcare more accessible.

On the other hand, those who 'Somewhat agree' makeup 13.64%, indicating a reserved agreement with the cost-saving premise of LLMs. It's notable that a relatively small percentage, 3.03% 'Disagree', while an even smaller 1.52% 'Strongly disagree', reflecting minimal resistance to the idea of LLMs as a means to reduce costs.

'Neither agree nor disagree' was chosen by 21.21% of the respondents, which could signify a need for more information or proof of the financial impact of LLMs before forming a definitive opinion.

Taken together, these responses highlight a strong belief in the potential of LLMs to diminish healthcare costs, which aligns with the ongoing pursuit of efficiency and sustainability in medical care provision. The data underscores a general trend toward recognizing the value of AI in fostering a more economical healthcare environment without compromising the quality of care.

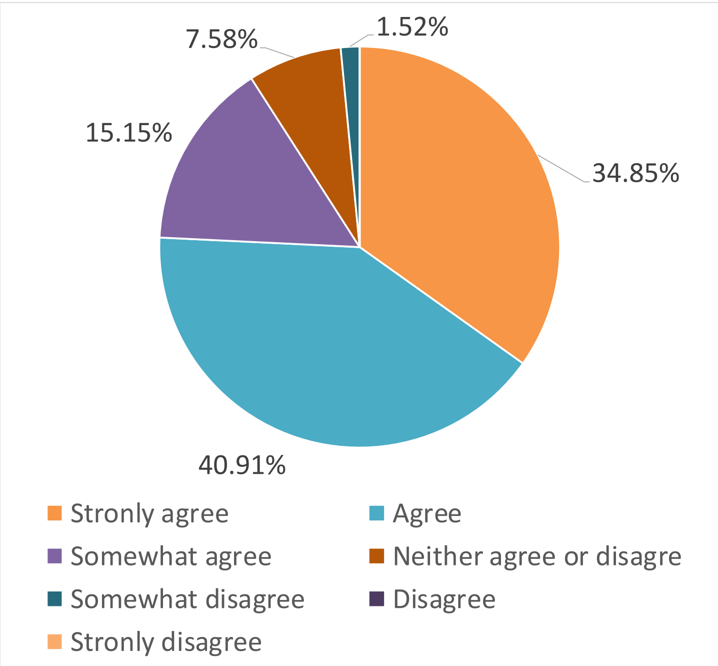

Fig. 5. Statistics of “Does LLM contribute to providing more personalized care and services for patients?”

4.2.6 To what extent would you accept and trust the diagnosis and treatment plans provided by LLM?

The survey results depicted in **Error! Reference source not found.** offer a significant insight into t he level of trust respondents place in the diagnosis and treatment plans provided by Large Language Models (LLMs). With a combined majority of 71.21% expressing 'Agree' and 'Strongly agree', it is evident that there is a considerable degree of confidence in the capabilities of LLMs to deliver accurate medical diagnostics and reliable treatment strategies.

Specifically, 37.88% of participants 'Strongly agree', reflecting a robust conviction that LLMs can be entrusted with critical aspects of healthcare decision-making. The 'Agree' category, accounting for 33.33% of responses, suggests that many are receptive to the integration of LLMs in clinical settings, acknowledging their potential to augment the healthcare process.

Conversely, those who are more hesitant, represented by the 16.67% who 'Somewhat agree', may recognize the potential benefits but also perceive the need for cautious optimism and further validation of LLMs in practical applications.

A small segment of 10.61% 'Neither agree nor disagree', indicating ambivalence or perhaps a lack of sufficient knowledge to form a concrete opinion on the matter. Notably, only 1.52% 'Disagree', and none 'Strongly disagree', indicating minimal outright scepticism towards the trustworthiness of LLM-provided medical advice.

This overwhelming tilt towards acceptance and trust in LLMs underscores the growing confidence in AI's role within the healthcare sector. It points towards a future where collaboration between human healthcare providers and AI could become more commonplace, offering a synergy that could enhance the efficiency and precision of patient care.

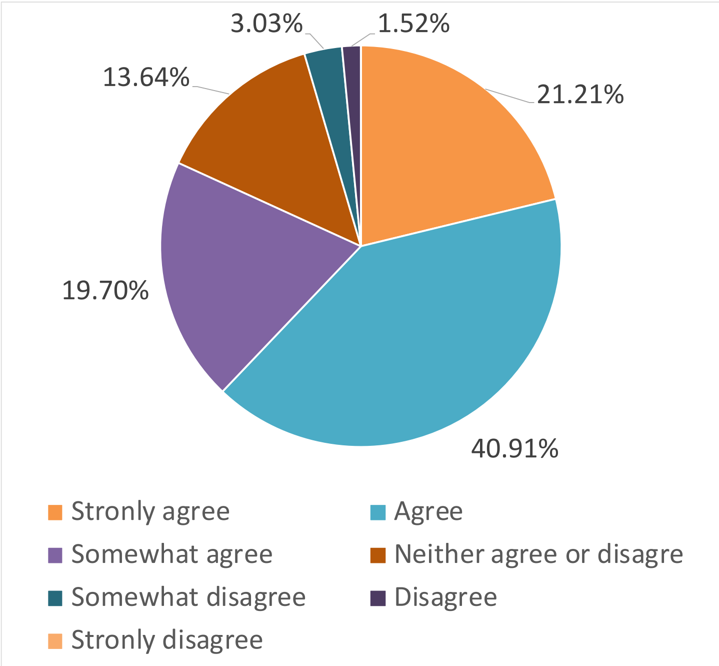

Fig. 8. Statistics of “Can the use of LLM in hospitals reduce the cost of each medical visit?”

4.3 Contributions

The study's comprehensive analysis provides valuable contributions to academia, industry practice, management strategy, and societal understanding of LLMs in healthcare.

4.3.1 Theoretical contribution

Expanding on the theoretical implications, the study's findings offer a multi-dimensional view of technology acceptance that could refine and extend existing theoretical frameworks within the realm of health informatics and technology adoption models. Specifically:

H4's validation suggests a direct positive impact of perceived efficiency on the acceptance of LLMs. This reinforces theories that posit efficiency as a critical factor in the user acceptance model, which can be pivotal in predicting and understanding the successful implementation of LLMs in healthcare settings.

H5 underscores the importance of user experience in accepting new technologies, aligning with the User Experience (UX) design principles and Human-Computer Interaction (HCI) theories. This suggests that when LLMs enhance the patient experience, their acceptance is higher, which may encourage theorists to integrate UX more deeply into models of technology acceptance in healthcare.

The non-validation of H6 poses a challenge to the conventional wisdom that cost savings are a primary driver of technology acceptance. This result could inspire new lines of inquiry in healthcare technology research, focusing on the nuanced and perhaps less tangible factors that influence acceptance and trust in healthcare innovations.

The study's theoretical contributions are significant for academics looking to develop a more holistic understanding of how LLMs and similar AI technologies can be integrated into healthcare practices. By considering the intricate relationships between efficiency, experience, cost, and acceptance, researchers can build more robust models that account for the complex nature of healthcare delivery and the multi-faceted impacts of technological advancements.

Furthermore, these findings could inform future research on the barriers to technology adoption. The non-significant relationship between cost and acceptance suggests that while cost-effectiveness is desirable, it may not be a decisive factor for LLM integration in healthcare. This insight prompts a re-examination of how economic evaluations are conducted for health technologies and suggests a potential shift towards value-based assessments that prioritize patient outcomes and satisfaction over simple cost reduction.

In essence, the study not only confirms certain expected relationships between technology and healthcare outcomes but also reveals counterintuitive findings that could pave the way for innovative theoretical approaches in understanding technology adoption in the complex ecosystem of healthcare.

For healthcare managers and decision-makers, the results underscore the need to promote the efficiency and patient experience improvements that LLMs can bring, rather than focusing solely on cost. This can shape strategies that prioritize the adoption of technology that significantly enhances patient care and operational effectiveness, aligning with the positive findings of H4 and H5.

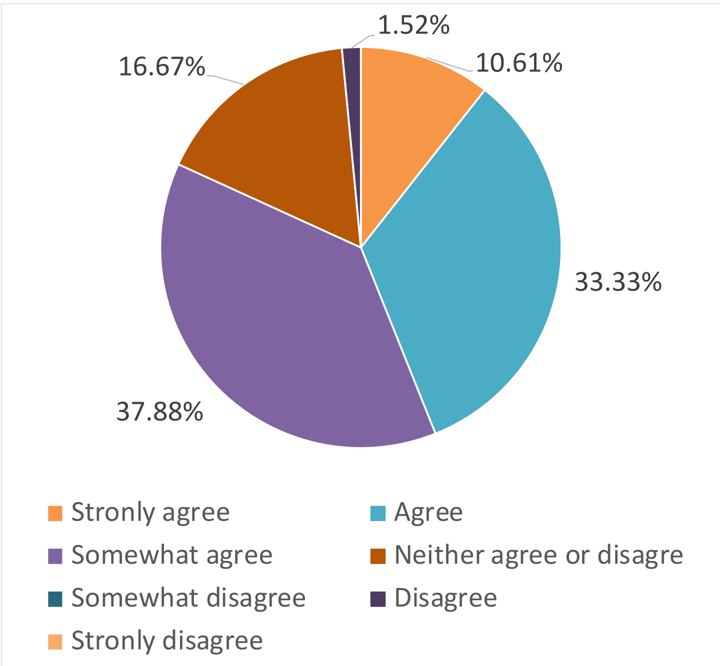

Fig. 9. Statistics of “To what extent would you accept and trust the diagnosis and treatment plans provided by LLM?”

4.3.2 Practical contribution

The validation of Hypotheses 1 through 5 confirms the practical benefits of integrating LLMs into healthcare systems. For instance:

i. H1: The positive correlation between LLM Healthcare Trends and Efficiency suggests that incorporating LLMs can lead to more streamlined operations, potentially reducing the time clinicians spend on administrative tasks, and allowing for more patient-focused care.
ii. H2: The link between LLM Healthcare Trends and Experience indicates that patients could benefit from more personalized interactions and clearer communication regarding their health, facilitated by LLMs.
iii. H3: Although H3's validation suggests that LLMs could reduce costs, the non-validation of H6 offers a nuanced perspective: while LLMs may reduce operational costs, cost reduction alone does not significantly influence the acceptance and trust in LLM healthcare. This insight is pivotal for healthcare providers who might over-prioritize cost-efficiency over other factors such as quality of care or patient satisfaction.

4.3.3 Managerial contribution

The findings of this research offer valuable insights for healthcare administrators and policymakers on managing the integration of LLMs into healthcare systems. The validation of hypotheses H1, H2, H4, and H5 implies that both efficiency and experience are critical factors that healthcare managers should prioritize to enhance acceptance and trust in LLM technologies. This suggests that healthcare managers could focus on:

i. Implementing LLM solutions that demonstrably increase operational efficiency, thus gaining support from healthcare professionals who value time and resource optimization.
ii. Designing LLM interfaces and interactions that are user-friendly and improve the patient experience, potentially increasing patient engagement and satisfaction with healthcare services.
iii. Developing training programs for healthcare professionals that highlight the efficiency and user experience benefits of LLMs, promoting a more receptive attitude towards these technologies.
iv. These management strategies can ensure that the integration of LLMs is aligned with the goals of improving healthcare delivery and patient care, ultimately leading to a more efficient, effective, and patient-centred healthcare system.

4.3.4 Societal contribution

On a broader societal level, this study illuminates the social implications of adopting LLMs in healthcare. The results from hypotheses H1 through H5 emphasize the societal benefits of integrating sophisticated AI tools into healthcare practices, which include:

i. Improved accessibility to healthcare information, enabling patients to make informed decisions about their health and wellness.
ii. Enhanced patient-physician interactions, where LLMs serve as tools for education and empowerment, leading to more collaborative healthcare.

iii. Potential for reducing the overall workload on healthcare professionals, allowing them to allocate more time to critical thinking and patient care rather than administrative tasks.
iv. The observation that cost is not a significant factor in the acceptance of LLMs (as indicated by the non-validation of H6) could suggest a societal trend towards valuing quality and outcomes in healthcare over mere cost savings. This insight is particularly relevant in discussions about healthcare financing and the allocation of public health resources, where the focus may shift towards investing in technologies that, while not necessarily cost-saving, contribute to better health outcomes and quality of life.
v. Collectively, these social contributions highlight the role of LLMs not just as technological innovations but as catalysts for enhancing the human aspects of healthcare. They point towards a future where technology is seamlessly integrated into the fabric of healthcare to support the well-being of individuals and communities.

4.4 Chapter Summary

This chapter has synthesized the research findings and their implications for the integration of Large Language Models (LLMs) into the healthcare industry. The statistical analysis confirms the reliability and validity of the survey results, providing a strong foundation for the subsequent interpretation and discussion. The data analysis indicates that the survey achieved its objectives, successfully capturing the perspectives of respondents on the potential contributions of LLMs to healthcare efficiency, experience, and cost.

Significantly, the acceptance of hypotheses H1 through H5 underscores the positive correlation between the perceived benefits of LLMs in enhancing healthcare delivery and the willingness of healthcare professionals and consumers to embrace these technologies. The research found that efficiency and improved patient experience are pivotal factors driving the acceptance of LLMs, while the cost was not deemed a significant deterrent, as evidenced by the non-validation of H6. This suggests that the healthcare sector is receptive to innovations that promise to elevate the quality of care, even if they do not immediately translate into cost savings.

From a qualitative standpoint, the majority of participants expressed a favourable stance toward the use of LLMs, reflecting a broad consensus on the value of AI in transforming healthcare practices. A minority of sceptical viewpoints highlights the need for continuous education and transparent communication about the capabilities and limitations of LLMs to foster broader acceptance.

The chapter also delved into the practical, theoretical, management, and social contributions of the research, offering actionable insights for various stakeholders in the healthcare ecosystem. It shed light on the strategic priorities for healthcare management in implementing LLMs and the broader societal trends towards prioritizing quality over cost in healthcare.

In conclusion, the chapter reaffirms the study's main assertion that the healthcare industry stands on the cusp of a transformative phase powered by LLMs. It calls for a concerted effort from healthcare providers, policymakers, and technology developers to navigate this transition toward an AI-enhanced healthcare landscape thoughtfully and responsibly. As the research demonstrates, while there is a clear recognition of the potential of LLMs, their successful integration hinges on addressing both the technical and human dimensions of healthcare.

5. Conclusion
5.1 Summary of Findings and Contributions

This research set out to explore the transformative potential of Large Language Models (LLMs) within the healthcare industry, focusing on their impact on operational efficiency, customer experience, and cost structures. The study's findings, derived from a mixed-methods approach that included surveys and interviews, suggest a promising horizon for LLM integration in healthcare.

The statistical analysis provided robust support for the hypotheses that LLMs contribute positively to operational efficiency (H1) and enhance patient experience (H2). Moreover, the findings suggested that while LLMs are perceived to potentially lower healthcare costs (H3), cost reduction alone does not significantly influence the acceptance of LLM-integrated healthcare solutions (H6). This indicates a shift towards prioritizing quality and effectiveness over mere cost savings.

The survey responses underscored a high level of trust and acceptance among healthcare professionals and patients concerning the use of LLMs for diagnosis and treatment planning (H4 and H5). This acceptance is closely tied to the perceived benefits of LLMs in improving the speed and personalization of care.

The core contributions of this research, encompassing theoretical, practical, managerial, and societal contributions, are encapsulated and presented in Figure 10.

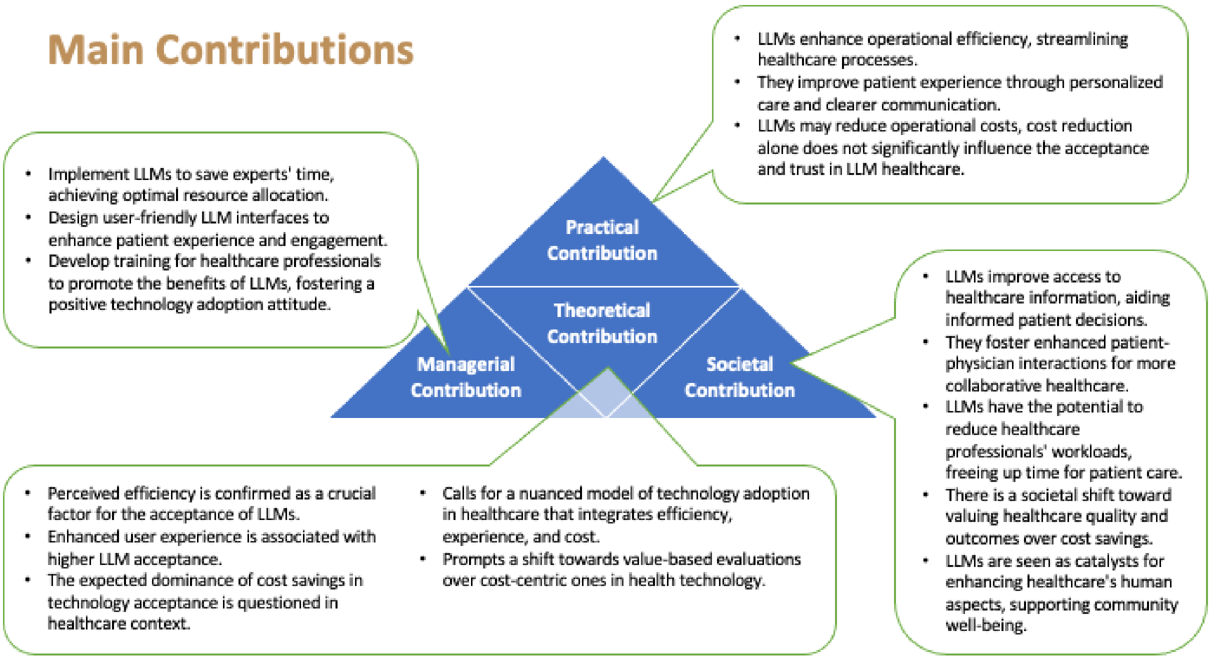

Fig. 6. Main contributions

5.2 Limitations and Recommendations for Future Research

This study provides valuable insights into the acceptance and use of Large Language Models (LLMs) in healthcare; however, it is not without its limitations. The sample is composed entirely of 66 participants from China, which may not reflect the diversity of experiences and opinions found in the global healthcare community. This geographic limitation is important because cultural, economic, and regulatory factors can influence the perception and adoption of AI technologies differently across regions. Additionally, the rapid evolution of AI poses a challenge to the study's long-term applicability, as findings may quickly become outdated due to technological advancements.

For future research, it is essential to incorporate a more globally diverse participant pool to ensure findings are applicable across various healthcare systems and cultural contexts. Expanding the study internationally would also allow for a comparison of how LLMs are viewed and integrated in different healthcare environments. Continuous updates to the research are necessary to align with the swift progress in AI, and it would be beneficial to conduct longitudinal studies to track changes over time. Investigating the impact of LLMs in varied socio-economic backgrounds, particularly in low-resource settings, would also shed light on the equity and accessibility of these technologies.

5.3 Concluding Remarks

This study provides a comprehensive examination of Large Language Models (LLMs) and their transformative impact on the healthcare sector. It elucidates how LLMs, as emergent technologies, have the potential to profoundly improve operational efficiencies, enrich patient experiences, and optimize cost management strategies within healthcare systems. The nuanced findings from this research suggest that the integration of LLMs into healthcare should be approached with a judicious balance, taking into account both their economic implications and their substantial qualitative advantages.

The implications of this research are far-reaching, offering pivotal insights for healthcare providers, policymakers, and stakeholders as they confront the complexities of digital transformation. By drawing on the empirical evidence presented, healthcare leaders can strategize the deployment of LLMs to not only achieve financial and operational goals but also to advance the paramount objective of patient welfare. Moreover, the ethical considerations and patient-centric values highlighted in this study underscore the necessity of a deliberate and conscientious adoption process for LLM technologies.

As the healthcare industry forges ahead in its technological journey, the insights gleaned from this research serve as an instrumental guide. They underscore the importance of embracing innovation with foresight and responsibility, ensuring that technological advancements align with the ethos of patient care and contribute to the overall betterment of healthcare delivery. In this way, this research serves as a foundational reference for future scholarly inquiry and as a strategic blueprint for the practical application of LLMs in enhancing the landscape of healthcare.

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