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The long-term impact of AI integration on economic sustainability in healthcare: a cost-saving perspective

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☐ **I have not used any AI-based tools.**

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Abstract

A transformative force that is increasingly being recognised as a key driver in healthcare is artificial intelligence (AI). It has the potential to strengthen economic sustainability in healthcare by improving efficiency, supporting decision-making both in clinical and administrative settings. Due to the growing demand for access to quality care and escalating costs of medical facilities, healthcare systems are under enormous pressure, demanding more effective solutions. This study investigates how AI integration in healthcare can contribute to economic sustainability in healthcare by generating cost savings in the long term.

This study is guided by a theoretical framework drawn from literature on healthcare management and AI adoption. Within this framework, cost savings are positioned as the central outcome of AI integration emerging from different pathways, including administrative efficiency, early disease detection and prevention, reduced admissions and readmissions, resource optimisation, workforce planning, clinical efficiency, easy access to care, and data-driven savings. In addition to immediate efficiencies, the framework highlights second- and third-order benefits achieved through process adaptation, continuous monitoring, and scalable integration, framing economic sustainability as an ongoing process rather than a fixed goal.

This research makes both theoretical and practical contributions by using an exploratory qualitative approach. The findings show that AI has the potential to create measurable efficiencies, reduce costs, and support healthcare delivery. This study concludes that AI should not be considered merely a technological upgrade, but rather as a strategic initiative aimed at making healthcare facilities more economically sustainable. For this potential to be fully realised, managers, healthcare professionals, and researchers need to work towards aligning innovation with long-term value creation.

Keywords: Artificial Intelligence, Integration, Healthcare, Economic Sustainability, Cost-savings

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1 Introduction

The purpose of this dissertation is to investigate *how is AI integration in healthcare is perceived to impact economic sustainability in the long term through cost savings?* This study critically examines the literature on artificial intelligence, its use in healthcare, sustainability concepts, and the factors that drive cost savings through AI adoption. The study aims to assess the economic sustainability of the healthcare sector in terms of the likelihood of these savings. The research is intended to provide a clearer picture of AI's long-term contributions, both real and perceived, to the economic sustainability of healthcare. This section provides the background of the research, identifies the research gap, and outlines the study's structure.

1.1 AI-driven healthcare and sustainability: emerging challenges

Healthcare systems today face challenges that, despite numerous advances in medical science and digital health technologies, still present significant issues. These issues include rising costs, uneven distribution of the medical workforce, and healthcare inequities (Wikström et al. 2023, 3). Demographics, such as ageing populations, will exacerbate these issues. Growing demand for highly specialised care will put more pressure on healthcare infrastructure, care teams, and budgets. (Horvath et al. 2025, 7). As the burden of chronic and degenerative diseases continues to grow, healthcare practices must adapt, and traditional medical paradigms need re-evaluation (Osareme et al. 2024, 383). Although digital health tools are often suggested as solutions to these challenges (Powell et al. 2016, 42), the healthcare sector must adopt a comprehensive approach that considers both medical and social factors to ensure sustainability and improve patients' quality of life (Osareme et al. 2024, 395). High treatment costs, limited access, and operational inefficiencies demand innovative strategies for lasting economic sustainability (Maphumulo & Bhengu, 2019, 5).

In recent years, the global medical landscape has been significantly transformed due to rapid advancements in information technology, and the use of Artificial Intelligence aims to replicate human cognitive functions. It is causing a paradigm shift in healthcare, driven by the increasing availability of healthcare data and the rapid development of analytics techniques (Jiang et al. 2017, 230). Machine learning, natural language processing, and predictive analytics are all recognized as game-changers in healthcare, supporting patients through more accurate diagnoses, personalized treatments, and enhanced administrative functions (Charalambous 2023, 2).

Digital health facilities are being implemented worldwide, but the rate of adoption varies from one country or institution to another. Economy and state institutions are the main strengths behind this shift. (Iyanna & Kaur 2022, 150). The whole digital transformation process is obstructed by many integration problems such as data privacy issues, interoperability difficulties, and infrastructure constraints (Charalambous 2024, 2). The increasing use of these technologies indicates not only that computing power has reached a significant level but also that an emergency in healthcare is unfolding high costs, limited resources, and unequal access to patient care. Even though many nations have embraced digital technologies as part of their health policies, there are still doubts about the long-term economic impacts of these technologies, including their ability to support health systems. (Iyanna & Kaur 2022, 150.)

AI offers the opportunity to analyze large, complex health data to predict disease progression, hospital readmissions, and treatment success. These technologies allow for early intervention, reduce unnecessary hospital stays, and improve care pathways, leading to potential cost savings and better operational efficiency. AI is increasingly being used in healthcare, with much untapped potential. (Tagliaferri et al. 2020, 93). However, AI also raises important questions about its long-term economic impact. The short-term efficiency gains from AI could result in a *"one step forward, two steps back"* situation, meaning that it could become less sustainable due to deployment costs, integration challenges within organizations, or side effects such as potential job loss or high electricity use. (Richie 2022.)

We need to consider the transformative power of AI not just in a technological context but also from the perspective of how it advances and supports sustainability. In several examples, AI has already shown its usefulness in promoting healthcare sustainability, such as waste reduction through predictive maintenance, managing energy consumption in hospitals, and enabling data-driven policy for resource allocation (Kumar et al. 2025, 5). The positive effects of AI in enhancing care delivery and operations are emphasized; however, its role in sustainable economic models for healthcare is overlooked (Al Meslamani 2023, 88). Though attention to sustainability in healthcare is increasing, most sustainability-oriented activity has focused on environmental and social aspects, such as decarbonizing care and improving equitable access to care (Molero et al. 2021, 17; Kumar et al. 2025, 5), with little reflection on how the implementation of AI can change the economic sustainability of healthcare systems (Zahid et al. 2022, 114).

So, it can be concluded from this discussion that AI-driven cost reductions, cost-efficient resource allocation, and workforce shortages are debated in existing literature, but there is little consideration for stakeholder interpretations or expectations. A more comprehensive approach is necessary to analyze how AI-enabled practices align with sustainability frameworks or how these technologies are viewed in terms of supporting long-term economic resilience (Bansal 2025). This requires an in-depth study that extends beyond evaluating just technological capabilities to incorporate stakeholder views and sustainability goals in the long term.

1.2 Research gap and the purpose of the study

The application of artificial intelligence in the medical field is a significant technological innovation that has the potential to transform the landscape of medical services, improve the quality of patient care, and enhance emergency response efficiency (Santamato et al. 2024, 1). AI can be a significant economic factor in the medical care system by reducing costs (Mikava & Mamulaidze 2023, 110). It can help both healthcare systems and patients to cut down expenses by improving diagnosis, operations, and treatment efficiency, as well as in preventive care measures. However, current research tends to emphasise immediate outcomes and often neglects the long-term economic effects. (Al Meslamani 2023, 1566). AI has the potential to bring cost reductions to the healthcare sector, but the literature is still insufficient on the issue of how such cost reductions will affect the future of healthcare economically. There are quite a few high-quality studies that present different ways of achieving cost savings and give quantitative projections of accumulated opportunity. In the case of Sahni et al. (2023), they offer a system-level, use-case scaling analysis for the U.S, which clearly states both the underlying assumptions and the scale. The authors, using national healthcare expenditure data and a set of possible AI applications, predict yearly net savings of "5–10% of U.S. healthcare spending” within the next five years by utilising the current technologies. Their approach is to upscale individual use-case savings to national totals while also separating savings by stakeholder, thus providing a breakdown of where the near-term opportunities are located. (Sahni et al. 2023, 1–3.)

The study by Khanna et al. (2022) developed economic models for diagnosis versus treatment at the facility level and demonstrated how the cumulative time and process advantages provided by diagnostic AI can result in greater per-facility savings as utilisation and integration become more sophisticated. Therefore, these studies suggest that AI produces tangible operational savings in the healthcare sector. Wolff et al. (2020), as part of their systematic review of AI in healthcare economic impact assessment studies, reported that current impact evaluations lack methodological rigour, leading to uncertain economic decisions. They mentioned that many evaluations are conducted at a single location, do not incorporate thorough costing, and have very short or no time frames—making it difficult to prove the long-term validity of results. More research is necessary to understand its long-term effects on economic sustainability in healthcare, as only a limited number of publications have addressed the economic impact assessment of AI in healthcare (Wolff et al. 2020, 7).

The economic impact of AI in the healthcare sector has been widely discussed. These studies are mainly categorised into three approaches, each offering valuable insights and highlighting certain limitations. The micro-level facility studies (e.g. Khanna et al. 2022) are the first to be mentioned and are based on individual sites, such as hospitals or specific care pathways, and reveal cost savings and efficiency gains from the use of AI at the local level. Nevertheless, applying such findings to the entire healthcare system poses a significant challenge. The second approach refers to large-scale projections, such as those of Sahni et al. (2023), which estimate national healthcare savings by integrating specific AI use cases that are quite optimistic; however, these models are also highly dependent on assumptions and usually cover a short time span. The last method includes several short-term health economic evaluations (Wolff et al. 2020), which investigate the costs of healthcare on a day-to-day basis concerning the buying or testing of new technologies, and hardly consider the large expenses that go along with implementation, maintenance, and long-term effects on the hospital budget. Each of these methods gives a clearer view of the short-term cost advantages of AI but does not touch on the issue of the long-term economic sustainability in healthcare, therefore the literature, on the whole, gives signals of reliable sources for short- to medium-term savings but there is no single analytical approach that would provide the comprehensive, long-term evaluation of whether such savings would result in system-wide economic benefits. This study aims to fill this gap by examining how the cost savings resulting from AI integration can impact economic sustainability in healthcare over time. Grounding the investigation into the experiences of various stakeholders

The main research question further specifies this purpose: *"How is AI integration in healthcare perceived to impact economic sustainability in the long term through cost savings?"* The main research question is further broken into two sub-questions:

1. *"How is AI integration in healthcare perceived to impact cost savings?"*
2. *"How are AI-driven cost savings perceived to have a long-term impact on economic sustainability in healthcare?"*

The first sub-research question aims to understand how the integration of AI in healthcare can lead to cost savings in healthcare settings. The second sub-question aims to investigate how AI-driven cost savings in healthcare affect economic sustainability in the long term. The research questions are formulated to align with the purpose of the study, which is to explore the perceived connection between AI applications and economic sustainability in healthcare in the long term. The main question is broad, focusing on how AI cost-saving benefits are seen as contributing to healthcare's economic sustainability. The first sub-question narrows the focus to understanding how AI results in cost savings. The second sub-question builds on this by examining how these savings are perceived to impact economic sustainability in healthcare in the long term. Together, the questions provide a comprehensive model for analyzing both the immediate and future economic impacts.

2 AI AND ECONOMIC SUSTAINABILITY IN HEALTHCARE: THEORETICAL FOUNDATIONS

This chapter reviews relevant literature, definitions, and theories related to the current study. The first sub-chapter is about the definition, evolution of the concept of AI, and the core technologies supporting AI. The next sub-chapter discusses digital transformation in healthcare, along with the integration and application of AI in healthcare. The third sub-section explores the concept of sustainability. The fourth section explains economic sustainability in healthcare and the importance of studying it. The following sections review literature on AI's role in achieving economic sustainability in healthcare, various cost-saving mechanisms enabled by AI, and a discussion on the long-term impact of these mechanisms. The final section summarises the theoretical discussion and provides the initial framework for this study.

2.1 Understanding Artificial Intelligence

The development and evolution of AI have occurred in phases, each representing a shift in how intelligence is understood and applied in machines. The question, *"Can machines think?"* aims to determine whether a machine can exhibit behaviours different from humans. (Turing 2007.) Symbolic AI was based on how programming systems could utilize formal rules and symbolic manipulation, as demonstrated in early systems such as the Logic Theorist (Nilsson 1989, 45–47). A period known as the *"AI Winter,"* marked by the rejection of predictions and a lack of support, halted progress in the field for some time (McCorduck 2004, 180–182). Eventually, advances were made in the direction of combining the rigid logic of symbolic AI with the adaptability of machine learning, which resulted in the birth of Explainable AI—a domain concentrating on the issue of working with models that are clear and accountable, especially in sensitive areas such as healthcare where the need is not only for correct predictions but also for the understanding of the reasoning behind them. (Samek et al. 2017, 39–41.) The different phases of AI history have shown its evolution from the most primitive theoretical concepts to the most automated and dependable systems. AI can be categorised into four types of systems: those that mimic human thought, those that behave like humans, those that reason, and those that perform actions based on logic. The above-mentioned distinctions are a great help in comprehending the construction of AI systems and in knowing their objectives. (Russell & Norvig 2021, 2–3.)

AI is the ability to adapt even when there are not enough information or resources. This helps explain how AI can work in uncertain situations, like emergencies or complex medical diagnoses. (Wang 2019, 1). AI is also called an *"ecosystem of technologies,"* as it doesn't just react to inputs, but also changes its behaviour over time to get better results. This way, AI is seen not just as a machine, but as something that works within society and evolves with it. (Floridi et al. 2018, 690.)

AI has been a subject of broad definitions and conceptualisations in the academic literature, which signifies its interdisciplinary character and the ever-changing nature of the technology involved. An illustration of the latter can be found in its definitions. AI is an aggregate of increasingly autonomous and self-sufficient computer systems that can perform complex tasks that are otherwise the province of human intelligence (Floridi et al. 2018, 690). The given definition highlights the two characteristics—autonomy and adaptability—that set AI apart from classical approaches to algorithmic use. Likewise, AI can be defined as the study of agents that receive percepts from the environment and perform actions (Russell and Norvig 2010, 7). Floridi and Cowls (2019, 12) argue that AI should be seen primarily as a socio-technical system that not only replaces but also coexists with human beings, thereby carrying ethical, legal, and social implications. This viewpoint is supported by Chollet (2019, 6), who argues that AI is nothing more than the system's ability to set and achieve difficult goals in environments where people cannot easily adapt, making adaptability and generalisation the two most important qualities of an intelligent system. In unison, these views portray AI as a diverse field that integrates computational modelling, reasoning, learning, and decision-making, with the aim of either replicating or enhancing human cognitive abilities in digital systems.

This study adapts the definition of AI as *"the practical ability of non-human systems or artificial agents to execute tasks, engage in problem-solving, interact with others, and behave in a logically coherent manner, much like human beings"* (Gil de Zuniga, Goyanes, & Durotoye 2024, 320). As, it treats AI from technological and behavioral perspectives simultaneously and aligns with the study's concern with healthcare and economic sustainability. This definition views AI as a range of practical capabilities, including the performance of complex, human-like tasks such as problem-solving, interaction, and logical reasoning. This reflects the situation in the health sector, where AI is called upon to continuously interact with data, clinicians, and patients to enable more efficient decision-making and operations. This definition lays a comprehensive, context-appropriate groundwork for assessing AI not just as a computational tool but also as an intelligent, adaptable agent that affects healthcare delivery and sustainability outcomes.

AI depends on multiple main technologies that allow machines to operate smartly like humans. Machine learning allows computers to get information from data and to make a choice without going through all the steps of the instructions (Mitchell 1997, 25). Deep learning employs a similar architecture to the human brain. These neural networks conduct information processing layerwise to uncover intricate patterns and decide (LeCun, Bengio, & Hinton 2015, 117). Natural language processing provides the ability to interpret and produce human language, which is a necessity for tasks like translation, chatbots, and virtual assistants (Lucy et al. 2020). Computer vision lets machines *"see"* and understand images and video. This technology is utilized in self-driving cars, medical scans, and facial recognition systems. (Goodfellow, Bengio, & Courville 2016, 341.)

The AI reinforcement-learning technique trains systems to learn through trial and error, or by learning from mistakes or experiences, in a manner like how a human would. It's particularly valuable when robots and other agents must process information over time. (Sutton & Barto 1999.) Data engineering refers to the organization and cleaning of data that AI systems require. Even state-of-the-art AI models cannot perform effectively without well-managed data. More attention is being given to making AI more explainable and ethical. This includes constructing AI systems that not only perform well but also can explain how they intend to arrive at a decision and ensure that the outcomes are just for all involved. (Doshi-Velez & Kim 2017, 6.)

The illustration in Figure 1 indicates that different AI systems themselves operate at various levels of sophistication: singly (just performing one task), in pairs (for instance, dealing with the operation of a task and the making of a decision), or through more complex three-step sequences (that include task execution first, then decision-making, and finally forecasting). Task execution might be straightforward, but this is not the case with subsequent decision-making and forecasting, especially when they affect each other. (Gil de Zuniga, Goyanes, & Durotoye 2024, 320.) Hence, the path to AI has been a continuous evolution, from the main philosophical discussions about the "thinking" ability of machines to today's multifaceted, layered systems. These stages not only display the progress in technology but also the wide-ranging complexities of AI applications, especially in the healthcare sector, where accuracy, adaptability, transparency, and ethical issues are the major concerns.

Figure 1. Venn diagram of Artificial Intelligence tools based on their levels of performance (adapted from Gil de Zuniga, Goyanes, & Durotoye 2024, 320)

The comprehension of AI, ranging from machine learning to deep learning, natural language processing, and computer vision, forms the basis for recognising its transformative power. The forthcoming segment will hinge on this understanding by analysing the alliance between digital transformation in healthcare and AI. It will investigate the current state of health services globally and the corresponding role of AI as a change-maker, in terms of redefining healthcare delivery, enhancing patient outcomes, and setting new paradigms for healthcare sustainability.

2.2 The healthcare sector through the lens of AI

The healthcare sector is experiencing major digital transformation, caused by AI. This change is not only about adopting new technologies—it is about turning upside down the way healthcare is given, managed, and experienced. This section investigates the worldwide condition of healthcare and the digital transformation that is happening simultaneously. On this foundation, it goes further to consider AI's incorporation into the healthcare sector, and it investigates how smart technologies are changing diagnostics, treatment, and efficiency in operations.

2.2.1 An overview of healthcare worldwide and digital transformation

On the one hand, the quality of healthcare worldwide is affected by several challenges that the system faces. An estimate in the United States suggests that there will be a shortfall of registered nurses by 2025, ranging from 200,000 to 450,000, which translates to 10–20% of direct patient care capacity. (McKinsey & Company 2014.) The World Health Organization foresees a global shortage of 10 million health workers by 2030, with the largest gaps in low and lower-middle-income countries (World Health Organization 2025). In Australia, the situation is like that in the US, where providers expect a decline in operating profits despite a small rise in revenues, primarily due to rising labor and supply costs (Deloitte 2025). There are still health inequities and access issues worldwide. In England, patients from certain ethnic groups, namely Asian, other, Indian, and Black African, encounter considerably more emergency hospital admissions for diseases such as TB than the White British population, with the admission rates for some groups being up to 29 times higher (UK Health Security Agency 2025). Only a minority of about 7 per cent of individuals with severe drug-resistant infections in low and middle-income countries are receiving the essential antibiotics, thereby resulting in the death of one out of five due to the drug-resistant infection, and the survivors are contained in the cycle of infection and transmission (The Guardian 2023).

Meanwhile, with the development of digital health, there is no doubt about the difficulties in adopting new technologies and safeguarding data. Among the problems the health sector encounters are interoperability issues, insufficient personnel training, and the high risk of system failure during transfer. What makes it even worse, with every step towards a digital future, the health sector becomes increasingly exposed to cyberattacks, leading to more frequent and costly incidents and, consequently, a higher demand for continuous security. (World Health Organization 2025.) The issue of climate change is a major hindrance to human health worldwide, and medical services are among the industries that suffer from the environmental crisis, thereby contributing to it. The health sector is responsible for approximately 4.4% of global annual carbon emissions. (Environmental Sciences Europe 2024.) The Australian reported that CT scans and MRIs are increasingly performed in EDs “as the pressure on the staff reaches boiling point,” while nurses are providing “less care” due to the demand for quicker care (The Australian 2025). By the end of September 2023, there were 7.8 million people in England waiting for hospital treatment, an indicator of the demand problems the system is facing (NHS England 2023). The transformation in health systems is facilitated by technology, as IoT-enabled healthcare not only drives up efficiency and data storage but also raises privacy concerns that must be addressed thoroughly (Nabha, Laouiti & Samhat 2025, 3).

In every corner of the world, health care systems are under pressure. One of the main reasons is rising costs; the second is patients' longevity; and the third, and most important, is the demand for individualised care. All these factors are forcing the system to develop new solutions, one of them is the significant impact made by AI by accelerating the entire process, reducing paperwork burden, and improving patient outcomes. (Jiang et al. 2017, 444.) The first goal is to move from the traditional approach of curing the sick to a preventive one that also includes personalised care (Topol 2019, 14–15). It seems that the major reasons for such a delay are the lack of access to digital tools, the inadequacy of the workforce, and the presence of disconnected systems, especially in many low and middle-income countries (World Health Organization 2021, 9). Consequently, health systems worldwide are changing almost daily and are facing the challenge of providing quality, access, and sustainability. The increasing demand in the healthcare industry is driven by the rapid introduction of digital health, which in turn may open several doors but still has many hurdles to overcome, such as incompatibility, hacking threats, government regulations, and technology access inequalities. These interconnected factors demonstrate the need to examine AI as a potential health system problem-solver in a multidimensional way. Therefore, the following section discusses the AI protocols & procedures to tackle the previously mentioned issues and make a notable change in the global care delivery system.

2.2.2 Integration of AI in healthcare

AI is rapidly changing the healthcare landscape by making clinical decisions more accurate, hospital operations more efficient, and patient experience better. It is no longer just a technology upgrade but is fundamentally altering the functioning of healthcare systems. (Jiang et al. 2017, 444.) A very clear, strong growth trend is depicted in Figure 2 over the years. The results highlight a major prospect for the utilization of AI technologies in healthcare, which is expected to increase significantly in the coming years, driven by both the demand for sophisticated digital solutions and the advancement of AI systems to facilitate healthcare delivery (Meena et al. 2023, 2509).

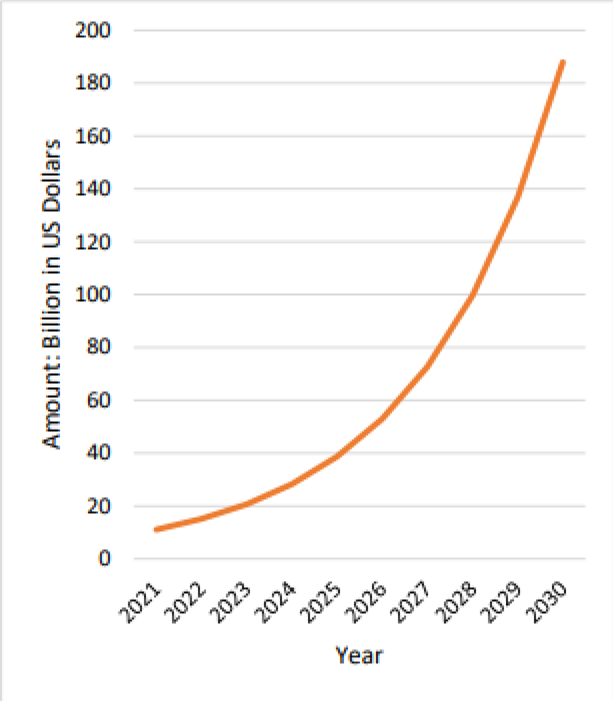

Figure 2. AI Application in Healthcare (adapted from Meena et al. 2023, 2509)

AI has provided one of its most remarkable services to healthcare through medical imaging. Images obtained from CT scans have shown AI systems to be much more accurate than humans at identifying the earliest stages of diseases like lung cancer. They even reduce incidences of false positives (Esteva et al. 2017, 115; Ardila et al. 2019, 416). Moreover, AI has a wide array of applications, including, but not limited to, forecasting and predicting actions. The application of AI enables the analysis of patient data from electronic health records and daily monitoring devices to predict when the patient's condition might deteriorate or when they may be at risk of a chronic illness, thereby enabling early intervention. The systems developed by DeepMind and IBM Watson are among others where AI is taking the lead in early diagnosis and triage (Miotto et al. 2018, 74; Rajkomar et al. 2019, 493.) When it comes to personalised medicine, AI is the driving force behind the integration of genetic, clinical, and behavioural data, which ultimately enables individual doctors to prescribe based on patients' needs. Tempus and Foundation Medicine, for instance, are two cancer therapy companies that employ AI to design individual treatment plans with the dual goal of achieving the most favourable outcomes and preventing unnecessary side effects. (Topol 2019, 101.) Administrative efficiencies are a further advantage of using AI. Nnatural Language Processing tools are now utilized to automate clinical documentation for coding and billing; automating such tasks could limit human error and administrative burden. Dragon Medical One and Med-PaLM from Google are examples of systems through which AI has optimized health care processes. (Ting et al.

2020, 135.)

AI is also increasingly involved in patient engagement through chatbot technology. AI-driven chatbots may aid the diagnosis and management of patients, health education, and efficient management of workflows (Xu et al. 2021). Big language models like ChatGPT are being investigated for their applicability in education, research, and documentation in healthcare. This instrument has the potential to serve as a scientific writing aid and a personal learning tool; however, it also carries the risk of bias, plagiarism, and inaccurate content. (Sallam 2023.) The deployment of AI in healthcare is confronted by hurdles, including data privacy, the need for ethical standards, the challenge of integrating disparate systems, the need for large-scale adoption, and the complexity of human-machine interaction (Udegbe et al. 2024, 500). The most significant factor contributing to the gradual acceptance of AI in the medical field is the increase in the volume of publications, as noted in a bibliometric study by Tran et al. (2019), who cite this rise as one indicator. It highlights the need for collaboration across disciplines and for the formulation of ethical policies to ensure the responsible application of AI (Tran et al. 2019). Therefore, the prospective use of AI in healthcare is a revolution encompassing diagnostics, personalized treatment, administrative efficiency, and patient monitoring. A wide range of healthcare applications is exploiting AI in the most effective manner, and each is contributing to the enhancement of medical service delivery and management. The figure 3 provides the detail regarding use of AI in medicate. These applications reflect the expanding integration of AI technologies across various aspects of medical care and administration, reinforcing its transformative potential in the sector. (Meena et al. 2023, 2507.)

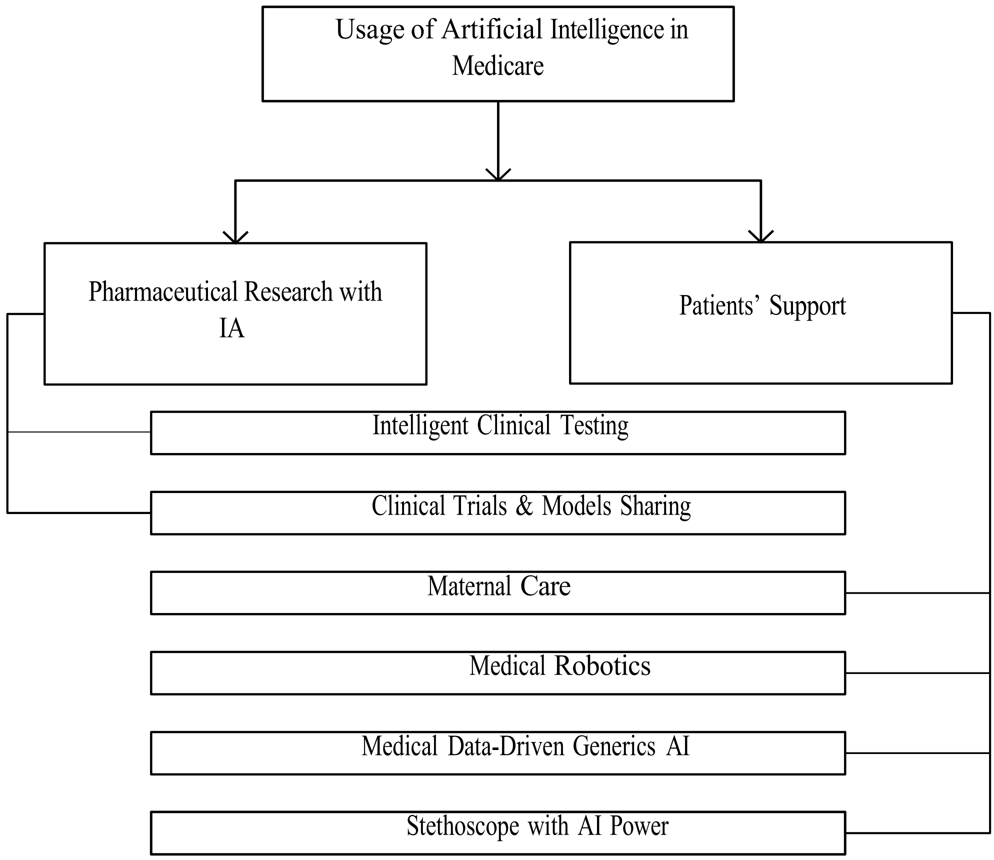

Figure 3. Usage of AI in Medicate (adapted from Meena et al. 2023, 2507)

The application of AI in different areas of healthcare is depicted in various ways in Figure 3 by Meena et al. (2023, 2507). AI is used in pharmaceutical research to speed up the entire drug discovery process by enabling target identification, analysing off-target effects, and performing repetitive tasks more quickly. In clinical testing, AI is reducing trial length by leveraging Real-World Data and improving data capture and analysis, and by sharing global AI models, data, and tools through collaborative initiatives that support research efficiency. AI in the field of patient support brings innovations such as the maternal care tool that detects high-risk pregnancies and ensures patients receive proper care, and medical robots for surgery, rehabilitation, and mobility, including advanced prosthetics. Genomics driven by data is applying AI for its benefit, providing tailor-made medical treatment, while stethoscopes designed with AI are improving noise reduction and portable health services in hard-to-reach areas. So, AI is gradually taking over, unburdening processes, speeding them up, making them more precise, and personalising them more.

The overwhelming evidence supports the view that AI has a significant impact on diagnosis, surgery, and administration. Support systems for diagnosis have begun using AI algorithms to thoroughly examine medical data (such as imaging study findings and clinical notes) to detect diseases (McKinney et al. 2020). An AI classifier was developed by Esteva et al. (2017) that correctly identified skin cancer at dermatologist-level accuracy. AI can not only enhance diagnostic accuracy but also reduce the occurrence of diagnostic errors. Predictive analytics is enabled by machine learning, which applies historical patient data to predict outcomes such as hospital readmissions or disease progression. AI can improve predictive capability using deep learning on electronic health records. (Rajkomar et al. 2018.) Obermeyer and Emanuel (2016) have highlighted the use of big data analytics as a means of enabling timely intervention, thereby prompting improved healthcare planning. Likewise, AI is indispensable in personalized medicine, where genetic, lifestyle, and clinical data are used to develop individual treatments. A team led by Miotto et al. (2016) developed the “Deep Patient” model, a system that employs unsupervised learning to forecast patient outcomes from electronic health records.

AI-enabled selection of therapies for cancer and precision therapies increases effectiveness and minimise side effects. Robotic surgery is an integration of AI to increase the accuracy of procedures, reduce surgery time, and decrease recovery time. (Topol 2019.) Herron and Marohn (2008) reported Surgical System, which enhances precision during minimally invasive robotic surgery, demonstrating significant advantages for surgical procedures and patient outcomes. AI-based virtual assistants and chatbots provide ongoing patient support through symptom checking, appointment scheduling, and medication reminders. The implementation of AI and machine-learning methods is gradually spreading across different medical fields, not just for disease detection but also for risk stratification and treatment optimisation. For example, AI systems in oncology, cardiology, and radiology have already taken over the role of diagnosis support, workload reduction, and management decision-making improvement (Ting et al. 2020, 135). AI has also been applied in the field of hepatology in the form of tools such as deep learning models applied to imaging and laboratory data to help personalise treatment plans, assess the disease progression, and ultimately increase the success of the treatment (Ting et al. 2020, 135). AI is even being used in the new field of cardio-oncology, where it might help in the foreseeable future to predict cardiovascular events caused by cancer treatment more accurately, thus allowing the doctor to do a precise risk stratification and provide intervention (Ting et al. 2020, 135). Besides detection and diagnosis, the areas where AI has gained the most maturity and has been the most powerful in the medical field are treatment optimisation, workflow enhancement, and personalised care especially in high-impact areas like oncology, cardiology, neurology, and hepatology (Ting et al. 2020, 135).

Having examined many different types of AI applications in health care, from discovery and clinical trials to external patient care and robotics, one thing is clear - technology is altering the healthcare landscape. But the question is that *how this AI integration in healthcare is perceived to impact economic sustainability in the long term through cost savings*. The next section turns to sustainability of healthcare. It discusses what it means for sustainability to embed into the healthcare innovations, especially AI, to create systems that fit into today's demands and that can flexibly pivot to tomorrow's realities.

2.3 Unpacking the idea of sustainability in healthcare

The intended purpose of this section is to build a conceptual understanding of sustainability and its application in the healthcare sector, particularly considering the escalating power of AI. It first defines sustainability, tracing its roots, outlining its main definitions, and detailing its various forms and the principles that govern them, to provide a basic understanding of the concept. The following section discusses sustainability in the healthcare sector, emphasising accessibility and quality. The economic aspect is then examined more thoroughly to clarify the necessity of studying economic sustainability in healthcare. An assessment follows of the role of AI in economic sustainability, arguing that digital innovation can improve healthcare systems' efficiency and reduce their costs, thereby making them more resilient in the long run.

2.3.1 Understanding the concept of sustainability

In this sub-section, a review of the literature on sustainability, sustainability in healthcare, and the necessity of research on economic sustainability in healthcare is provided. The phrase "sustainable development" was first used in the World Commission on Environment and Development report "Our Common Future" in 1987. It is explained as "the development which satisfies the needs of the present generation without hindering or denying the right of future generations to meet their own needs". (Brundtland & Mansour 2010, 2.) Sustainability, in its original conception, was not limited to environmental protection but also extended to the realms of social justice and economic equity. It called attention to the pressing need for equitable resource distribution, particularly in developing regions, where rapid industrialisation and population growth often amplify environmental degradation and social disparities. Prioritising the needs of the poor, acknowledging that eradicating poverty and reducing inequality are essential prerequisites for any meaningful form of sustainable progress. Furthermore, sustainability is inherently dependent on a society's technological capacity and institutional framework, suggesting that both social and technological systems must evolve to ensure that the well-being of current populations does not jeopardise that of future generations. (Hajirasouli & Kumarasuriyar 2016, 2.)

Moore et al. (2017) define sustainability as the continuity and persistence of practices that lead to positive behavioural changes, while allowing for adaptation and change in response to challenges and opportunities. This definition of sustainability not only preserves the system but also treats it as a process of adaptation and learning, shaped by changing social and environmental contexts. Pluye et al. (2004, 121) similarly provide a practical interpretation, describing sustainability as the uninterrupted ability of programs or initiatives to persist and evolve over a long period. According to this perspective, sustainability not only means continuity but also its institutionalisation, where practices are gradually ingrained in organisational routines, policies, and cultural norms. This necessitates the creation of systems that are resilient, self-sustaining, and able to respond to new social needs. The literature generally indicates that sustainability is a complex, multidimensional concept that extends beyond eco-friendly practices. Over the years, interpretations of sustainability have shifted from an emphasis on resource conservation to an acknowledgement of broader issues such as human development, governance, and systemic adaptation. Thus, sustainability can be seen not only as a goal to be achieved but also as a continuous dedication to maintaining, rather than disrupting, the balance, fairness, and long-term stability across all aspects of human activities. The definition of sustainability, which is referred in this study, is as follows:

> "*Development that meets the needs of the present without compromising the ability of future generations to meet their own needs*" (Brundtland & Mansour 2010, 2).

The significance of this definition lies in its clear delineation of the coexistence of present-day development priorities and the obligation to manage resources in ways that will benefit future generations. The study, by grounding its thesis evaluation on this universally accepted definition, firmly positions itself with the basic notions of sustainable development.

2.3.2 Different forms of sustainability

A new dimension is added to the concept of sustainability, treating it as an active process with many facets—that is, the environmental, social, and economic aspects. Sustainability as a dynamic process is examined through the long-term viability and adaptability of various programs, policies, and institutions. Over time, the interpretation of sustainability has evolved into a framework encompassing three interconnected pillars: economic, social, and environmental sustainability (Moldan, Janoušková & Hak 2012, 4). Sustainability is typically explained as comprising three main domains: economy, environment, and society—sometimes referred to as equity, ecology, and economy (Vos 2007, 335). Regardless of the interpretations, the aim is to balance these domains so that they can benefit and enhance one another.

Environmental relationships and human engagement are not isolated, but rather intimately connected as a process that involves a continuous flux of materials and energy, whereby one influences the other, thus affecting each (Giddings et al. 2002, 193). *Environmental sustainability* centres on the health and sustainability of natural resources. Natural resources have a dual function: they serve as sources that provide input for economic design, and as sinks for waste products (Daly 1974). To be sustainable, one must respect the natural renewal rate of renewable resources. Any industrial waste must be treated so that the environment can absorb it without harm. (Goodland 1995; Basiago 1998, 155.)

The concept of *social sustainability* denotes a community's capacity to support and preserve its welfare, as well as that of future generations, through the values of equity, diversity, inclusion, and social unity. Among the actions that lead to such a situation are providing social services to the population, eliminating poverty and inequality, preserving culture, and establishing relations in the neighbourhood. "Indicators of social sustainability", in this sense, are "social capital, civic engagement, joining cooperative groups, and the quality of life" (Colantonio, 2009, 4).

Economic sustainability is often described in the academic literature as a series of actions that "maintain an organization's economic viability over a long period while at the same time lessening its negative impacts on the environment" as well as "promote the development of a better society" (Morelli, 2011, 6*)*. When considering economic sustainability, a model of success is referred that is based on sustainable economic growth, which is socially and environmentally sustainable. This means that one can generate economic value in a way that allows future generations to meet their own needs without exhausting natural resources. (Dyllick & Hockerts 2002, 134.) The prominent role that economic sustainability plays has been magnified as the costly health care systems are simultaneously under pressure from the government to provide more and better services. The OECD report states that the pandemic has brought forward acute health expenditures in many countries, and maintaining fiscal balance will be a major policy challenge, leading to a need for efficiency gains (OECD 2024, 14). In the U.S., different areas of concern have been indicated in various reports regarding the affordability and the future financing of care, thereby putting forth the necessity for reforms that would focus on widespread cost containment, value-based care, and dialogue on the differences that exist structurally in the practice and the spending (Ferris et al. 2024, 1852). European literature has also taken a similar view, suggesting that the dual public-private financing model might exacerbate the conflict between fiscal health and the goal of equal access to health care (Pammolli et al. 2012, 623). Additionally, the environmental impact of healthcare, including the sector's ecological footprint and the emerging field of health-system sustainability measurement, is increasingly recognised as a policy-relevant issue. These environmental impacts are now understood to be closely linked to financial sustainability, making them a shared goal for adaptive health systems. (Padget et al. 2024, e675–e683; Kluge et al. 2023, 1552–1554.) Taken together, these studies highlight why economic sustainability has become a priority for researchers

This study examines economic sustainability in healthcare, recognising that sustainability is broadly considered to encompass three interconnected domains (i.e., economic, environmental, and social). By focusing on economic sustainability, the study highlights the pressing challenges of economic sustainability in health systems, primarily in terms of costs and long-term viability.

2.3.3 Sustainability in healthcare

Sustainable healthcare is a concept that embraces the environment and prioritises the well-being of patients, workers, and the community. Scholars defended a structural definition of sustainability that aims to conserve resources while reconciling ecological, social, and economic priorities. However, the actual practice is still often limited and piecemeal in clinical labs (Molero et al. 2021, 141). A main objective of sustainable healthcare is the provision of timely, high-quality care regardless of a patient's financial status. Under this conception, equity is understood as the requirement that all people have equal access to healthcare services. Although equity is widely recognised as a desirable objective, counterintuitive consequences may arise. For example, health systems designed to promote public health can inadvertently result in environmental harm. Pollution in this context refers to environmental contamination, such as that generated by medical waste, which may contribute to the spread of disease. (Buffoli 2013, 411.)

Given these challenges, Hudson and Vissing (2013, 6) caution against the overgeneralization of sustainability in health policy. They argue that when sustainability is defined too broadly, merely as a framework for decision-making, its practical utility is diminished. Instead, they propose a more precise definition of sustainability, one that centres on universally valued outcomes such as human health, thereby offering a clear and actionable framework for evaluation.

The Sustainability-Oriented Innovation (SOI) Framework bears the basis for healthcare sustainability. This framework is linked to the creations that support the long-term sustainability of the economy, the environment, and society. It merges sustainability objectives with innovation activities, thus providing more opportunities for innovation that can lead to a sustainable outcome. This framework is based on the belief that innovation brings about sustainable change, enabling companies to upgrade their environmental and social performance along with their economic status. (Bocken et al. 2014, 43.)

Harsanto et al. (2024) identify six dimensions of the Sustainability-Oriented Innovation framework. These dimensions are interrelated: the innovation emphasis dimension, the sustainability emphasis dimension, the intra-organizational integration dimension, the inter-organizational integration dimension, the ambidexterity dimension, and the physical life cycle dimension. Collectively, they provide a detailed picture of how firms can embed sustainability into the innovation process, with a clear focus on aligning resources, creating stakeholder synergy, and acknowledging a product's sustainability throughout its physical life cycle. (Harsanto et al. 2024.)

Sustainability-oriented innovation refers to deliberate changes to an organisation's values and beliefs, as well as its relations to products, processes, or practices, designed to develop and capture social, environmental, and economic benefits. Adams et al. (2016) present a synthesised conceptual framework depicting these practices and processes, which calls for an essentially systemic approach to integrating sustainability into the development and launch of innovations. Therefore, Sustainability-Oriented Innovation must draw on diverse ideas from external collaborators, stakeholders, and systemic issues (Florida 1996). Building on this, some sustainability frameworks adopt a more expansive "ultra-firm" viewpoint, highlighting how firms can progress through various phases of organizational response and innovation. For example, Berry and Rondinelli (1998) outline three corporate environmental response phases: non-compliance, compliance, and beyond compliance, with the latter phase indicating a radical shift in how both institutions and stakeholders perceive and execute their roles. Similarly, Tukker and Butter (2007) present a three-level model: system optimization (e.g., improving fuel efficiency), singular innovations (altering specific elements of production and consumption), and systems-level innovations, which address societal functions through systemic changes, including infrastructure and urban conditions. Drawing on these models, three contextual levels of Sustainability-Oriented Innovation activity can be viewed in terms of the following: reactive (firms react to external regulations or pressures), embedding (firm-wide sustainability goals and processes are embedded into existing business functions), and systems change (systems transformation is achieved through changes to the entire system). These conceptualizations form the basis for a preliminary Sustainability-Oriented Innovation framework, as illustrated in Figure 4. (Adams et al. 2016, 10.)

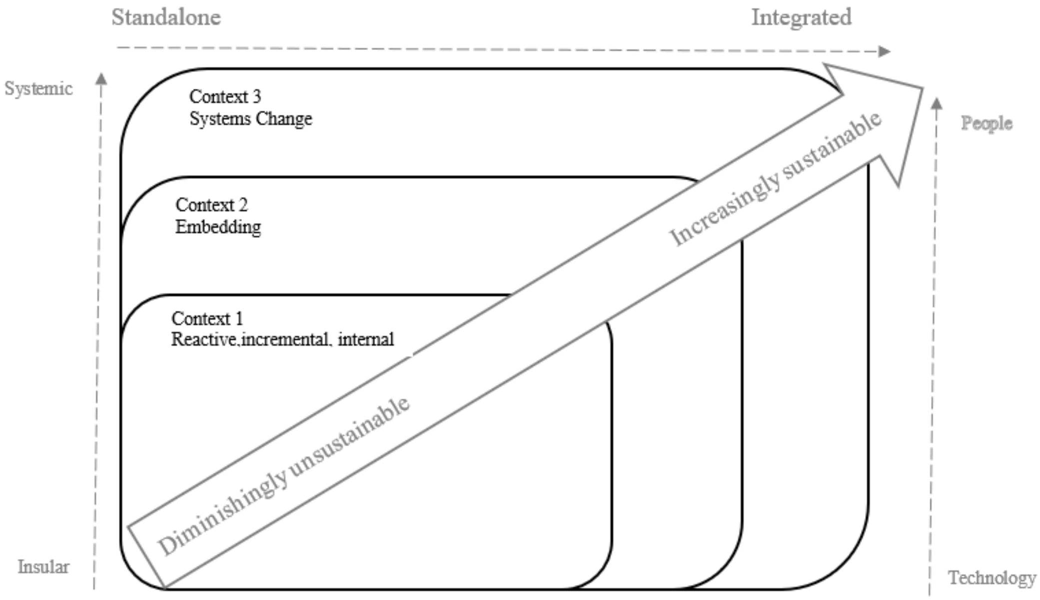

Figure 4. Initial model of SOI (adapted from Adams et al. 2016, 11)

Cost has been the main dimension of economic sustainability in this framework, which, in turn, has enabled a standard of service to remain at the same level of quality or even improve. To put it differently, healthcare AI is considered economically sustainable if it drives cost-effective operations, thereby enabling more efficient care and reducing readmissions and unnecessary medical interventions. Predictive analytics, for example, assists hospitals in estimating the number of patients who will arrive, thereby ensuring the right number of doctors and staff (Bocken et al. 2014, 46).

2.3.4 Need to study economic sustainability in the healthcare

Sustainability in healthcare has become one of the most discussed topics in academic and policy circles in the past several decades. Most often, it is examined from two major perspectives: environmental impact and medical care quality. Less attention, however, has been given to the economic aspect of sustainability. (RĂDOIU et al. 2022, 11.) The economic side has been less developed than the environmental and ethical, even though the growing costs and inefficiencies in healthcare systems are recognised everywhere, and the economic sustainability arguments are still underutilised (Kuhlmann, Dussault & Wismar 2020, 78). The absence of economic sustainability as a factor in health care policies has been particularly noticeable in long-term strategic planning and decision-making processes, where economic sustainability has often been treated as collateral rather than the central value that requires innovation and scrutiny (Vogus & McClelland 2020, 123). It is still the case that most healthcare funding systems are more reactive to immediate budgetary needs than proactive systems that deliver long-term fiscal sustainability (Charlesworth et al. 2021). Besides, the lack of a universal framework or a set of indicators for economic sustainability creates a barrier for researchers and policymakers to evaluate progress or interventions in a significant way (World Health Organisation, 2025).

Sustainability in healthcare has become a hot topic in both academia and policymaking, yet it has largely been assessed via two dominant dimensions: environmental impact (carbon footprints, waste management, etc.) and clinical quality (patient outcomes, safety, etc.). The financial aspect of the sustainability equation, however, still has a long way to go before it is fully developed. One reason is that authors analysing healthcare financing often argue that discussions centre around cost-effectiveness or quality of care, but lag far behind when it comes to the sustainability of the financing model itself. (Liaropoulos & Goranitis 2015, 4.) On the one hand, escalating costs and inefficiencies in healthcare systems are very much acknowledged, but on the other hand, the focus on economic sustainability—as a distinct domain of sustainability—remains underexplored (Organisation for Economic Co-operation and Development 2015, 3). The gap is particularly evident in the process of long-term strategic planning and policymaking. Economisation, which means making systems mainly able to take on their financial burdens, has very often been regarded as a facilitator of other issues rather than the basic value insisting on continuous innovation and examination that is required (Organisation for Economic Co-operation and Development 2024, 4–6). Most healthcare financing arrangements remain largely reactive: they are influenced by immediate budget cycles, cost shocks, or external crises, rather than being proactive systems that guarantee Long-term fiscal sustainability. One recent policy analysis states that while health expenditure should be gradually increased, most health systems are not ready to face the demand and cost increases from consumers, which will impact budgeting (Organisation for Economic Co-operation and Development 2024, 9). The lack of a standard framework or indicators for economic sustainability hinders not only researchers and policymakers from making assessments of progress or evaluating interventions, but also from communicating them meaningfully (Liaropoulos & Goranitis 2015, 2).

Healthcare spending in the world's biggest economies is rising to such a level that it is becoming a serious issue. For instance, the proportion of GDP assigned to health care in Organisation for Economic Co-operation and Development countries went from about 7% in the early 2000s to almost 9% by 2019, and in the absence of major policy changes, it may well go beyond 11% by 2040 (Organisation for Economic Co-operation and Development 2024). In many countries, the impact of an ageing population is already evident: the elderly generally need more medical care, hence they take up more resources, while the working-age population that pays taxes gets smaller, thus the government has less ability to bear the cost burden (Glinskaya et al. 2024). So, rapidly rising health expenditures, an ageing population and the growing prevalence of chronic diseases simultaneously are a big challenge for the economic sustainability of health care systems.

Proper management of the contemporary pressures requires health policies to be developed that will address these different areas: the integrated care models (an advance from high-cost acute care to community-based and preventive services); the cost-effectiveness and value-based models (making sure that resources are allocated to the interventions with the highest health-economic returns); the preventive strategies that are more robust (lowering the costs of treatment through early intervention); and the innovations in fiscal governance (utilization of multi-year budgeting, performance-oriented budgeting, risk-sharing financing pools, and improved collaboration between health and finance ministries). An empirical study involving 32 OECD countries demonstrates that value-based healthcare and better performance positively impact government budget balances, debt burdens, and fiscal sustainability, but these advantages heavily depend on the demographic context and the level of health spending (Tang et al. 2025, p. 479). Without a comprehensive approach, even the richest countries will be under increasing pressure: reactive budgeting or incremental cost-control will not be enough to handle structural changes.

The convergence of rising healthcare costs, an ageing population, and a higher incidence of chronic illnesses makes it difficult for healthcare systems to maintain economic sustainability. Health policies that effectively manage these challenges must prioritize integrated care models, cost-effectiveness, reinforced preventive strategies, and approaches directed at older adults' specific needs, without sacrificing quality or equity.

2.3.5 The role of AI in economic sustainability in healthcare

AI in healthcare is not only the future but also a present reality that significantly reduces costs in diagnostics and treatments. An economic model comparing a decade of AI-based and traditional education found enormous cost savings. The study suggested that hospitals would save around $1,666.66 every day in the first year, and by the tenth year, the total savings would increase to $17,881. In the same way, AI in the care process would yield even more benefits, amounting to $21,666.67 in the first year and $289,634.83 per day by the end of the tenth year. (Kumar et al. 2025, 14-15.) The situation gets even better because AI, apart from saving money, is also a great helper in forecasting healthcare needs, ensuring access to effective treatments and medications at reasonable prices, and making the day-to-day operations of the hospital more efficient. For instance, algorithmic patient flow predictions could help the hospital better understand the number of workers and the amount of other resources needed, which in turn could lead to less waste and better overall cost control (Kapoor et al. 2026, 3–4).

AI applications could be the major drivers of cost reduction, with concurrent increases in efficiency. On the other hand, the review also noted that economic evaluations for many of the studies available at the time were quite partial, especially in their treatment of capital and operational costs and in their failure to state an existing alternative for comparison. (Wolff et al. 2020, 8–9.). This lack of information makes it clear that there is a need for a meticulous, strict economic assessment of AI adoption. When all the monetary aspects are considered, healthcare providers and policymakers will be in a much better position to decide on AI integration into clinical practice in a way that is both economically and socially safe.

2.4 Cost-saving mechanisms of AI integration in healthcare

This sub-chapter is further divided into five sub-chapters illustrating the different pathways contributing towards cost saving by AI integration in healthcare. Overall, this section helps to demonstrate how AI adoption in healthcare can support different administrative tasks and clinical efficiencies into measurable economic benefits.

2.4.1 Administrative efficiency

The demand for healthcare administration and workflow management to deliver modern, high-quality, cost-effective systems has been steadily rising. AI-driven scheduling systems have demonstrated their ability not only to improve throughput but also to reduce the cost per case through active resource management by reducing time wastage and matching demand with supply (Sahni et al. 2024). AI-powered predictive analytics present a radical approach to healthcare administration, with better forecasting, task prioritisation, and decision-making support, all of which contribute to healthcare efficiency and reduced administrative costs (Sahni et al. 2024).

The use of AI-based technology to automate medical administrative tasks, such as documentation, billing, and scheduling, has been an important factor in making healthcare operations more efficient and productive. One of the applications is in Natural Language Processing and speech recognition, which can automatically transcribe doctor notes and make a patient file, which means less data entry for the doctors, so they can spend more time with the patients. (Ng et al. 2025, 236.) AI systems, on the other hand, can identify issues at the very beginning of the billing cycle, leading to a significant reduction in the cost of claim reprocessing (Miotto et al. 2018). AI-backed predictive analytics is viewed as a revolutionary phenomenon in healthcare administration, as it not only enhances forecasting precision but also supports real-time decision-making, which in turn leads to improved clinical efficiency and lower administrative costs (Rajkomar et al., 2019, 131). For instance, the incorporation of AI-based technology reduced documentation time by 30%, allowing more of healthcare professionals' time to be directed towards patients — a factor that improves both productivity and financial performance (Rajkomar et al., 2019). Use of Natural Language Processing technology in electronic health record documentation resulted in the improvement of documentation completeness and adherence to the standards of clinical documentation, the reduction of clinical ambiguity, as well as protection in the legal aspect (Rajkomar et al. 2018, 222).

In some instances, AI-powered scribe technology and digital scribes have significantly reduced documentation time in various evaluations. As a result, doctors can now allocate more time to patients and spend less on Electronic Health Record maintenance. A multicenter, real-world evaluation showed a marked reduction in documentation time and task load after scribe deployment (Pelletier et al. 2025). The use of AI in billing, prior-authorisation, and claims workflows has been reviewed and analysed across industries and proven to cut administrative costs and denial rates, leading to large-scale, measurable operational savings. Economic modelling through the current deployable AI use cases suggests that the hospital sector run-rate net savings would be tens of billions annually (or around 4-10% of hospital costs in the modelled scenarios) if the use of AI in clinical operations, scheduling, supply-chain, and documentation were combined. (Sahni et al. 2024.)

The expected overall savings from several AI use cases at the system level (clinical operations, outpatient access, documentation, supply chain) are predicted to the level of $60 billion to $120 billion annually (approximately 4% to 10% of hospital costs) for US hospitals in the case scenarios considered (Sahni et al. 2024). When viewed as a whole, these technologies indicate that medical AI-based automation can turn hospitals and clinics not only into more productive and cost-effective places but also into better-quality care providers.

2.4.2 Early detection and preventive care

Preventive care strategies are becoming increasingly effective due to AI technologies, which enable even more precise identification of at-risk individuals and facilitate rapid interventions. Healthcare is becoming increasingly cost-effective due to these technologies, which enable early disease detection and improve the preventive care system. One advantage of early detection is that it allows doctors to act promptly, before the patient develops severe complications, thereby preventing the need for expensive treatments and hospitalizations (van Leeuwen et al. 2021, 1077). At the same time, when used for large-scale screening and monitoring, AI has a much greater financial and clinical impact by detecting the disease at earlier, less problematic stages. For instance, the incorporation of AI into the diagnostic process for acute stroke has practically halved the number of cases with missed large-vessel occlusions, resulting in quicker treatments, better recovery, and significant lifetime cost savings for the patient population. (van Leeuwen et al. 2021, 1077.)

In the same way, the use of AI-powered imaging for HCC monitoring in high-risk cirrhotic patients proved cost-effective, with an incremental cost-effectiveness ratio of around €9,888 per QALY gained compared with standard screening (Maas et al. 2025). The whole process of early detection not only improves survival rates but also cuts down the economic burden that comes with advanced cancer treatment, where costs could rise enormously due to surgery and chemotherapy to the point of several-fold increase. The use of AI in sepsis detection and early warning systems has also led to significant cost savings. A Swedish health-economic analysis found that AI's involvement in sepsis prediction shortened Intensive Care Unit stays by 1 patient day, and the resulting savings were estimated at about €2.8 million annually from preventing critical illness. (Ericson et al. 2022.) Moreover, these results corroborate with systematic reviews that point out that predictive algorithms, when incorporated into clinical decision-support systems, can shorten hospital stays, eliminate unnecessary procedures, and reduce the complications that occur downstream, all of which support the economic sustainability of the healthcare system (Zhang & Chen 2025, 7422).

From a preventive medicine perspective, AI-supported risk-stratification models enable early diagnosis and disease-specific treatments, and therefore, the deadliest conditions, such as diabetes, congestive heart failure, and chronic obstructive pulmonary disease, may no longer be as prevalent. Resultantly, the frequency of readmissions decreases, and the derived cost savings cascade throughout the entire healthcare system, comprising primary and secondary care (Bulut, 2025). Further, AI-driven preventive analytics in a healthcare system bring about resource reallocation, the elimination of unnecessary diagnostics, and improvements in clinicians' time bills—thereby lowering operational costs—according to economic assessments (Rao et al. 2025). Taking it all together, the evidence derived from the most recent cost-effectiveness studies proves that the combination of AI-based early detection and preventive-care interventions not only gives back the drilled-down financial numbers but also better community health, and more efficient operational process, thereby solidifying AI as the mainstay for the sustainable medical enquiry and transformation (van Leeuwen et al. 2021, 1077; Bulut, 2025 1631851).

2.4.3 Admission and readmission reductions

The machine learning models are very effective at predicting hospital admissions, again by considering patient-level characteristics such as demographics, clinical history, and social determinants of health. The early detection of high-risk patients allows doctors to take the necessary steps to prevent unnecessary readmissions, e.g., by performing interventions specifically targeted at high-risk patients (Rajkomar et al. 2018, 446). Hospitals that have adopted AI-enabled risk stratification models report the most compelling advantage: fewer readmissions that could have been avoided. For instance, one study indicates a drop from 11.4% to 8.1%, and one readmission was avoided for every 11 patients treated through the AI-assisted pathway (Romero-Brufau et al. 2020). In fact, AI-assisted clinical pathways for patients with Chronic Obstructive Pulmonary Disease have been found to cut the 30-day readmission rate by not only recognizing patients earlier but also providing more individualised discharge planning. Reducing unnecessary hospitalizations directly impacts the hospital's budget, as it can save $10,000 to $15,000 per bed in some healthcare systems (Wang et al. 2022, 48). AI-powered triage solutions have also played a major role in dropping the number of non-urgent cases in the emergency room. One study reported a decrease of about 15%. This is a valuable outcome, particularly given that emergency room visits are usually three to four times more expensive than outpatient services. These tools improve diagnostic reliability and predict worsening of the patient's condition. They also provide timely medical intervention. As a result, they lead to better outcomes and reduce long-term costs, including those associated with readmission penalties, litigation, and malpractice claims. (Friedman, Delgado & Weissman 2024.)

As per Madelon M. Voets et al. (2022, 343), "By using precisely calibrated predictive-modelling frameworks, one can expect a reduction in the rates of medical errors and patient readmission. The latter comes along with a decrease in the financial burden that is usually caused by preventable complications and related legal liabilities." In another pioneering research by Rich Caruana et al. (2015, 1501), the interpretable AI model was conceived to predict the risk of death due to pneumonia, thus preventing misdiagnoses, unnecessary hospitalizations, and overtreatment—all without increasing operational or legal risks. Embedding machine learning into electronic health records has proven highly effective in stratifying patients who require intensive post-discharge follow-up, significantly reducing 30-day readmissions and providing measurable financial benefits to healthcare payers (Rajkomar et al. 2018, 1124). These predictive capabilities allow for targeted interventions such as follow-up care and home care referrals, which can prevent avoidable readmissions and mitigate penalties.

2.4.4 Resource optimisation

AI-based solutions have become a major factor in optimizing resource allocation in healthcare by predicting demand, reducing waste, and improving operational efficiency. During the COVID-19 pandemic, AI-powered supply chain management systems were used to forecast demand for medical supplies like personal protective equipment, enabling purchasing at the best price and reducing stock losses (Khan et al. 2024, 58). Setting aside, predictive analytics systems not only demonstrated their capacity to reduce inventory holding costs by shortening replenishment cycles and preventing losses from expiration but also contributed to long-term savings (Grand-Clément et al. 2021, 212). In addition, Machine Learning techniques are among the major contributors to allocating ventilators and ICU beds during the initial phase of the pandemic, which eventually resulted in both hospital readiness and the budget being used efficiently (Grand-Clément et al. 2021, 217). Moreover, predictive tools were among the major factors in the rise in workflow efficiency, by identifying bottlenecks and improving patient flow, thereby reducing redundancy and improving coordination among departments (Blanco, Gázquez & Leal 2023). Additionally, AI-based decision-making systems have improved procurement strategy and logistics management by considering both financial and environmental metrics, thereby facilitating data-driven investment and operational decisions (Long et al. 2023). AI technologies deliver not only the highly sought-after qualities of a strong healthcare system but also result in less waste and the implementation of more economical and environmentally sound methods of service delivery across both clinical and administrative functions (Khan et al. 2024, 62).

Predictive tools enhance operational efficiency further by identifying unnecessary processes, encouraging better communication between departments, and facilitating clinical interventions at the right time, which, in turn, lessen operational burdens and costs (Romero-Brufau et al. 2020, 571). In addition, AI-based decision support systems, along with real-time monitoring solutions, increase care continuity, lower the risks and associated costs, and, as a result, enable faster and better-informed decision-making (Obermeyer & Emanuel, 2016, 263). AI also assists healthcare organizations in making evidence-based investment decisions by predicting demand, identifying usage patterns, and developing cost-effective strategies, all of which help minimize resource waste and create an environmentally friendly, efficient service delivery process (Topol 2019, 177).

In the context of financial planning, AI provides valuable decision support for budgeting and investment. Economic models suggest that predictive AI applications allow healthcare systems to allocate resources proactively rather than reactively, resulting in reduced waste and improved efficiency (Wolff et al. 2020, e16866). Targeted strategies informed by AI have been shown to yield higher returns on investment by reducing the demand for costly acute care services, particularly in underserved populations (Obermeyer & Emanuel 2016, 1220). Moreover, predictive analytics can perform cost-effectiveness evaluations of screening programs, helping funding agencies allocate resources to the most effective treatments (Areia et al. 2022, 845). AI-informed targeted strategies were reported to be more profitable in terms of investment, as they reduced the use of expensive acute care services, especially among underserved populations (Mehta et al. 2023, 1023). It is a major landmark that AI-powered resource optimization is possible in various healthcare settings. The proof is that AI systems can be deployed not only in high-income and low- and middle-income countries but also without sacrificing either quality or cost-effectiveness, indicating the universal nature of AI-based resource optimisation strategies (Mollura et al. 2020).

2.4.5 Workforce planning

The use of AI prediction models in emergency department admissions and the operating room has already demonstrated substantial improvements in healthcare operational efficiency. More accurate forecasts of patient demand, made possible by these models, lead to better staff scheduling and improved bed management in hospitals (Rajkomar et al. 2018, 446). The predictive systems offer several advantages, including improved resource allocation, reduced operational burdens, and enhanced patient flow. For example, machine-learning-based forecasting of ED volume has facilitated shift optimisation by accurately predicting and thereby adjusting staffing. Research on pediatric emergency department forecasting has indicated that, for some shifts, staffing levels can be increased by as much as 30%, which in turn contributes to a decrease in the average patient-to-physician ratio of 4.32 patients over the entire shift. (Vural et al. 2025, 10.)

On a broader scale, systematic reviews have confirmed that AI-based admission and flow prediction models outperform traditional methods in terms of accuracy (85–95%). Consequently, they directly contribute to reducing avoidable hospitalizations, improving bed occupancy rates, and alleviating emergency department overcrowding. (Nunes et al. 2025.) The use of AI in hospitals brings not only day-to-day operational benefits but also positive effects on human resource management and cost control. AI can assist hospitals in allocating and scheduling staff so that employees' skills align with the expected patient volume. As a result, no staff members are left without work, nor are they overburdened when patient numbers are low. (Qureshi, Waheed & Jawed 2025.) For example, one study reports that AI-based workforce scheduling in healthcare has led to a 30–40% reduction in overall staff scheduling time, more accurate placement of staff in appropriate roles, decreased reliance on premium "emergency" and consequently, a reduction in overall labour costs (Nunes et al. 2025). Since staffing expenses typically account for more than 50% of a hospital's operational costs, any significant reduction in these costs can be achieved without compromising patient care (Porto & Fogliatto 2024).

The research by Wang et al. (2021, 77) found that implementing AI-led scheduling tools would increase nurse utilization in hospital units by 12%, reducing overtime costs and increasing service quality. Likewise, in large hospital systems, AI-supported staffing systems have been credited with reducing ineffective staffing by 18%, leading to less hectic daily operations and more patients being treated. As a result, the use of AI in patient flow prediction and workforce automation has led to the formation of an efficient and resilient labour force. Overtime and premium staffing are reduced, and workforce capacity is better in sync with variations in patient demand. The combined impact of these factors not only results in cost savings through reduced staffing and resource overheads but also in quality improvements through better supply-demand matching, improved clinician-to-patient ratios, and reduced burnout. In addition, the savings generated can be channeled into AI systems, staff training, and more enhanced staffing models, creating a virtuous cycle of workforce optimization, better care delivery, and long-term sustainability.

2.5 Long-term impact projections of cost savings on economic sustainability in healthcare

Research examining the long-term economic implications of AI in healthcare increasingly focuses on system-wide outcomes rather than isolated pilot settings, with cumulative effects and sustained operational costs emerging as key themes. As already discussed, existing literature generally identifies AI's potential to lower expenditure and improve health outcomes through mechanisms such as reductions in unnecessary procedures, lower resource utilisation, and enhanced diagnostic performance. However, findings also show that the extent and persistence of economic benefits differ across clinical environments and are shaped by factors including deployment strategies and organisational practices within health systems. (Wolff et al. 2020; El Arab et al. 2025). Large-scale dissemination of AI technologies is frequently associated with projections of improved economic efficiency and shifts in budget structures. For example, some analysts estimate that AI adoption could correspond to reductions of 5%–10% in US healthcare spending—equivalent to USD 200–360 billion annually—alongside quality improvements (Sahni et al. 2023). Further, Obermeyer et al. (2020, 33) describe AI's adaptability and capacity for continual learning as attributes that support prolonged integration and recurrent benefits over time.

As discussed by El Arab et al. (2025), at present, AI's impact on financial aspects primarily manifests as the most reliable evidence of cost reduction in cases where it assists or speeds up specialists' workflows, particularly in radiology, ophthalmology, and screening for diagnosis. Such efficiency, reduced complications, and greater performance in the application of AI in diagnostic fields lead to financial impacts that can be measured in years, even though they may not be uniform over a long period. Such variations in long-term effects are again due to factors such as diagnostic precision, clinical follow-up processes, and the reimbursement model. Research studies on preventive and chronic disease management, among the broader applications of AI, point to a significant economic potential, given the role of timely intervention in making future treatment less intensive. The magnitude of realised cost advantages appears tied to the degree of systemic integration, patient engagement, and continued investment in supporting infrastructure, human resources, and governance structures. Overall, existing analyses describe net economic effects as contingent on how widely and effectively AI-enabled practices are embedded and maintained in routine care environments. (Wolff et al. 2020.)

Policy and industry reports frequently project large-scale cost reductions associated with broad AI adoption in healthcare, although these projections differ considerably based on assumptions about adoption speed and scale (Al Meslamani, 2023). These variations reflect the uncertainty surrounding how quickly systems may incorporate AI and how efficiently benefits may materialise. Research also indicates that the longer-term economic effects of AI are closely linked with factors such as equity of access, governance structures, and workforce dynamics. In several analyses, institutions with more resources appear more likely to capture financial benefits, while reinvestment patterns influence whether savings contribute to workforce support or preventive health efforts. Overall, forecasts of long-term economic outcomes are shaped not only by technical performance and cost measures, but also by the way advantages are distributed across different actors within the health system. (Topol 2019; Khanna et al. 2022.).

Continuing through the existing literature, there are indeed activities aimed at establishing a more robust long-term forecasting by incorporating stricter evaluation techniques, such as randomised controlled trials and systems modelling. When economic evaluations are based on both quantitative and qualitative inputs, the resulting projections are more robust and helpful for decision-making. (Wang, 2024; Wu et al., 2024.) Figure 5 shows the AI for the IMPACTS Framework, which has been devised as a multidimensional framework for scrutinizing the long-term, real-world impact of clinician-facing AI systems. The framework divides evaluation into seven interrelated areas: integration into clinical workflows ; monitoring, governance, and accountability mechanisms ; performance and quality metrics ; acceptability, trust, and training among users ; cost and economic evaluation ; technological safety and transparency ; and scalability and broader system impact. (Jacob et al. 2025.) These areas are indicative of the range of factors observed to affect the ongoing value and implications of AI adoption across different healthcare settings.

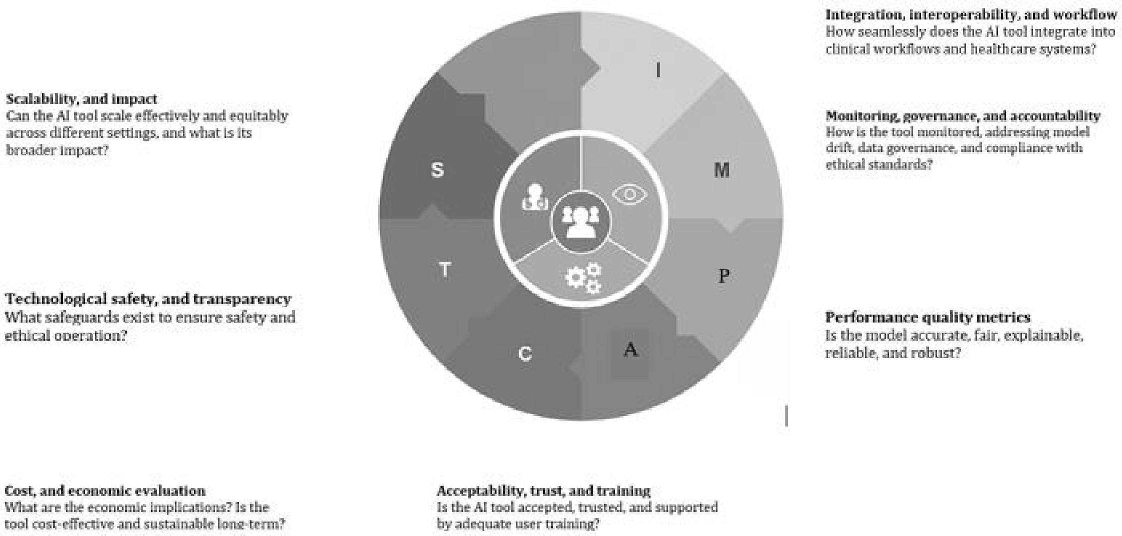

Figure 5. AI for IMPACTS: a comprehensive framework for evaluating the long-term real-world impacts of artificial intelligence (AI)–powered clinician tools (adapted from Jacob et al. 2025, 16)

One of the significant aspects highlighted in the AI for IMPACTS Framework is the integration of AI instruments into medical practice and their compatibility with existing IT systems. Research shows that smooth integration can lead to fewer task duplications, the elimination of unnecessary procedures, and the sharing of benefits across departments. (Jacob et al. 2025, 6.) On the other hand, the integration of a limited nature has been associated with problems such as the need to enter data twice or disrupted workflows, which, in turn, can lead to the non-realization of potential economic gains. The need for continuous monitoring and management is also stressed as a factor to be considered. AI systems are prone to change over time, which may introduce bias, degrade performance, or misalign with the latest workflows. Supervisory activities—though they entail continuous operational costs—are seen to sustain efficiency gains by providing accuracy, fairness, and clinical relevance. (Jacob et al. 2025, 8). The references further indicate that the financial influence of AI closely correlates with measurable downstream outcomes rather than being linked solely to technical performance. Upgrades in diagnosis or treatment recommendations are associated with reduced complications, readmissions, or hospital stays, which translate into cost savings. (Topol 2019, 133; Berwick et al. 2008, 759.)

Long-term evaluations of AI in healthcare also impact the overall economic ramifications, including the total cost of ownership as one of the most important elements. The analyses detail the initial investments —infrastructure, licensing, and setup —and provide a comprehensive picture of the recurring costs incurred in the governance, monitoring, and maintenance of models. Some literature even goes a step further to include reinvestment channels such as training of personnel, increased access to the service, and upgrading of infrastructure among the factors that contribute to the overall savings as well as system sustainability (Jacob et al. 2025, 12; Berwick et al. 2008, 759). It has been noted that technologically safe and transparent systems remain in the other areas that have a great influence on long-term outcomes. According to research, such systems will not only gain the trust of the healthcare provider but will also indirectly develop the economic benefits by cutting down on legal, reputational, and clinical risks through compliance and support for informed consent (Topol 2019, 132; Jiang et al. 2017, 363). Scalability is consistently highlighted as a criterion for economic impact on a system-wide basis. Pilot studies often report that costs per patient have decreased; however, the literature suggests this might not always hold when scaling up, due to differences in working practices, data quality, or funding arrangements. The discussion of the different stages of adoption and economies of scale calls for consideration of the fact that the overall economic impact of AI is determined by the technology's dissemination and the marginal costs associated with it. (Jacob et al. 2025, 16.) Within this framework, economic sustainability is presented as a property that emerges from the sociotechnical system in which AI operates, which includes integration, governance, clinical outcomes, adoption, safety, and scalability. According to existing studies, the interrelated factors are described as collectively shaping the translation of technology into healthcare.

The cost-saving mechanisms presented in Section 2.6 prioritize accuracy enhancement, faster throughput, and waste reduction (e.g., less complicated cases, decreased readmissions) over the Performance & Quality sector of the AI for IMPACTS framework (Topol 2019, 133). For instance, improved diagnosis leads to noticeable savings in the downstream processes, and this is supported by systematic reviews of AI cost-effectiveness (Khanna et al. 2022, 3–5). The Integration domain of the framework underlines the necessity of incorporating AI tools into daily routines, ensuring they can work with others, and having adoption across the whole system. While Section 2.6 discuses about the saving of workflow (e.g., scheduling optimization, and administrative automation), it does not consider cross-system integration completely. Thus, the framework expands the dialogue by providing the formal recognition of the importance of system-wide integration instead of mere pilot projects in an isolated manner. Section 2.6 has pointed out specific ways of cost savings, such as reductions in readmissions and resource wastage. However, it has not been consistent in including full lifecycle costing, maintenance, and governance costs. The Cost and Economic Evaluation domain of the framework covers this scenario by considering both fixed and repeat costs, pathways for reinvestment, and long-term modelling of economic implications (El Arab et al. 2025, 5). This is consistent with the argument in literature that most of the economic evaluations do not consider total cost-of-ownership and multi-year perspectives (Wolff et al. 2020, 4).

Even if Section 2.6 mainly revolves around efficiency gains, it still barely touches on the issues of organisational risk, model drift, bias, or post-deployment monitoring. The IMPACTS framework has all these issues addressed by deeming monitoring, governance, and technological safety as indispensable for the continuous creation of economic value (Jacob et al. 2025, 8–10). In the absence of such measures, AI systems might go downhill or even be biased, thereby restricting the economic benefits that can be achieved in the long run. The systematic reviews point out the importance of methodological quality and evaluation design as key factors that determine the long-term viability of AI interventions (Kastrup et al. 2024, 15). Section 2.6 gives coverage to workforce planning and training (Wang et al. 2021, 77). However, the issue is looked at mainly from the standpoint of efficiency and utilization. The IMPACTS framework broadens this view by assigning stakeholder trust and adoption as separate domains (Jacob et al. 2025, 10). It has been found in empirical studies that lack of adoption or mistrust by the clinician can cut down the savings that are realised (Shortliffe & Sepúlveda, 2018, 2200) which points out that consumer cost-saving measures cannot be relied on to ensure system-level economic impact. Cost-saving mechanisms are mainly pinpointed by Section 2.6, in separate contexts, such as radiology or scheduling (Khanna et al. 2022, 3–5). The IMPACT framework, however, does not go into the topic of the generalisation of these savings across the system extensively. The scalability domain of the framework stresses large-scale adoption, generalisability, and economies of scale (Jacob et al. 2025, 16).

Section 2.6 points out the existing cost-saving mechanisms, while the AI for IMPACTS framework outlines the ways and conditions in which these mechanisms can lead to the economic sustainability of the health sector in the long run. The study connects the micro-level mechanisms (for instance, improved diagnostics and scheduling optimisation) with system-level outcomes (for example, governance, workflow integration, scalability) (Jacob et al. 2025, 6–16). Governance, transparency, and adoption/trust are mentioned as under-examined domains in mechanistic literature that are critical for long-term viability (Topol 2019, 133). The foundation established by the framework allows linking cost-cutting measures to a broader socio-technical ecosystem, recognising that integration, monitoring, adoption, safety, and scaling influence the realised economic outcomes. It shifts the focus from merely considering isolated efficiency to sustainability by connecting the savings obtained through cost-saving mechanisms with lifecycle costing, long-term horizons, and reinvestment pathways.

2.6 Theoretical framework

In this section, a theoretical framework is developed in Figure 6 to summarise the findings from existing literature. The initial theoretical framework outlines the theoretical structure of the study, which will ultimately answer the main research question: *"How is AI integration in healthcare perceived to impact economic sustainability in the long term through cost savings?".* The left side of the theoretical framework lists the various cost savings observed in healthcare due to AI. These savings are manifested not only in the immediate financial benefits but also in the long-term sustainability.

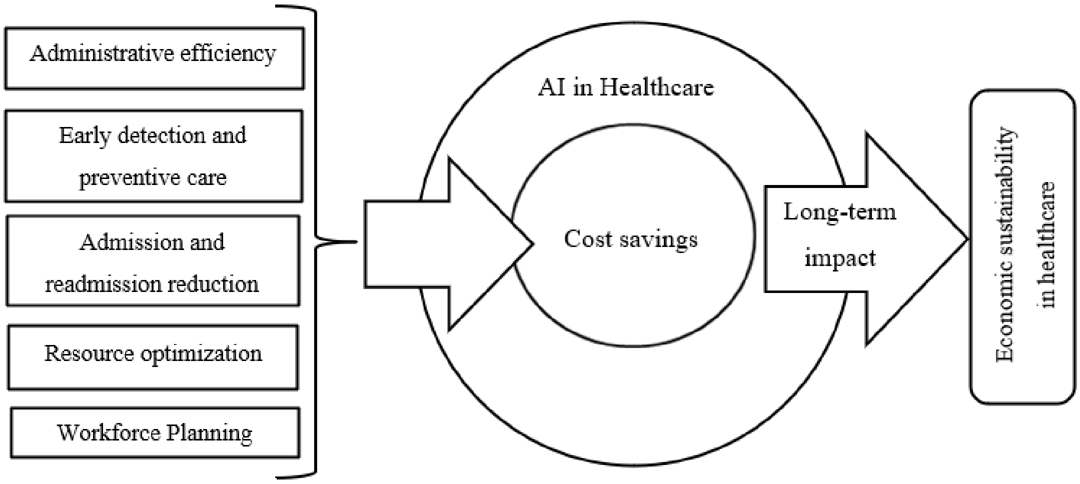

Figure 6. Initial Theoretical Framework

Administrative efficiency provides a clear picture of how AI can reduce operational costs by automating repetitive tasks, reducing paper waste, and reallocating resources to the most effective uses. AI also helps in preventive care and diagnosis within the industry by using diagnostic tools and predictive analytics to spot the health risks, making the treatment process less costly and more effective at an earlier stage. Preventive measures involving AI technology such as outreach to the unvaccinated, constant monitoring of chronic disease patients through wearable sensors, and the digital treatment of mental health—do not only yield better health outcomes but also substantially lower the overall financial cost created by the expensive therapies applied at later stages (El Arab & Al Moosa 2025, 4). It is indeed a significant factor that AI is the main actor in patient monitoring, treatment planning, and discharge management, thereby reducing unnecessary hospital stays and lowering the economic burden on healthcare systems. Similarly, resource optimization enables the current resources—staff, infrastructure, and medical equipment—to be used efficiently, with maximum output and minimal waste. AI contributes significantly to human resource planning by providing staffing predictions.

The framework is founded on the idea that AI is primarily a tool in healthcare for saving costs, and the innermost circle illustrates the cost savings that lead to tangible outcomes, while the outer circle shows the broader view of AI in healthcare systems. All the above-mentioned ways have a combined effect on the efficiency of health systems. AI reduces costs, improves the efficiency of medical services, and shifts the focus from curative to preventive care, enabling health systems to achieve economic sustainability. Through the framework, the interrelationships of cost-saving strategies are visualised in a web-like structure, with economic sustainability as an outcome and administrative automation, preventive care, and workforce optimisation as its backbone. For AI in healthcare to achieve economic stability in the long term, it must not only demonstrate its cost-effectiveness at the time of adoption but also deliver measurable results, such as reduced emergency visits, shorter hospital stays, better chronic disease management, and increased patient satisfaction (Berwick et al. 2008). In other words, this framework points out that AI is a cost-saving tool for the short term and a necessity for the sustainable healthcare system in the future. So, this study investigates empirically how healthcare institutions perceive and adopt AI innovations to achieve economic sustainability in long term.

3 RESEARCH DESIGN

Methodology is the term that signifies the belief system directing research activities, providing a detailed description of the familiarity needed for the information on a given topic to be credible and reliable. Research methodologies can be roughly divided into two main types: quantitative and qualitative (Eriksson & Kovalainen, 2015). This section will characterize the selected technique and justify it. It will cover the whole empirical part of the study, combining the qualitative research method, the data collection technique, and the character of the chosen interviewees. The use of a semi-structured interview format and further data analysis via theme analysis were the procedures selected for this research. The data analysis and its reliability were finally assessed.

3.1 Research approach

The various areas through which the research design justifies the research questions and helps readers trust the study's numbers, which support the qualitative research adopted in this study. Researchers are applying the qualitative research method to explore a phenomenon or research topic in depth and with interpretation. Researchers practising the quantitative method would focus on providing explanations, testing hypotheses, and conducting statistical analyses of measurable outcomes, whereas qualitative researchers provide worldviews, understandings, and processes of real-life contexts. Thus, the qualitative method is interpretive by nature and allows researchers to delve into complex issues and meanings rather than being limited to numbers alone (Eriksson & Kovalainen, 2015). AI's use in the healthcare sector is a complicated issue that involves technology, workflows, clinical processes, policies, and even organisational decisions. Quantitative approaches usually reduce complexity to a certain level, e.g., cost savings, represented by a single number. Conversely, qualitative research is the way to go for a deeper understanding of economic sustainability with the help of AI over time. Besides, the different stakeholders' views, experiences, and strategies are also coming into play through this methodology. Thus, behaviours and cost-saving processes are among the factors that are becoming quite visible in this study and could affect economic sustainability in the long run. Additionally, qualitative methods reveal how organisational and environmental factors shape AI's economic impact, offering insights that numbers alone cannot provide—particularly in the context of healthcare policy and service delivery (Eriksson & Kovalainen, 2015).

The previous chapter discussed observations and findings drawn from the literature that contributed to the research questions and methodology. While the research method will be elaborated further, this section focuses on participant selection criteria and the approach taken to conduct empirical research, ensuring that the study’s qualitative framework is grounded in practical and relevant data collection processes (Eriksson & Kovalainen, 2015).

3.2 Data collection

The most common qualitative data collection methods are interviews, surveys, observation, and information from various documents, depending on the research problem, used resources, etc. Depending on the applicable research problem, they can be used as alternatives, in parallel, or in various other ways, not limited to research problems. (Bryman 2016, 464.) Qualitative interviews can generally be divided into three types: structured interviews, semi-structured interviews or unstructured interviews, and group interviews (Myers & Newman 2007, 4). The structured interview would be too narrow in this study, delimiting the interviews, and the group interview would not provide the depth of views as in the individual interview. A semi-structured interview, also called a thematic interview, is a common data collection method in qualitative research. The semi-structured interview method was appropriate as the study wanted to leave room for the interviewees' views and opinions to be able to obtain the broadest data possible. It is also appropriate for this research because of its versatility and flexibility. (Kallio et al. 2016, 2955.)

The objective of this study is to examine *"How is AI integration in healthcare perceived to impact economic sustainability in the long term through cost savings?"*. The investigation aims to see how AI applications can contribute to cost savings through greater efficiency and better allocation of resources over time by analysing the experiences and reflections of different stakeholders from healthcare who have implemented and experienced using AI. Different ideas, experiences, and perspectives were required to be extracted from different sources. The semi-structured interview method fits this type of purpose well because the interviews were intended to be based on themes that have evolved because of previous studies. In addition, the interviewees focused on different issues according to their perception and introduced new themes.

Face-to-face or online synchronous interviews are still very often recommended for qualitative data collection, but in this study, the semi-structured interviews were conducted through email. This choice was made for practical reasons, mainly, the participants were spread out all over the world, and their availability for real-time participation was very limited. In his book, Bryman (2016, 464) opines that researchers often modify interview styles to fit the situation and the logistical limitations of subjects, if the method is consistent with the research goals. Among the various methods of data collection, email interviews stand out as the best option for this study. As they reduce the possibility of errors and increase the overall clarity of data because they allow participants to think carefully about the questions, express themselves in a lucid way, and even edit their answers before they are finally sent (Amri, Angelakis, and Logan 2021, 2). Also, the fact that these interviews are conducted asynchronously means that participants are not under the same pressure to give quick replies as they would be in a synchronous interview, which is why the answers could be more thoughtful and deliberate. In addition, the nature of email communication ensures that there are transcripts ready, thus lowering the risks of errors through transcription and consequently improving the accuracy of the data. (Meho 2006, 1291.)

Nevertheless, the email interview method has its drawbacks that are recognized by scholars. One of the main problems is the absence of non-verbal and paralinguistic cues which can inhibit the building of rapport or lead to misinterpretation of emotions (Bryman 2016, 473; Amri, Angelakis, and Logan 2021, 4). These restrictions are particularly highlighted in the case of semi-structured interviews, in which flexibility, probing, and spontaneous follow-up questions are crucial (DiCicco-Bloom and Crabtree 2006, 316).

To overcome these issues, the current research took a multi-round email interview method to alleviate the worries, which permitted sending follow-up questions after receiving the first answers. The interviews started with a general guide but were succeeded by extra, participant-specific questions to explore the themes that were coming up or to clear up the unclear statements. This back-and-forth communication preserved the main features of a semi-structured interview—structured but flexible questioning—while it was already fitted to the asynchronous nature of email interaction. According to DiCicco-Bloom and Crabtree (2006, 315), the semi-structured format is not determined by the communication mode but rather by the interviewer's skill in modifying questions in reaction to the participant's feedback.

The interview schedule was developed prior to the interviews, incorporating themes and questions outlined in Appendix 1. A semi-structured interview includes two levels of questions: key themes and supplementary questions (Kallio et al., 2016). Field-testing was applied during the development of the interview guide to trial the scheme with a potential participant. Feedback from the test of the interview structure enabled the process to clarify questions, thus improving the data quality collection. There was a change in the wording, the definition of concepts, and the articulation of themes in such a way that clarity and efficiency were attained (Kallio et al., 2016). The interview schedule for this study was constructed theoretically based on the operationalisation framework presented in Table 1. The main interview themes were: (1) AI integration in healthcare, (2) perceptions of cost savings, (3) economic sustainability in healthcare, and (4) long-term impacts. The interviewer retained flexibility to add comments or follow-up questions if an important point emerged during the interview that required further elaboration.

Table 1. Operationalisation Framework

Research Question	**Sun-question**	**Theme**
How is AI integration in healthcare perceived to influence economic sustainability in long-term through cost savings?"	How AI integration in healthcare is perceived to influence cost savings?	AI integration in healthcare
		Cost-saving perceptions
	How are AI-driven cost savings perceived to have long-term impact on economic sustainability in healthcare?	Economic sustainability in healthcare
		Long-term impact

The operational framework not only ties the research sub-questions to the central themes but also directs the interview process and the entire data collection. The first theme covers AI integration in healthcare and its acceptance by the public and professionals, as well as its role in adoption and integration processes. The second theme reviews cost-saving practices and methods, linking them to the concept of efficiency in the health care context. The third theme addresses the economic sustainability of the health care sector, with special reference to the role of AI in reducing costs, a major factor in supporting state-funded health care systems. The fourth and final theme concerns participants' opinions on the prospects of AI for making health care systems economically sustainable in the long run. The thematic nodes are interrelated: a focus on immediate financial benefits might affect the first expectation of the system's long-term sustainability. Thus, this is a significant aspect for the general understanding of the larger impact of AI adoption in the healthcare sector (Creswell & Poth, 2016).

The presence of participants, along with their in-depth knowledge and experience of the phenomenon under study, is a key factor in obtaining significant and detailed data. At least, the participants must have some acquaintance with the topic. In such cases, this requirement is even more crucial because the insights are then guaranteed to be grounded in practical experience. (Guest et al., 2006.) The interviewees were selected from a variety of professional roles, including doctors, nurses, AI researchers, and healthcare professionals, all of whom had firsthand experience of AI in the healthcare sector. The participants were from different nations; thus, a global perspective was offered, which is key to understanding the different ways AI is used, the issues, and the advantages that come with the various healthcare systems. This mix enhances exploration of the ways in which AI contributes to cost savings and the economic sustainability of healthcare. The participants in the study were finally chosen based on these considerations, and nine of them were selected.

The first participant is an oncology research and clinical trials expert with a Ph.D. in cancer biology. She has been involved in various sectors, including academia, consulting, and CROs, in the US and the UK. Moreover, she has more than ten years of experience in oncological research and healthcare. She is currently the Oncology Lead at a clinical trials consulting firm in California, where she manages studies in preclinical and clinical oncology, leads protocol development, and supports translational research through AI applications, all aimed at improving cancer therapy. Her daily practice is heavily reliant on AI technology, which is integrated through the creation of clinical trial dossiers, data profiling, and the optimisation of the patient recruitment strategy. All these AI-powered tools improve clinical trial performance and act as a catalyst for more streamlined operations, thereby contributing to more targeted and efficient oncology research.

The second participant is a consultant physician in internal medicine at a large hospital in Ireland with more than 15 years' experience. He is involved in various activities, including patient care, conducting medical research, developing health policies, and improving the effectiveness of hospital operations. He has been at the forefront of adopting new technologies, such as AI, for healthcare delivery. His AI applications have been very diverse, for example, in diagnostic interpretation using radiology imaging, predictive analytics to detect patient deterioration early, and tools to enhance medical documentation efficiency. Also, he has participated in system-wide projects that test AI applications to improve patient outcomes and better use hospital resources. All these experiences give him insights into how AI integration can help healthcare systems be more efficient and cost-effective (Topol, 2019).

The third participant is a Nursing Science researcher at Åbo Akademi University in Finland and a registered nurse with 12 years of healthcare experience. She has spent five years in the acute-care unit and seven years in teaching and research. Her research and professional interests are in clinical nursing and nursing education. More specifically, she has studied AI's capability to enhance patient care, nursing education, and clinical decision-making. The blending of her clinical and academic experiences equips her with knowledge of using AI to improve nursing workflow and patient outcomes.

With more than 20 years of experience in global drug discovery, development, and commercialization, the fourth participant has acquired not only a broad range of knowledge but also an impressive portfolio encompassing both small and large molecules. Development of pharmaceuticals has always been at the core of his career; this partly explains why he has overseen major projects in drug discovery, regulatory submissions, and product matching in the USA. He has been part of various organizations, from startups to large corporations, where he has not only participated in three IPOs and filed three New Drug Applications (NDAs), but also taken a leading role in these areas. Moreover, he has been involved in the successful development of several products, including Intermezzo™, Kerydin®, Eucrisa®, and Veltassa®, providing input across CMC, regulatory filings, product supply chains, and commercialization strategies. He has been using AI-enabled predictive modeling in his consulting work to optimize regulatory pathways, improve supply chain efficiency, and reduce costs.

The fifth participant is a researcher in artificial intelligence at the University of Waterloo, Canada, specializing in computer vision, 3D reconstruction, and multimodal language models. His research focuses on medical image segmentation and cancer detection, particularly for breast and colon cancer. He participated in a medical image segmentation competition that challenged each imaging modality and improved cancer detection using synthetic images generated by AI. His work includes developing an AI model capable of automatically segmenting across different imaging modalities, demonstrating AI's potential to improve diagnostic accuracy and efficiency in medical imaging, thereby reducing costs and enhancing patient care.

The sixth participant is an ophthalmologist who holds board certification and has more than 15 years of medical experience. He is a fellow of the American Academy of Ophthalmology and is affiliated with the INOVA Fair Oaks Hospital. His clinical career includes 3 years of comprehensive ophthalmology practice for pediatric and adult patients at Kaiser Permanente Medical Center in Springfield, VA, and the founding of Virginia Adult and Pediatric Ophthalmology in Centreville, VA. In addition to his clinical work, he has participated in international medical missions in various countries, including Latin America and India, and has provided eye care to people living in areas with little or no access to healthcare. He has already applied AI in ophthalmology for various purposes: diabetic retinopathy screening, age-related macular degeneration assessment, glaucoma diagnosis, cataract surgery solution, and retinal image analysis.

The seventh participant is a translational researcher who has worked for more than ten years in Contract Research Organization (CRO) settings in Pakistan. She works to connect foundational science with clinical and preclinical trials and has a strong focus on developing protocols and standard operating procedures (SOPs), quantitative polymerase chain reaction (qPCR) assays, gathering evidence for regulatory submissions, and communicating with investigators, sponsors, and quality assurance teams. In addition, she reviews the data and writes submission-ready documents. She has direct exposure to AI implementations in clinical trials. Her institution has already adopted several AI tools, including natural language processing for evidence screening and protocol deviation categorization, as well as predictive analytics for enrollment forecasting and risk identification.

Automation tools are also in place for document preparation and medical writing, thus showcasing AI's role in accelerating clinical trials, enhancing accuracy, and cutting down costs and time (Topol, 2019).

The eighth participant is a lecturer at the International Islamic University of Pakistan, a major drug scouting chemist at Hayat Pharma in Lahore, and a Principal Route Scouting Chemist. His research focused on drug discovery and development, ultimately enhancing healthcare delivery. He works with AI professionals to open new avenues for his research and develop practical applications. His company is already working on AI systems that will be very helpful in pharmaceutical industry, thereby inviting emerging technologies into healthcare and pharmaceutical sciences.

A psychiatrist, an expert in three fields —Psychiatry, Child and Adolescent Psychiatry, and Addiction Medicine —is the last participant. He obtained his residency in Psychiatry from Virginia Commonwealth University and Fellowship in Child and Adolescent Psychiatry at the University of Maryland and Sheppard Pratt Hospital, USA. He has clinical and educational experience of more than 15 years, and his career includes inpatient psychiatric units at medical facilities and public-school classrooms. In his medical practice, he uses AI to improve diagnostic precision and assist with treatment planning. AI-enabled platforms help research patient histories and recognize symptom patterns; thus, it is a win-win situation for efficiency and healthcare quality. Details of all nine interview participants are summarised in Table 2, including their job descriptions and geographic origin.

Table 2. Details of Interview Participants

Participant	Job Description	Country
1	Oncology Researcher	USA
2	Consultant Physician	Ireland
3	Researcher in Nursing Sciences	Finland
4	Pharmaceutical Consultant	USA
5	AI Researcher	Canada
6	Ophthalmologist	USA
7	Translational Researcher	Pakistan
8	Assistant Professor	Pakistan
9	Psychiatrist	USA

Saturation is an important concept to consider in this context. It refers to the point at which additional data collection no longer yields new insights, and further interviews do not provide any new information relevant to the research question (Fusch & Ness 2015, 1408). In the interviews conducted, several key topics emerged, although new informants occasionally expressed differing perspectives on them. Nevertheless, I was able to interview enough participants to gain a comprehensive understanding of the phenomenon and the overall research subject.

3.3 Ethical Considerations

Respecting and protecting the rights, dignity, and welfare of the participants was the main guiding principle of the research throughout its duration, as mandated by ethical principles and institutional guidelines. The University of Turku's research ethics guidelines served as the basis for the project, and compliance with the European Union's General Data Protection Regulation (GDPR) was also ensured (European Commission, 2018, 11). To begin with, the most prominent and convincing aspect of this research was the application of the three major principles of the Belmont Report (National Commission for the Protection of Human Subjects of Biomedical and Behavioural Research 1979, 4) as the 'respect for persons', ‘beneficence’, and ‘justice’. These principles served as the mainstay of the ethical policy of this research. *Respect* for persons demanded that the subjects be treated as self-governing individuals and their consent was to be taken in a free manner. *Beneficence* required the researcher to do the best while doing the least harm. *Justice* demanded that the selection of subjects be done legally, and the distribution of research participation’s burdens and benefits was equitable.

Before participating in the research, each participant was provided with an informed consent form outlining the aim, objectives, and methodologies of the study. This form not only stated that participation was voluntary but also emphasised that participants could withdraw at any time without penalty and that their data would be kept confidential and secure. Furthermore, participants were informed in advance about how their data would be processed, stored, and used after collection. They could choose to be identified by a pseudonym or remain completely anonymous in the final reports, based on their preference. The consent process highlighted the importance of transparency and individual choice in deciding their level of involvement.

The research opted for a GDPR-compliant approach to comply with the ethical and legal standards of data protection. Personal data were shown to be collected, processed, stored securely, and finally disposed of by a Privacy Notice (Appendix 3). The researcher could only access encrypted data through password protection and installed on the devices meant for storage. Following Resnik (2020) and Israel and Hay (2006), it was agreed that ethics and integrity remained the core pillars of reliable academic research. In this respect, the research process was accordingly set to acknowledge participants’ rights, to keep their identities secret, and to act in a trustworthy way scientifically. The conducting and managing of the research in this manner guaranteed that no participant would suffer or be at risk from participation or data disclosure. The study's ethical considerations were executed with care and openness, thereby ensuring that the research was conducted responsibly and fully in accordance with institutional and international ethical standards.

During the entire process of writing this thesis, AI-based tools were employed in a limited and transparent manner to facilitate, but not to substitute, the research and writing process. Generative AI (ChatGPT) was instrumental in such tasks as summarizing academic sources, improving the clarity and readability of certain sections, and helping with citation formatting. The use of Grammarly facilitated the detection of possible grammatical inconsistencies and the improvement of the overall linguistic quality of the text. As declared in Appendix 4, Each suggestion made by AI was meticulously scrutinized, corroborated, and altered to meet the requirements of accuracy, integrity, and compliance with academic standards. In no circumstance were AI tools utilized to produce novel arguments, perform data analysis, or generate significant academic content. The full credit for the analysis, interpretation, and conclusions reported in this thesis belongs to researcher alone.

3.4 Data analysis

Data analysis is one of the major stages in the empirical research process. In cases where the data have already been interpreted, the researcher produces the insights, builds them, and finally provides answers to the research questions. The data-processing workflow generally comprises describing the material, classifying it, combining the elements, and finally interpreting them (Bengtsson, 2016, 49). Qualitative research often relies on content analysis as one of its main methods for analysing data, which also serves as the foundation for other interpretative approaches. In the present research, content analysis was chosen as the method that should produce an in-depth description of the phenomenon under study. The first step of the analysis was to identify the relevant data segments. The researcher evaluated the dataset by isolating, labeling, and collecting segments aligned with the research interest, discarding material that was not related. The extracted segments were then arranged, categorized into themes or types, and summarized to yield a unified view. (Schreier et al. 2019, 8).

For data interpretation, this study employed thematic analysis following the six-phase model proposed by Braun and Clarke (2006). Thematic analysis offers flexibility and is less rigidly tied to a particular theoretical framework than some other qualitative methods, while still allowing for a rich and detailed analysis of the data. Thematic analysis aims to identify and report patterns or themes within the data (Braun & Clarke 2006, 78–82). A theme captures something significant in relation to the research question and typically encompasses multiple related ideas. In thematic analysis, it is the researcher’s responsibility to determine the form of each emerging theme and assess its significance. The prominence of a theme is not determined by the frequency of its occurrence in the data, but by its relevance to the research question (Braun & Clarke 2006, 82). The data in this study was analysed impartially, with the research questions guiding the process and the most pertinent themes emerging naturally. The selection of final themes was not immediate, as the data revealed numerous interesting patterns that could have been explored further.

The objective was to move from unedited interview transcripts to a transparent understanding of the integration, use, and sustainability of AI in medical practice. The process began with multiple readings of the email interview transcripts to grasp the overall meaning. The researchers then identified and highlighted segments of text directly relevant to the research questions as meaningful units. Each segment was subsequently coded using NVivo software to ensure consistent data processing and maintain transparency throughout the entire analysis (Joffe 2011, 213).

Braun and Clarke (2006, 86–87) note that the first step of thematic analysis—familiarisation with the data—can begin during data collection, as the analyst starts to notice recurring patterns and focuses on them. So, the material was read actively and repeatedly to gain a general understanding of the area while simultaneously looking for patterns. In addition, comments were made directly in NVivo during this process. The next step involved creating initial codes. Coding serves as a tool to highlight and capture the features of the data that are of interest to the researcher. During this phase, the emphasis was on coding the data as broadly and deeply as possible, including even less common themes. Descriptive labels were assigned to specific statements that reflected participants' perspectives. Examples of open code included AI as augmentation rather than replacement**,** workflow efficiency through automation**,** predictive analytics for early detection**,** cost-saving potential**,** and need for training and usability improvement**.** These codes were derived directly from participants' own words. For instance, one respondent noted, "AI supports clinicians by analyzing complex datasets, not by replacing their judgment," which exemplified the theme of AI as a supportive, rather than substitutive, tool.

Once the entire dataset had been processed through coding, the next phase involved organizing and merging the codes into potential main themes (Braun & Clarke 2006, 88–89). The presence of codes does not automatically guarantee themes; themes exist as constructs shaped by the researcher's interpretation and decisions. It is the researcher's responsibility to develop themes either deductively or inductively. In the deductive approach, themes are largely derived from prior studies and theoretical frameworks, whereas the inductive approach relies solely on the data itself. Combining both approaches is also possible. (Braun & Clarke, 2006, 83), as was the case in the present study.

Theoretical considerations informed the development of themes from the outset, starting with the planning of the semi-structured interviews. The interview questions provided a foundation for the analysis themes throughout the process. NVivo was used for thematic exploration, and an initial thematic map adapted from Braun and Clarke (2006, 90) was employed to visualize the main themes and sub-themes. The identified themes were then subjected to the fourth stage of analysis. Following Braun and Clarke's (2006, 91) guidance, each theme was assessed for internal consistency and coherence, as well as distinctiveness from other themes. At this stage, some initial themes were combined, giving rise to new, more comprehensive themes.

The transcripts were re-evaluated and read again to ensure that no significant points were overlooked (Braun & Clarke 2006, 91). Coding moved from specific data segments toward more abstract concepts and overarching themes. For example, the codes administrative burden reduction**,** documentation streamlining**,** and scheduling optimisation were merged under the single theme Administrative Efficiency and Workflow Optimization**.** Similarly, the codes early disease detection**,** predictive care**,** and proactive intervention were combined under the broader theme AI Enabling Early Detection and Preventive Care.

The process of theme review and refinement was ongoing to ensure that the themes accurately reflected the underlying data (Miles & Huberman 1994, 12). To maintain rigour, continuous comparison was applied (Bogdan & Biklen 2007). Newly created codes were compared against existing ones to avoid duplication. For instance, although AI for resource optimization and AI for cost reduction were frequently mentioned, they were treated as closely related but distinct sub-themes under the main category Economic Sustainability in Healthcare. One participant noted, "AI reduces costs by optimizing staff deployment and preventing unnecessary ICU stays," providing empirical support for this theme.

During open coding, descriptive labels were assigned to excerpts reflecting recurrent ideas such as administrative automation, predictive analytics, cost reduction, and preventive care. The resulting structure produced eight main themes — *Administrative Efficiency*, *Clinical Efficiency*, *Easy Access to Care*, *Early Detection and Preventive Care*, *Admission and Readmission Reductions*, *Data-Driven Savings*, *Resource Optimization*, and *Workforce Planning* — each encompassing several subthemes. These were then reviewed and validated against the data to ensure coherence, internal consistency, and relevance to the study's research questions on the long-term impact of AI integration on economic sustainability in healthcare. These themes, along with their coding frequencies, are presented in the form of a bar chart in Figure 7 below.

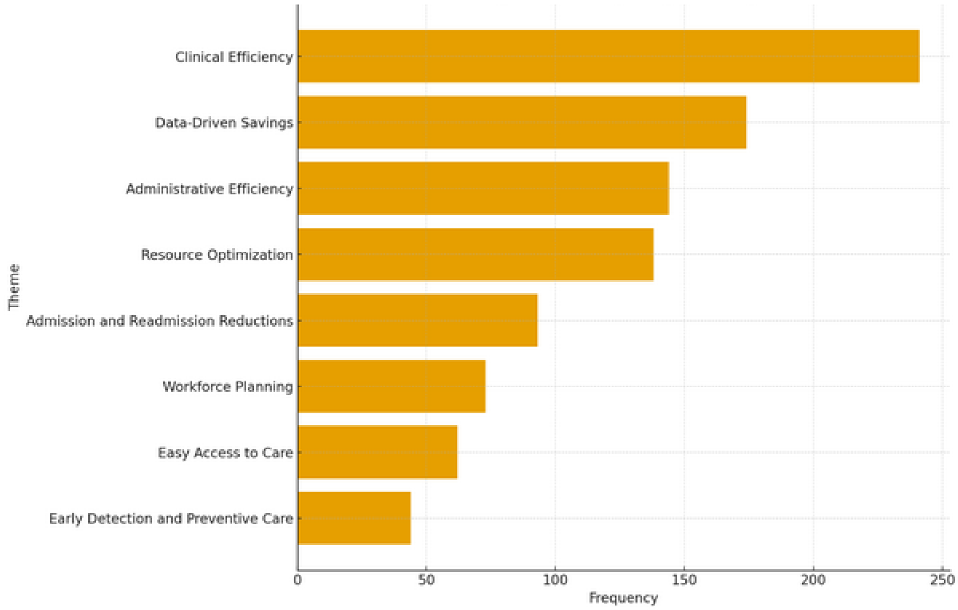

Figure 7. Frequency bar chart for coded themes of cost savings

The bar chart in Figure 7 provides a visual overview of the occurrence of the eight main themes across the interview texts. Not only do these charts demonstrate the frequency of each major theme in the dataset for cost savings, but they also show the diversity in emphasis among different interviewees. Visuals in general indicate that some themes—Clinical Efficiency, Data-Driven Savings, and Administrative Efficiency—appear across most interviews. Conversely, the themes of Easy Access to Care and Early Detection and Preventive Care are seen to be less prevalent and more sporadically distributed across the transcripts, indicating that these topics might be regarded as more situation-specific or dependent on the organization's readiness and the implementation's priorities. Resource Optimization and Workforce Planning categories show a higher level of concentration of references, as do the interviews of senior administrators and executives, reflecting their strategic participation in the planning of the organisation and the performance of its operations. On the other hand, clinicians focus more on the themes of Clinical Efficiency and Admission and Readmission Reductions, indicating that they support their argument with direct experience of the patient-facing processes and that AI can help improve the day-to-day workflow through the supported process.

3.5 Evaluation of the Study

This qualitative research's trustworthiness was assessed using the four traditional criteria of Lincoln and Guba (1985), namely, credibility, transferability, dependability and confirmability. These criteria provide methodological rigour in qualitative inquiry as they make sure that the outcomes are genuine, repeatable, and based on the real experiences of the participants rather than the bias of the researcher. The evaluation not only explains how each criterion was met in this study but also admits the study's methodological constraints. Credibility involves the extent to which the findings mirror the participants' actual thoughts and experiences (Lincoln & Guba 1985, 301). Several techniques were employed to make this study more credible. First, the researcher indulged in prolonged engagement with the data, which resulted in the contextual meaning and participant intent. The use of NVivo software increased transparency and made the systematic coding and retrieval of data for verification much easier (Joffe 2011).

During the process of collecting data, member checking was used and the participants had the chance to go through the process of their responses through follow-up correspondence. This made it certain that the interpretations mirrored the participants' views accurately. On top of that, the research design was influenced by Kallio et al.'s (2016) five-stage framework for the development of qualitative interview guides, which consists of: (1) recognizing necessities for the utilization of semi-structured interviews, (2) applying existing knowledge, (3) creating the interview guide, (4) conducting pilot testing, and (5) finalizing the guide. Utilizing this framework made it possible for the questions to be based on theory, arranged in a logical order, and checked for understandability before the entire data collection started. Moreover, the pilot interview added to the credibility by giving the opportunity for slight changes in terms of wording and focus to be made.

The triangulation was performed by matching the new themes with the existing literature on AI adoption in healthcare which led to the conclusion that the research findings were in accordance with but also gave new insights to the established literature. Through the examination of both older and more recent studies, a comprehensive and time-wise diverse perception of AI's impact in the areas of clinical and administrative applications was achieved. Nonetheless, a major drawback that has a direct impact on the credibility of the findings is that email interviews were used instead of face-to-face or video-interviews. Although the use of this method increased the number of participants from different countries and time zones, it might have come at the cost of getting less detailed responses and the researcher not being able to pick up on non-verbal cues thereby affecting the quality of the interpretation.

Transferability is denoted by the degree to which results can be used or transformed for other situations (Lincoln & Guba 1985, 316). Thick description was utilized in this investigation to present the rich contextual details of the participants' professional backgrounds, organizational settings, and the national healthcare systems. Such a detailed commentary not only provides the necessary context but also enables the readers to judge if the results can be applied in other healthcare environments or policy contexts (Shenton 2004). The participant group of the study—comprised of upper management healthcare professionals from various countries and disciplines —not only reinforces the potential transferability of the findings but also it presents different perspectives regarding AI's integration and sustainability in healthcare. However, to a certain extent, transferability is still restricted by the rather small sample size (nine participants) and the exclusive focus on individuals in leadership or management positions. As a result, the views of front-line clinicians, patients, and technical developers were kept to a minimum, and future research could involve these groups in order to make the findings contextually applicable on a wider scale.

Dependability is a concept that refers to the stability and consistency of research processes throughout a period (Lincoln & Guba 1985, 317). To achieve dependability in the study, an exhaustive audit trail was kept, where all the methodological choices marked and data gathering methods recorded too, the versions of the interview guides used and the coding strategies. The research went on through the stages — recruitment and analysis — in a stored manner, so that it could either be scrutinized or reproduced by others. Dependability was also enhanced through the transcription of the analysis process (Elo & Kyngäs 2008), which by open coding, category formation, and theme development came to use NVivo. The application of uniform analytic methods, in concert with continual contemplation on the appearing themes, made it certain that the results were not swayed by random or inconsistent interpretation. On the other hand, one of the factors that diminish dependability is the fact that the researcher who coded and analyzed the data was mostly one. This way, the researcher's interpretation was consistent but at the same time the situation created the risk of subtle bias. Inter-coder reliability checks or peer debriefing with independent researchers to confirm coding decisions would be the ways to go for the future studies in terms of reliability. Confirmability is about the extent to which the findings mirror the views of the participants and not those of the researcher (Lincoln & Guba 1985, 318). This was made possible by reflexivity and accurate documentation of the sources of the data. Reflexivity was a key element throughout the research allowing to keep notes that helped uncover and reduce potential assumptions or preconceptions of the researcher.

Interviews were preserved in a way that made them very secure, which enabled an audit of the data trail connecting raw transcripts to final interpretations. Besides, NVivo software also created a transparent documentation of code development, so that the analytical procedure could be traced back to the real words of the participants. However, it must be pointed out that total objectivity is not achievable in qualitative research methods. The researcher's professional background with the subject of AI in healthcare may, at a very subtle level, have affected interpretive focus. However, the researcher's professional background with the subject of AI in healthcare may have, at a very subtle level, affected interpretive focus. The researcher hoped to reduce this through self-reflection and comparison with theoretical frameworks, but confirmability may still be affected by interpretive subjectivity that is intrinsic to qualitative inquiry. The combination of credibility, transferability, dependability, and confirmability made this study trustworthy. Besides, the use of established frameworks, transparent documentation, and systematic analysis was instrumental in maintaining methodological rigour. However, limitations such as the small sample size, reliance on a single coder, and email interviews still need to be acknowledged. Awareness of these limitations is crucial for setting the scope of the findings and directing future research toward more diverse, collaborative, and multimethod approaches.d in this thesis belongs to researcher alone.

4 PERCEPTIONS OF AI AS COST-SAVING MECHANISM IN HEALTHCARE

This chapter offers insights into the empirical aspect of the study. The goal of the research is to map the long-term impact of AI integration on economic sustainability, specifically through cost savings in healthcare by investigating the main research question: *"How is AI integration in healthcare perceived to impact economic sustainability in the long term through cost savings?"* To guide this research, two sub-questions are addressed for greater clarity: (1) *How is AI integration in healthcare perceived to impact cost savings?* (2) *How are AI-driven cost savings perceived to have a long-term impact on economic sustainability in healthcare?* In this chapter, we review the study's findings by first describing different forms of AI integration in healthcare from the interview participants' perspectives, then outlining the cost savings attributed to AI integration, and finally discussing how these cost savings impact the economic sustainability in healthcare over the long term.

4.1 AI Integration in healthcare

For clarity, it is essential to examine how respondents perceive AI integration in healthcare to ensure accurate and meaningful data analysis. The first theme centres on interview participants' perceptions, experiences, and understanding of specific tools, methods, and strategies used for AI integration. Participants' views generally align with those discussed in the literature review. Notably, throughout the interviews, participants view AI not as a replacement but as an aid, emphasising the importance of the human in the loop, ensuring that judgment, empathy, and patient relationships remain the clinician's responsibility. AI's capabilities are meant to support clinicians, enabling them to focus on these relational aspects. This approach was stated by participant 2 as follows:

> *"AI integration in healthcare, as I see it, isn't about robots replacing doctors. It's about strategically incorporating artificial intelligence tools to enhance our clinical abilities and improve patient care."* (Participant 2)

Participant 9 reinforced this by highlighting the collaborative relationship between human and machine:

> *"AI integration isn't about handing over control to machines. It's about creating a synergistic relationship where AI handles the computationally intensive tasks and provides valuable insights, while clinicians retain ultimate responsibility for patient care."* (Participant 9)

Similarly, Participant 6 described AI as a supportive layer within healthcare systems:

> *"AI integration means embedding intelligent systems into clinical and administrative workflows to optimise patient care, decision-making, and resource management. It involves using AI as a supportive tool to complement, rather than replace, human judgment."* (Participant 6)

The insights of the participants together show that there is a common view of AI as a supportive technology which upholds, not limits, the autonomy of professionals and the integrity of clinical ethics. Looking from an analytical point of view, the above statements indicate a very close agreement with the "human-in-the-loop" integration model of AI, where the expertise of the human mind is the one that guides, interprets, and validates the AI outputs. The participants' stress on the necessity of maintaining the tools of human empathy and professional judgment points out that the success of AI implementation depends mainly on the extent to which it complements human capabilities. Moreover, the study suggests that AI is not just seen as a tool that can work on the computational side or the operational side, but rather as part of the model of care that is relational, where the contact, empathy, and ethical reasoning of humans are the ones that cannot be replaced. The narratives of the participants are optimistic and at the same time cautious: they point out the importance of AI in handling complicated datasets and the overall efficiency of the system, but they still want to keep clinical supervision to maintain patient trust and the integrity of the corresponding standards.

The results of the present study are in accordance with the literature, which stresses that, although AI can improve precision, speed, and prediction ability, it is still unable to imitate the human aspect and emotions in care. Even the most advanced technology cannot replace empathy in the medical field, for even the most complex algorithms cannot create compassion or the subtle ethical reasoning that is sometimes necessary in the patient-doctor relationship (Montemayor, Halpern, and Fairweather 2022, 1353). Similarly, Topol (2019) has pointed out that the real benefit of AI is the enabling of human doctors—freeing them from monotonous administrative duties and giving them more time for human-to-human contact with the patients. These theoretical views endorse the interpretation that the proper AI integration should be through human-centred design and should keep the moral and emotional values of medical practice intact.

A key theme that emerged is that AI integration should be achieved by embedding it into existing workflows, such as diagnostics and treatments, not just by adding a separate product. When AI is integrated into existing healthcare systems, it offers insights at the point of decision-making.

This approach avoids misaligned context and fits seamlessly into care processes. It increases adoption, minimises workflow disruptions, and raises the likelihood that model outputs will impact care. A similar fact is supported in existing literature, as integration of AI into diagnostic workflows also enables ongoing surveillance and tracking of clinical outcomes. It enables post-deployment validation and governance, allowing organisations to measure real-world effects, equity, and safety (Wells et al. 2025, 514). AI integration into normal workflows—from recruitment and trial conduct to imaging reads and medication prescriptions—is correlated with enhanced efficiency and acceptance among populations with low access. It also leads to improvements in operational or clinical outcomes. In contrast, independent prototypes often fail because they complicate clinicians' already busy workflows (Hau et al. 2023, e2332049). Embedding AI is not merely a technical integration but a fundamental organisational change. It involves aligning tools with clinical priorities, regulatory requirements, and patient safety goals (You et al. 2025, 3). Participants emphasised the importance of interoperability and alignment with established care delivery principles. They pointed out that successful integration depends as much on process compatibility as on technology, as stated by Participant 3

> *"Specifically, it means embedding AI-driven functionalities within our existing workflows. It's not a standalone system, but a set of tools working alongside clinicians."* (Participant 3)

Participants described integration of AI in healthcare in functional terms, such as AI's computational power to analyse complex datasets (images, speech, behaviour) on scales and with precision that surpasses human abilities. This description emphasises AI's role as a decision-support tool that enhances the clinician's cognitive capabilities, particularly in early detection, pattern recognition, and the development of more accurate differential diagnoses. Another participant illustrated how this plays out in a clinical setting:

> *"For child psychiatry specifically, AI offers the potential to analyse subtle cues in speech, behaviour, even physiological data that might be missed by a human observer, especially in a short clinical encounter."* (Participant 9)

Integration is also defined as an ongoing, adaptive process requiring validation, governance, monitoring, and refinement. Participants emphasized that true integration is not simply adopting a tool but involves reshaping care delivery, maintaining accountability, and ensuring fairness. This definition positions integration as a socio-technical change that must align with clinical, ethical, and organisational values. Another participant emphasised the ongoing governance and adaptation needed as follows:

> *"A successful integration also requires robust data governance, rigorous validation of AI algorithms, and ongoing monitoring to ensure accuracy and fairness. It's a continuous process of learning, adaptation, and refinement."* (Participant 5)

When combined, participants view AI integration in healthcare is meant to support, not replace, medical professional expertise. Physicians maintain accountability, while AI offers extensive data analysis. It works best when seamlessly integrated into existing systems. The main advantage of AI is its ability to identify patterns in complex, emergent data, allowing early detection of health issues and enabling more personalised care. This definition presents integration not as a one-time, mandatory technological change but as an ongoing process.

4.2 Perceptions of cost savings from AI integration in healthcare

This section highlights examples of cost savings perceived by participants from using AI in healthcare. According to participants' perspectives, as already discussed in the literature review, *Administrative Efficiency* involves automating repetitive, non-clinical tasks (such as charting, prior authorization, billing, scheduling) to free up staff time for value-added work. As explained by one participant:

> *"The automated prior authorization system is starting to reduce the administrative burden on our staff, freeing them up to focus on patient care."* (Participant 3)

There is consensus among participants that cost savings can be achieved through (a) fewer labour hours spent on repetitive tasks, (b) fewer denied claims and billing errors, which lead to faster revenue recovery, and (c) less waste due to no-shows and rescheduling. As one participant explained, automated charting and appointment scheduling tools have reduced the administrative burden on staff by approximately 15–20% in these areas. Clinical efficiency relates to AI tools that enable quicker and standardised diagnostic workflows, such as image analysis, as well as a "smart second opinion." In the Table 3 below, these savings are categorized into eight themes based on the codes generated during analysis of participant interviews.

Table 3. Coded themes of cost savings as perceived by interview participants

Cost Savings	Themes	Explanation of Perceptions	Participants
Administrative Efficiency	- Automated scheduling- AI-assisted billing & coding - Automated prior authorization- - AI-generated routine reports	Reduces administrative workload, enhances accuracy, and lowers personnel costs by automating repetitive tasks and streamlining documentation processes.	1, 2, 4, 7, 8
Clinical Efficiency	- Predictive analytics for risk stratification - AI-assisted diagnostics and speech analysis -Second-opinion validation - Treatment response prediction	Improves clinical workflows and diagnostic accuracy, reduces clinician burnout and errors, and minimizes unnecessary tests, thereby lowering costs.	2, 3, 5, 6, 9
Easy Access to Care	-Telehealth and remote monitoring - Addressing service shortages - Reducing wait times - Integration into existing workflows	Expands care accessibility, particularly in underserved areas, while reducing costs associated with in-person consultations and delays in treatment.	3, 6, 8, 9
Early Detection and Preventive Care	- Predictive screening and NLP-based monitoring - Wearable sensor data and behavioral analytics - Early detection of ophthalmic and psychiatric conditions	Enables proactive interventions, prevents disease progression, and reduces the need for expensive late-stage treatments.	1, 5, 6, 9
Admission and Readmission Reductions	- AI-supported discharge planning- Predictive models for readmission risk - Remote post-operative monitoring - AI triage systems	Reduces unnecessary hospital admissions and readmissions, leading to significant cost savings and improved patient flow	2, 3, 7, 9
Data-Driven Savings	- Error reduction and data accuracy -Minimizing redundant procedures - Evidence-based decision-making -Quality improvement through analytics	Supports efficient resource use and improved clinical outcomes by leveraging large datasets without proportional staff increases.	1, 2, 4, 5, 7
Resource Optimization	- Predictive resource allocation - AI-optimized supply chain management- Staff and equipment utilization	Streamlines healthcare delivery, maximizes capacity, and minimizes waste in resource distribution and utilization.	1, 4, 7, 8
Workforce Planning	-Skill-based staffing and task delegation - AI-supported scheduling - Reducing clinician burnout -Expanding specialist reach	Supports sustainable staffing, optimizes human resource deployment, and improves morale and retention through workload balancing.	2, 3, 8, 9

Note: Informant numbers correspond to participants listed in Table 1 (e.g., 1 = Oncology Researcher, USA; 2 = Consultant Physician, Ireland, etc.).

The clinical effectiveness and efficiency benefits come from (a) increased throughput per clinician and equipment (more patients per unit time), (b) fewer repeat tests, (c) fewer diagnostic errors and unnecessary downstream treatments, and (d) improved targeting of treatments, leading to better outcomes. As one participant stated:

> *"AI-assisted analysis of Optical Coherence Tomograph) and fundus images has significantly reduced the time it takes our technicians and ophthalmologists to interpret these scans, optimizing the use of our expensive equipment and personnel."* (Participant 6)

Detecting disease or risk signals as a means of *Early Detection and Preventive Care*, prevents costly health outcomes (advanced surgery, hospitalization, long-term disability). Early detection and preventive care become useful once AI achieves good sensitivity/specificity trade-offs, established care pathways are in place for flagged patients, and equitable access ensures benefits for underserved populations. As evidence, participants stated:

> *"Our AI-powered diabetic retinopathy screening program has allowed us to identify a significant number of patients with early-stage disease, avoiding the much higher costs associated with advanced disease management."* (Participant 6)

> *"The biggest long-term cost savings will likely come from improved preventive care and early intervention, but it will take time to see those benefits fully realized."* (Participant 2)

As stated by one participant, AI-powered tools can be deployed in underserved communities, bringing high-quality care to those who need it most, thereby reducing health inequities. In *Access to Care*, AI helps expand access through telehealth optimization, chatbots, and triage, while also strengthening limited specialist capacity. Cost savings occur indirectly by enabling earlier or closer-to-home care, reducing emergency department visits, and improving population management. AI could reduce access gaps based on geography if used intentionally. Operationally, telehealth optimization must be combined with reimbursement and staffing models that create a viable care coordination interface for visits. As one participant stated:

> *"Extend our reach to underserved populations through telehealth and remote monitoring, and provide 24/7 support to families through AI-powered chatbots."* (Participant 8)

As another participant noted:

> *"AI is helping us forecast patient demand and optimize staffing levels, better allocating resources to areas where they're most needed."* (Participant 2)

Resource Optimization uses AI to map scarce resources (equipment, time, supplies) to demand for maximum cost savings. The core benefit is a significant reduction of costs through risk-based prioritization, supply-chain optimization, inventory control, and allocation of telehealth versus in-person care. One participant stated:

> *"AI can analyse usage patterns to optimize inventory levels of supplies and medications, reducing waste and minimizing storage costs."* (Participant 4)

Participants generally agreed that these savings come from lower inventory costs, less waste, fewer idle high-cost resources, and better Return on Investment on equipment. *Workforce Planning* encompasses the use of AI in demand forecasting, skill-based rostering, task shifting, and scheduling optimisation to minimise burnout and turnover. Cost savings stem from reduced overtime, lower recruitment costs (due to lower employee turnover), and more efficient utilization of the existing workforce. The social cost is also improved because satisfied clinicians provide better quality of care. Success depends on transparent algorithms, workforce buy-in, and training for shifts in role (to ensure safety and regulatory compliance). As two participants stated:

> *"AI to forecast patient demand based on historical data, seasonal trends, and demographic factors, adjust staffing levels accordingly."* (Participant 3)

> *"AI helps optimise clinician schedules; we have seen noticeable improvement in clinician satisfaction since implementing this system."* (Participant 6)

Data-Driven Savings encompasses continuous learning loops (Key Performance Indicators, Return on investment models, model refinement, and quality improvement) whereby AI functions both as a tool and a data source for value measurement. Cost savings occur through iterative optimization: identifying waste, estimating its financial impact, and reallocating efforts. As described by participants:

> *"Continuous KPI tracking ensures performance optimization. We continuously monitor KPIs to identify any deviations from expected performance."* (Participant 1)

> *"We conduct a formal ROI analysis, taking into account both direct costs and indirect costs, with longitudinal tracking to capture long-term impact."* (Participant 4)

In brief, the use of AI in the healthcare has enormous potential to increase efficiency, decrease costs, and enhance patient care. AI improves efficiency by automating administrative tasks, such as billing and scheduling, allowing staff to devote their time to patient care while decreasing errors. Clinically, AI accelerates diagnostic processes, thereby reducing human error and the need for retesting. Early detection and diagnosis are also enhanced by AI, decreasing the long-term costs of care. Through telehealth and remote monitoring, AI expands access for underserved communities. Additionally, AI helps optimize resource allocation and workforce planning, reducing staff burnout and turnover.

The literature also gives priority to workflow integration and human-machine collaboration. For example, a research aimed at the application of machine learning in the clinical environment found that the active participation of the clinical staff in the scaling of workflow and model was very beneficial, and that proper alignment of stakeholder roles and financial support in training were the key factors in the adoption of the new technology (Sendak et al. 2020, e15182). A different study in radiology mentions that the inclusion of AI into the imaging process through standardized and compatible systems is a major factor in the new technology's adoption being on a larger scale rather than just having the new tools in place (Tejani et al. 2024). Besides that, the examining of AI integration in the healthcare sector points to the fact that the organizational culture and work practices must change when the AI systems are deployed, thereby indicating that the integration process is not merely technical but rather a change in work practice.

4.3 Cost savings as an incremental process

The participants repeatedly emphasised that the economic benefits of AI in healthcare are progressive, not dramatic. The layered effect of economic impact occurs over time, with each layer constituting a different time horizon. These yield cumulative savings and build toward sustainability as one participant explained:

> *"It's been more about incremental improvements and preventing costs down the line."* (Participant 2)

Economic studies on AI applications agree with this layered view. Systematic reviews observe that although short-term cost savings are often reported, long-term modelling is much less frequent and many advantages are termed "incremental" rather than immediate (Voets et al. 2022). In this sense, AI does not support the idea of a quick cost-cutting solution. Instead, it promotes a more realistic, gradual approach where savings come from ongoing efficiency, low waste, and preventive measures that tackle problems before they escalate into crises, rather than through overnight changes. Based on feedback gathered from interview participants, cost savings from AI integration in healthcare can be categorised into *short-term, mid-term, and long-term,* depending on the nature of costs. The most immediate savings, which can be called *Short-Term (1–3 years)*, come from administrative efficiencies and reductions in admissions and readmissions. As one participant stated:

> *"We anticipate continued savings in administrative costs through automation, which frees up staff time and reduces overhead in the first few years of implementation."* (Participant 2)

This is in line with the findings of existing literature and economic evaluations of AI in healthcare, where early cost reductions are mainly attributed to workflow and administrative improvements (Bulut 2025). By automating repetitive processes, including billing, claims, and scheduling, AI contributes to measurable reductions in overhead costs, such as administrative labour and processing time. These operational efficiencies result in lower expenses, allowing employees to focus on more complex or value-generating tasks. In this first phase, the economic impact of AI is mainly operational, targeting inefficiencies in healthcare's back office. While savings may seem modest compared to overall budgets, they can serve as a foundation for broader systemic cost reductions in the future. In the second phase, which can be called *Mid-Term (3–5 years)*, predictive analytics and preventive interventions can reduce costly escalations of illness, leading to clinical efficiency, early detection, and preventive care. As one participant explained:

> *"If we can use AI to identify children at risk for serious mental health conditions and intervene early, we can prevent those conditions from escalating and requiring more intensive and costly treatment."* (Participant 9)

The mid-term horizon indicates a shift from focusing on operational cost reductions to emphasising clinical savings. AI impacts patient outcomes in ways that lower costs and reduce the need for expensive interventions. This demonstrates how savings emerge as health outcomes improve. As stated in existing literature, with the help of data-based risk stratification, the practitioners can take preventive measures on time that will result in fewer hospital admissions, faster recovery and reduced healthcare costs in general (Hossain et al. 2024, 3-4). This mid-term phase signifies a very important turning point where the improved outcomes have the main role in creating value, while cost savings are simply a side effect of the better clinical quality rather than just the efficient use of operations (Bulut, 2025, 142). The most significant savings can materialise over the *Long-Term (5+ years)*, as AI enables personalised and preventive care on a large scale. One participant highlighted this by stating:

> *"AI will play a crucial role in personalised medicine, helping us achieve higher treatment success rates, reduce relapse rates, and ultimately lower long-term healthcare costs by developing more effective prevention programs."* (Participant 1)

The long-term projections (over 5 years) highlight cost savings of the greatest magnitude arising among all the benefits offered by AI through the adoption of personalised, preventive care on a broad scale. The new order of things denotes the passage from small efficiency gains to a total transformation of the system, where AI becomes the core technology behind the creation of tailored health interventions and their distribution (Dixon et al. 2024, 10-11). At this phase of the long run, AI is considered not just a support tool for decision-making but an agent of change that alters the paradigms of care and reengineers the clinical workflows (Lee et al. 2022, 214-216). Eventually, the integration of operational, medical, and preventive cost efficiencies results in a healthcare system driven by improved patient outcomes and reduced chronic disease burden. Consequently, the value created is not only patient-centred but also sustainable (Bulut, 2025, 144; Hossain et al. 2024, 6-8). During this stage of development, AI is seen not just as a supportive tool but as a transformative force capable of changing care models altogether. Personalised treatments can be uniquely designed for individuals, with proactive relapse prevention applied at scale. In the long run, AI is applied to system transformation, whereby the aggregate of operational, clinical, and preventive savings contributes to a healthcare system that is both cost-effective and sustainable.

4.4 Economic sustainability in healthcare: a continuous process

Respondents defined *sustainability* as delivering quality care, avoiding unnecessary costs, and ensuring just access. The definition below illustrates this connection:

“Sustainability means building systems that balance clinical effectiveness, cost efficiency, and equitable access.”

Turning specifically to *economic sustainability*, respondents identified its strong connection to sustaining quality healthcare in the long term by ensuring effective use of resources, illustrated as follows:

“Economic sustainability in healthcare is the ability to maintain high-quality healthcare delivery over the long term by reducing waste, optimizing resources, and preventing expensive late-stage disease interventions.”

A similar theme was evident in one participant's perspective, which is closely framed around a value-based model of care. In this view, *economic sustainability* is defined as:

“Economic sustainability means delivering high-quality, evidence-based care in a way that is financially viable over the long term, without compromising patient outcomes or access to care.”

In general, the sources suggest that the use of AI contributes to more sustainable healthcare resource consumption. For example, Bulut (2025, 140) reports that “AI-driven applications contributed to cost efficiency by reducing expenses by 8–12 %.” Another economic evaluation review notes that AI “has major potential to make healthcare financially sustainable” (Rao et al. 2025, 3). Together, these findings confirm that the informants’ perspectives—supported by analytical interpretation and literature evidence—reinforce the idea that achieving economic sustainability in healthcare through AI is not a one-off cost-cutting exercise, but rather a continuous and dynamic process of improvement, reinvestment, and expansion of access to care.

The data shows that AI boosts economic sustainability by preventing expensive late-stage disease and reducing inefficiencies in healthcare, where costs are controlled through improved prediction, automation, and early treatment. These savings can then be redirected to support staff well-being and promote equitable access to care. (Dixon et al. 2024, 11–12.) This development represents a key foundation of economic sustainability, as the funds saved through AI deployment are reinvested to strengthen the healthcare system financially and to enhance workforce capacity (Bulut, 2025, 145). Reinvesting these savings in workforce training, clinician support tools, and expanded access for underprivileged populations serves as an effective service delivery enhancement strategy. At the same time, it helps mitigate burnout, which might otherwise compromise the quality and consistency of care (Hossain et al. 2024, 8–9). Over time, this cycle will enhance both the healthcare sector's operational capacity and the quality of patient care, making AI an increasingly powerful driver of long-term economic sustainability in healthcare (Lee et al. 2022, 217–219). AI enables a shift to preventive and efficient care, and cost savings are reinvested in workforce wellbeing and access, sustaining the cycle.

Consequently, economic sustainability attributable to AI integration is best perceived as a virtuous cycle, as AI enables cost savings by improving prevention and efficiency, which creates resources that can be reinvested into workforce wellbeing and equitable access. This reinvestment, in turn, strengthens the healthcare system, enabling further advancements in AI and ensuring ongoing economic sustainability. This sustainability cycle of cost savings in healthcare is illustrated in Figure 8 below.

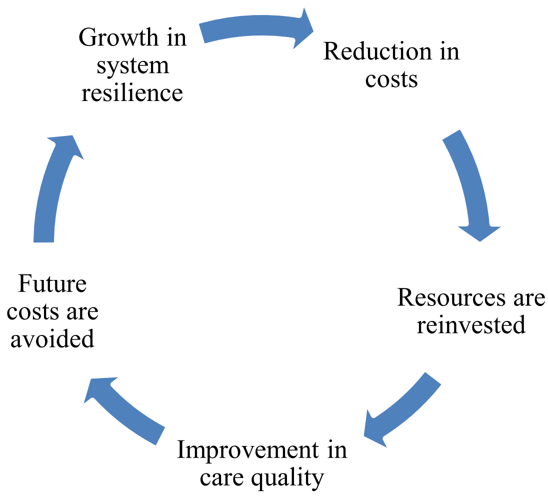

Figure 8. Sustainability cycle of cost savings in healthcare

The source of the cycle stems from AI's ability to reduce upfront costs by enhancing efficiency in clinical and administrative tasks. Participants shared examples of cost savings during their discussions. One participant explained that AI saves costs by utilising resources wisely, reducing medication errors, operating staff more efficiently, and preventing unnecessary ICU admissions. Therefore, AI creates savings through waste reduction, error correction, and the more efficient use of limited resources, forming the basis of economic sustainability. Participants emphasised that the real benefit of AI is not just cost saving. The value lies in how those savings are reinvested. These savings are the fuel for systemic change in healthcare, as evident from the following statements of participants:

> *"The cost savings generated by these AI applications aren't just about the bottom line. They allow us to reinvest in essential areas like staff training, new equipment, and research which ultimately enhance the quality of care we provide."* (Participant 2)

> *"It's not just about cutting costs; it's about reallocating resources to improve care and address critical needs."* (Participant 4)

Reinvestment ensures that AI cost savings are directed toward ongoing capacity building such as workforce training, infrastructure rebuilding, and research. By channelling these savings back into the organisation, reinvestment turns temporary financial gains into lasting systemic improvements. When resources are reinvested strategically, they significantly improve care quality. Participants in the study consistently linked sustainability directly to patient outcomes. As one participant elaborated:

> *"AI-driven staffing tools help maintain safe nurse-to-patient ratios, ensuring consistent quality of care across different patient groups."* (Participant 3)

AI can help turn cost savings into better results and a fairer distribution of health resources. This aligns with the definition of sustainability, which emphasises a balance between efficiency, effectiveness, and fairness. Enhanced quality can lower the need for expensive future interventions. Preventive, timely, and equitable care helps reduce the financial impact of late-stage diseases and system inefficiencies. One participant explained that evidence from critical care shows predictive analytics for sepsis can lead to earlier detection and prompt treatment, which reduces mortality and shortens hospital stays. Overall, AI acts as a cost-saving strategy by turning early savings into long-term reductions through fewer preventable crises and complications. The final product of this process is enhanced system resilience, the ability for healthcare systems to continue thriving financially, operate effectively, and keep patients at the forefront, even amidst mounting demands. As described by participants:

> *"Economic sustainability isn't about maximizing profits. It's about creating a healthcare system that can continue to deliver high-quality, affordable care for generations to come."* (Participant 8)

"AI-driven cost savings are a valuable tool for enhancing economic sustainability, but they need to be implemented thoughtfully and strategically, with a focus on improving both the financial health of our system and the well-being of our patients." (Participant 6)

Ultimately, system resilience occurs when AI-driven cost savings, reinvestment, and improvements in both cost and quality continually reinforce one another, creating a sustainable cycle. According to existing literature, the cost reductions through AI are further multiplied through the redeployment of funds into human resources, facilities, and research, thereby creating a virtuous cycle of efficiency, quality, and access (Jiang et al. 2021, 14). Additionally, studies have shown that predictive analytics, for instance, early detection, not only reduce ICU admissions and mortality but also create quantifiable financial benefits that can be invested back to preventive care (Komorowski et al. 2018, 563). In this way, the AI-induced savings and reinvestment flows are pivotal for reaching and maintaining long-term economic viability and robust healthcare systems.

4.5 AI's long-term impact on economic sustainability in healthcare

Respondents unanimously acknowledged that AI has delivered significant benefits in terms of early efficacy. However, they agreed that the financial implications and long-term sustained effectiveness would be challenging to predict and measure. Current tracking primarily focuses on short-term indicators, including fewer medical complications, improved patient outcomes, and faster ICU turnover. While these are valuable outcomes that show benefits, determining the long-term economic impact of AI adoption across healthcare systems is a more complex task. As participants stated:

"Currently, assessments are preliminary, focusing on efficiency gains, reduced complications, and improved ICU turnover."
"Full long-term cost data is still emerging."

This reflects a cautiously optimistic outlook. On one hand, AI may lead to significant cost savings and operational improvements. On the other hand, respondents noted that maintaining those savings will require ongoing evaluation and strong evidence. They emphasized the need to go beyond efficiency metrics. A common theme among participants is that AI is not a "set it and forget it" solution. The level of economic benefit relies on ongoing monitoring of performance, cost effects, and unexpected results. One participant emphasized this point directly:

"AI isn't a 'set it and forget it' solution; it requires ongoing monitoring and optimization." (Participant 5)

The literature also supports this point as AI-assisted procedures can lead to the improvement of clinical results in the short run and the reduction of operational costs, but the long-term economic sustainability will require continuous evaluations, adaptive implementations, and post-deployment monitoring (Sendak et al. 2020, 621). The studies also point out the need for combined monitoring systems that will follow the clinical efficacy and financial impact over a long period, thus reinforcing the need to dynamically manage AI to obtain the sustained benefits (Jiang et al. 2021, 17; Komorowski et al. 2018, 565). To put it differently, the economic value of AI is not something given or fixed; rather, it depends on active control, gradual improvement, and alignment with organisational goals.

Adaptive AI use means that AI serves a supportive, situationally meaningful function. This approach avoids undue reliance while prioritising clinical reasoning. *Adaptation* also applies to changes in usability and ongoing improvements in training. Systems must adapt to new technology and changes in organisational focus. These changes could include workforce wellbeing, advance equity and social justice, or addressing new diseases. Participants also regarded *monitoring* as equally important. Monitoring ensures that early efficiency gains (such as reduced errors, shorter ICU stays and streamlined documentation) are systematically tracked and converted into solid evidence of financial return. Without these systems, economic sustainability remains uncertain. Continuous monitoring also protects against algorithmic drift, data bias, and workflow misalignment, which could weaken trust and diminish cost benefits. *Scaling* AI integration became a practical concern in all interviews. Participants agreed that while pilot projects show early signs of savings, the challenge lies in scaling these benefits across entire organizations sustainably. Scaling strategies include phased adoption and partnerships. As one participant emphasized:

> *"Partnerships and phased investments also support sustainability."* (Participant 4)

Another participant highlighted the importance of training:

> *"Through continuous training, usability improvements, phased adoption, and ensuring AI complements human expertise."* (Participant 1)

Lastly, workforce readiness and equity in implementation are crucial, especially in addressing "generational gaps in adoption" and ensuring no part of the healthcare workforce is left behind. Therefore, scaling is not about rapid expansion but deliberate, strategic growth—based on evidence, supported by training, and reinforced by reinvesting savings into infrastructure and staff development. When integrated, adaptation, monitoring, and scaling form the triad of long-term economic sustainability. Monitoring provides the data needed to demonstrate value and identify risks. Adaptation ensures AI evolves with user needs, clinical judgment, and patient-centered priorities. Scaling transforms isolated successes into organization-wide and system-level impact. As one participant summarized:

> *"AI can significantly enhance efficiency, but success depends on training, user-friendly design, and continuous monitoring."* (Participant 7)

This reflects that sustainability is a dynamic process, not a static outcome. The long-term economic sustainability of AI integration in healthcare, therefore, depends on feedback loops: monitored outcomes inform adaptation, which refines systems for wider scaling, which in turn generates more robust data to sustain and justify reinvestment.

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5 CONCLUSIONS

In this section, the results of the empirical study are compared to the academic literature and the theoretical framework. The section is structured to reflect this comparison. The theoretical contribution aligns the empirical results with the framework for the long-term impact of cost savings on *economic sustainability* in healthcare through AI integration, thereby updating the framework. Managerial implications outline how cost savings gained through AI integration in healthcare can benefit different stakeholders. Finally, the study's limitations and areas for further research are suggested.

5.1 Theoretical contribution

The initial theoretical framework has been updated with additional changes that enhance understanding of how AI creates value in healthcare. It connects AI applications to cost savings and system sustainability over time. The model shows that AI has an impact across multiple domains, including administration, resource optimisation, workforce planning, clinical efficiency, early detection, data-driven savings and patient access. The framework, shown in Figure 9, describes how AI in healthcare leads to cost savings and economic sustainability in the long term.

As one starts from the left side of the framework, several branches explain AI in-depth. The economic sustainability of healthcare is mainly attached to AI-generated cost savings. If AI is applied correctly, it will not only improve clinical and administrative processes but also lead to measurable cost savings. This study in the administrative area corroborates other literature by highlighting how AI facilitates faster, easier handling of billing, scheduling, and compliance reporting, among others. The mentioned applications allow medical practitioners to spend their time on patient care instead. AI is certainly a strong force in changing the healthcare sector by reducing administrative overhead and supporting economic sustainability, while addressing human error and inefficient processes that characterise non-clinical overhead, such as billing, scheduling, and compliance (Jiang et al. 2017, 363). Besides, AI analytics can be paired with workforce planning, leading to skill development and burnout mitigation, thereby enhancing productivity (Bates et al. 2003).

The use of AI in the clinical field enables early disease detection and timely, cost-effective treatment. Diagnostic services, especially in radiology and pathology, enable quicker and more precise identification (Topol 2019, 132), thereby reducing avoidable costs and unnecessary readmissions. Risk stratification is another area where AI helps, enabling healthcare systems to use their limited resources more efficiently (Krumholz 2014, 1496). The current research aligns with the literature in that AI is involved in early detection and prevention through proactive alerts and interventions, thereby minimising disease progression, hospital admissions, and readmissions. The resulting efficiencies translate into significant cost savings for health care systems. The research also highlights clinical efficiency as a separate domain for cost savings, thereby bringing together stakeholders and improving outcomes across both clinical and non-clinical activities. Besides, the study has pointed out access to care as another independent domain. Telemedicine solutions powered by AI open new avenues for patients while reducing total system costs. Also, the use of data-driven methods such as big data and predictive analytics is recognised as one of the major factors that drive cost savings and improved diagnostic accuracy and treatment effectiveness. As the applications become increasingly sophisticated, AI is set to revolutionise the performance of the entire system.

At the centre of the framework lies a large circle labelled “AI in healthcare”, showing how AI applications are broadly adopted in both clinical and administrative settings. At the centre of this circle is a smaller circle representing cost savings, indicating the financial benefits at the core of AI. A key contribution of this framework is that it prioritises cost savings as the primary and tangible outcome of AI adoption. While most models treat cost savings as secondary or incidental, this model positions them at the centre of AI adoption in healthcare, emphasising that efficiency benefits ultimately translate into tangible economic savings.

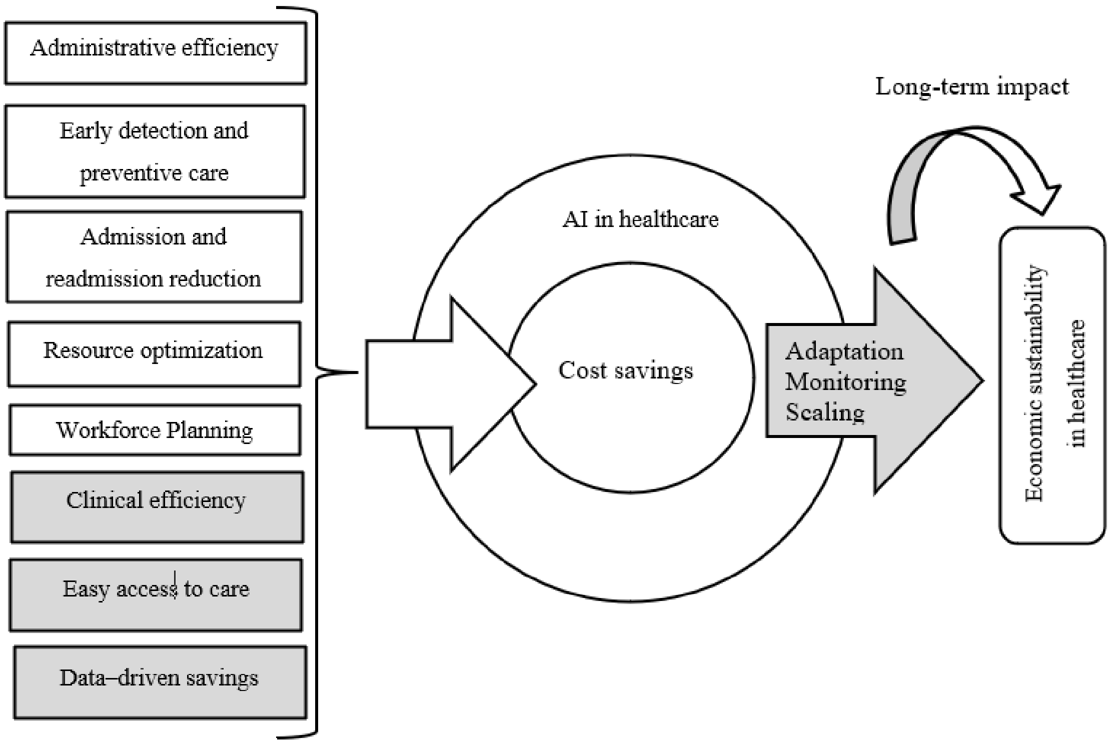

Figure 9. Revised version of the theoretical framework

The framework adds a new dimension to the ongoing debate about the relationship between short-term efficiencies and long-term economic sustainability by arguing that short-term efficiencies can indeed be the survivors of the very great change to come economic landscape. It implies that savings and efficiencies are not automatically sustainable but rather require continuous adaptation, monitoring, and scaling up. This approach aligns with broader discussions on digital transformation in healthcare, where the need for governance and continuous assessment of new technologies is emphasised. The long-term effectiveness criterion will depend on the above reductions, namely emergency visits, inpatient days, chronic disease management, and patient overall satisfaction (Berwick et al. 2008, 759). Consequently, the use of technology in the form of AI would have to go the extra mile to demonstrate its worth post-implementation and, at the same time, put in place very strong governance structures capable of supporting the economic impact. The already-discussed cost drivers (preventive care, screening, administrative overhead, and resource planning) are all linked to economic sustainability through AI in healthcare, as shown in Figure 10. Thus, sustainability is more of a continuous process of re-adaptation and re-learning than just an endpoint. This framework sheds light on why and how healthcare systems embrace AI to achieve this aim. It also underscores the point that, to capture the short- and medium-term benefits, active governance, ongoing review, and stakeholder engagement are compulsory. Otherwise, the initial gains might not lead to the sustainable improvements expected. Over time, the widespread integration of AI combined with an organisational focus on transformation can support scalability, enhance operational efficiency, and generate the long-term value sought across the health system. This framework demonstrates that AI-enabled technologies not only improve operational processes but also produce cost savings throughout the healthcare system, thereby contributing to overall economic sustainability.

Further, this research takes the theory of Sustainability-Oriented Innovation (SOI) (Adams et al. 2016) one step further by providing empirical evidence of AI efficiency's development across the three domains of the SOI framework and by identifying cost reduction as the main factor linking operational innovation to long-term system change. The original SOI theory emphasises innovation that creates economic, environmental, and social value simultaneously (Adams et al. 2016), but it does not clearly state that financial savings are the primary driver of sustainability. The current research extends the SOI theory by showing that operational gains, such as automated billing and scheduling, can be reinvested in scaling and governance, thereby supporting the call to incorporate cost-centred feedback loops into innovation models (Adams et al. 2016 ; Harsanto & Permana 2019).

The staged economic impacts of AI adoption in healthcare sectors as discussed earlier in section 4.5 can be understood through a revised version of the initial SOI model by Adams et al. (2016, 11), presented in Figure 10 below.

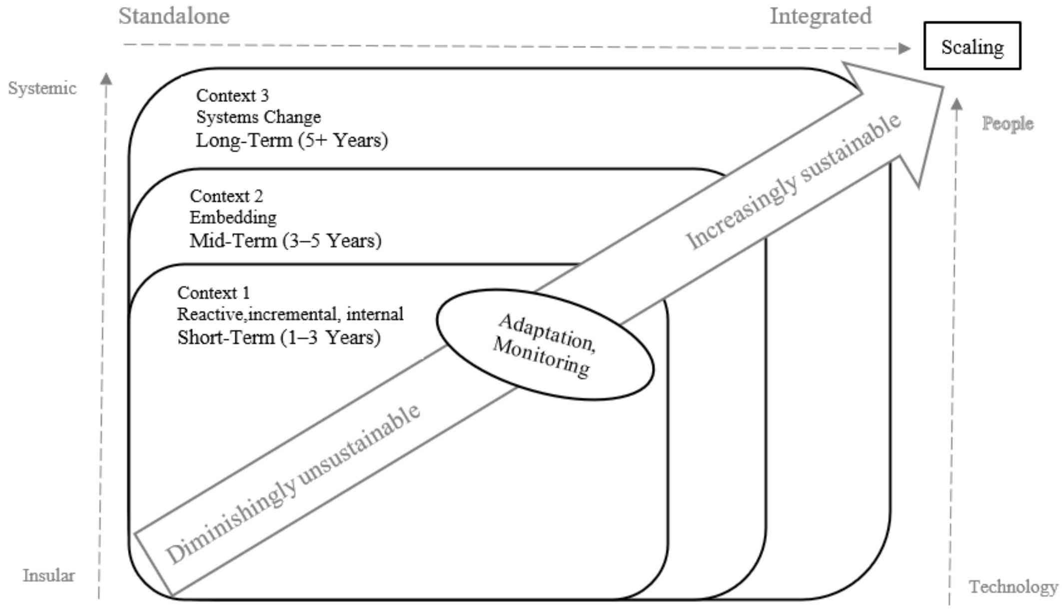

Figure 10. Revised version of initial model of SOI (adapted from Adams et al. 2016, 11)

As depicted in figure 10, short-term (1–3 years) economic savings map to Context 1 in the SOI model. In this context, AI enables operational and economic efficiencies. For instance, some participants described the use of AI to automate administrative functions such as billing, scheduling, and claims management, which leads to measurable reductions in overhead, allowing staff to provide more value-adding labour. While these short-term economic savings may not constitute a large portion of an overall budget, they provide the basis for sustainability, offering quick wins that legitimise investments and help build organizational confidence in AI adoption (Bocken et al. 2014, 46).

Mid-term (3–5 years) impacts correspond to Context 2 of the SOI model. Here, clinical efficiencies and patient-centered outcomes produce economic efficiencies. In this context, AI shifts from operational efficiencies towards preventative interventions and predictive analytics. For example, screening for children at risk for acute mental health conditions provides opportunities for early interventions, helping avert costly escalation of care. During this stage, clinical sustainability emerges. The use of AI reduces costs and improves quality outcomes. AI-supported integrations can decrease the need for acute care interventions and contribute to healthcare system resilience (Bocken et al. 2014, 44).

Long-term (5+ years) economic savings align with Context 3 of the SOI model. This context highlights the transformative potential of sustainability and the need for fundamental system redesign. It is illustrated by the role of AI in personalized medicine and preventive care at the population level. These applications drive sustained economic savings through reductions in readmissions, a lower chronic disease burden, and relapse prevention. Over time, AI reshapes traditional treatment methods and encourages the development of new models for sustainable care. This aligns with the SOI framework, where sustainable innovations transition from incremental changes to major system redesign.

The first three timeframes of economic impact all depend on adaptation and monitoring. Adaptation and monitoring are critical to sustainability. Participants emphasised that AI must enhance or augment but not replace human judgment. Adaptation enables the specific and flexible use of AI for feedback and clinical insight, all under human oversight. This approach helps continuously improve usability. Monitoring is equally important. It ensures an evidence-based return on investment and helps prevent algorithmic drift, bias, or misalignment in workflows. According to the SOI framework, adaptation requires iterative refinement of operations and governance by stakeholders (Dixon-Woods, 2011).

Lastly, in scaling AI represents the highest order of sustainable innovation. While pilot projects can increase the rate of innovation, system-wide adoption depends on focused scaling. This requires phased implementation and educational investments. Funding often comes from savings achieved through efficiency improvements. Scaling is not about rapid expansion. It involves intentional, evidence-based, and gradual development, balancing both economic and social aspects. In the SOI framework, scaling guides the sustainability path, transitioning from operational efficiencies (Context 1) and clinical improvements (Context 2) to systemic, adaptive, and equitable innovation (Context 3). Theoretical contributions are significant for both research and practice. This study, by placing cost savings at the centre of innovation theory, shifts the discussion from viewing AI as a quality enhancer to recognising it as a driver of long-term financial resilience. The model provides practitioners and policymakers with a guide to incorporating AI into flexible governance frameworks, ensuring that the benefits from pilots are not only tracked and confirmed but also increased to create real, lasting value in the world.

5.2 Managerial implications

The findings offer important implications for managers seeking to digitally transform healthcare organisations. The framework emphasises that adopting AI is not simply a technological decision aimed at cost savings, but a strategic choice with systemic implications. In other words, leaders must move beyond short-term savings to treat AI as a lever for long-term organizational viability and economic sustainability.

First, managers should evaluate the cost-effectiveness of AI adoption. While direct savings may appear initially, they represent only a superficial effect. The deeper value of AI lies in its support for proactive care, clinical decision support, and administrative efficiency. Thus, measuring AI efficiency only through short-term savings risks underestimating its true contribution. Instead, managers should adopt a portfolio approach, balancing projects that provide immediate cost reductions (e.g., automated scheduling) with long-term, transformative initiatives (e.g., chronic disease monitoring and predictive analytics).

Second, organisations must strike a balance between clinical and non-clinical applications. While clinical decision support is highly visible, non-clinical applications can deliver equally significant value. Leaders should adopt a holistic approach, ensuring resources are allocated across domains and that AI solutions are tied to system-wide performance rather than isolated initiatives.

Third, short-term efficiencies must translate into long-term effectiveness. Managers can ensure this by establishing robust AI governance structures, continuously evaluating performance, and scaling successful applications. Without proper oversight, early efficiency gains risk erosion. Oversight policies, staff training programs, and infrastructure must therefore be aligned with implementation.

This study also finds that AI can optimize staff planning and alleviate burnout. Managers should not view AI as a replacement for healthcare professionals but as a tool to reduce administrative burdens and optimize workforce allocation. This approach supports retention, staff satisfaction, and patient care quality.

Patient access and equity must remain central managerial priorities. AI-powered telemedicine and data-driven alerts expand access for marginalized groups, eliminate barriers, and strengthen patient relationships. Leaders should ensure that solutions are designed for equitable access and universal usability to avoid reinforcing disparities.

Finally, managers must prioritize adaptation, monitoring, and scaling. Regular evaluation ensures that AI remains aligned with organizational needs. Leaders should invest in governance and feedback mechanisms to secure sustained effectiveness across teams. Crucially, economic sustainability should not be treated as an endpoint, but as a dynamic, ongoing process. Long-term success metrics should extend beyond financial returns to include patient outcomes and workforce wellbeing.

5.3 Limitations and future research

This study has certain limitations that should be acknowledged when interpreting its findings. The aim of this research was exploratory rather than generalizable to deepen understanding of how AI contributes to cost savings and economic sustainability in healthcare practice. Consequently, the value of this study lies in its analytical depth and conceptual contribution rather than its statistical representativeness.

First, this study was based on healthcare professionals' perceptions and reported experiences, rather than on quantified data measuring financial outcomes or efficiency metrics. While participants provided detailed accounts of how AI is being implemented and where they observed value creation, the study did not empirically verify cost reductions or productivity improvements. Future research should therefore include quantitative or mixed-methods designs to empirically measure AI's financial and operational impact such as reductions in administrative expenditure, hospital readmissions, or resource utilization efficiency.

Second, the findings reflect AI's current stage of adoption, as healthcare systems worldwide are still in the process of integrating AI technologies. The framework presented in this study captures an evolving phase of digital transformation, where many applications remain experimental or in early deployment. As AI continues to mature, new themes and dynamics are likely to emerge, particularly regarding long-term governance, scalability, and integration into routine clinical and administrative workflows. Future research should track these developments longitudinally to understand how sustainability outcomes evolve.

Third, the study primarily examined AI adoption within organizational and professional contexts, but it did not account for broader systemic and policy-level factors that may shape adoption and sustainability. Elements such as national healthcare policies, funding mechanisms, ethical governance frameworks, and vendor procurement practices can critically influence how and why organizations adopt AI. Future studies should therefore expand the scope to include macro-level analyses, comparing how regulatory and institutional conditions affect the sustainability of AI-driven transformations across healthcare systems.

Fourth, while the framework encompasses both clinical and non-clinical domains, this study did not explore in detail how these areas interact dynamically. For instance, improvements in administrative automation may indirectly enhance clinical quality, while predictive analytics in clinical workflows may also reduce organizational overhead. Further research adopting a systems-level approach could better map these interdependencies, offering a more holistic understanding of how AI generates value across multiple organizational layers simultaneously.

Finally, this study focuses primarily on cost savings and efficiency outcomes but recognizes the need for continued inquiry into ethical, social, and equity dimensions of AI in healthcare. Future work should consider how economic sustainability can coexist with ethical principles of fairness, inclusivity, and patient-centred care, particularly as AI becomes embedded in decision-making processes. While this study provides an empirically grounded and theoretically informed framework for understanding how AI contributes to healthcare sustainability, further research is essential to validate and extend its findings. Future studies should integrate quantitative assessments, longitudinal perspectives, and policy analyses to capture the multifaceted and evolving nature of AI's role in healthcare economics and governance.

6 SUMMARY

This study examines the economic sustainability of healthcare in the long term in relation to the integration of AI in care delivery, with particular attention to identifying cost-saving opportunities. The research is motivated by mounting pressures on healthcare systems worldwide, including rising costs, an aging population, workforce shortages, and the increasing prevalence of chronic diseases. While AI is widely recognized as a transformative technology in clinical decision-making, diagnostic reporting, and administration, less attention has been given to how cost-saving opportunities contribute to long-term economic sustainability. This thesis addresses that gap by examining both immediate efficiencies and downstream impacts.

The literature review indicates that AI can generate efficiencies in healthcare, including early disease detection and screening, reducing admissions and readmissions, streamlining administrative processes, optimizing workforce planning, improving resource allocation, and enhancing preventive care. These efficiencies reduce waste, increase productivity, and improve patient outcomes, leading to measurable cost savings. However, prior research often focuses on AI's clinical and technical potential without fully exploring the link between cost savings and economic sustainability.

This study employs the Sustainability-Oriented Innovation (SOI) framework as an analytical lens, bridging the fields of healthcare, economics, and innovation studies. Methodologically, the research uses qualitative methods, relying on semi-structured interviews with diverse stakeholders. Thematic analysis shows that AI adoption is perceived to create value in both clinical and non-clinical domains. Clinically, AI supports early diagnostics, prevention, and patient monitoring, resulting in fewer hospitalizations and better outcomes. Administratively, AI enhances billing, scheduling, compliance, and workforce utilization, enabling staff to focus more on patient care. Predictive analytics further support workforce planning and resource allocation, reducing fatigue and aligning skills with demand.

This analysis produces a revised theoretical model for AI adoption, positioning cost savings as the central and initial outcome, which leads to economic viability. The model highlights that sustaining these gains requires adaptation, ongoing monitoring, and effective scaling. Without continuous evaluation, early efficiencies risk being lost.

This study makes several contributions to the literature. It identifies cost savings as the primary outcome of AI adoption, extends the focus beyond clinical research to include non-clinical applications, and demonstrates how short-term efficiency links to long-term transformation. It underscores the necessity of governance and agility for sustaining change and reframes AI as a driver of economic sustainability across healthcare systems rather than simply a technology choice.

From a managerial perspective, the findings suggest that healthcare executives should focus on cost-saving opportunities by leveraging both clinical and administrative applications, integrating AI as a supportive tool rather than a replacement for human resources. Finally, this study acknowledges its limitations, including reliance on a small sample and subjective perceptions, and the absence of exploration into broader systemic, sociopolitical, and cultural factors influencing AI adoption. Future research should validate the framework, employ longitudinal approaches to measure cost and outcome impacts, and address emerging issues such as ethics, governance, and equity.

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8 APPENDICES

Appendix 1 – Initial Guide for Interview

Background

- Could you briefly introduce yourself and your professional background?
- What is your current role and involvement in healthcare operations or administration?
- How long have you been working in the healthcare sector, and in what capacity?
- How familiar are you with the use of Artificial Intelligence (AI) in your healthcare organisation?
- Has your organisation already integrated AI technologies? If yes, in what areas?

Theme 1 – Understanding AI Integration in Healthcare

- How would you define or describe AI integration in the context of healthcare?
- What types of AI applications are currently being used in your institution (e.g., diagnostic tools, administrative automation, and predictive analytics)?
- What were the main drivers for adopting AI in your organization?
- What goals or expectations did your organization have while introducing AI?

Theme 2 – Cost-Saving Mechanisms of AI

- In your experience, how has AI contributed to reducing healthcare costs?
- How do you perceive the cost-saving potential of AI?
- Can you provide examples where AI enabled early detection or preventive care helped to avoid more costly treatments?
- Have you seen evidence of AI reducing unnecessary admissions or readmissions?
- How has AI influenced administrative efficiency e.g., billing, scheduling, documentation etc.?
- What role does AI play in resource optimization or workforce planning in your setting?

Theme 3 – Economic sustainability in healthcare

- How have you defined sustainability in healthcare?
- How have you defined economic sustainability in healthcare?

- How economically sustainable practices in healthcare can contribute to overcome current problems?

Theme 4 – Long-Term impact on economic sustainability in healthcare

- Do you perceive that AI-driven cost savings contribute to economic sustainability in your healthcare setting? How?
- How does your organization measure or project long-term cost impacts of AI technologies?
- Has AI integration yielded measurable cost saving benefits over time? If so, can you elaborate?
- How to maintain or scale these economic benefits in long term?
- What challenges exist in maintaining or scaling these economic benefits in long term?

Reflections

- What are the most significant cost-saving outcomes from AI integration in your experience?
- What lessons have been learned about aligning AI integration with economic sustainability goals?
- Based on your experience, what are three key conditions necessary for AI to contribute to long-term cost savings in healthcare?
- Is there anything else you'd like to share regarding AI's role in sustainable healthcare?

Appendix 2 – Informed consent

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Informed Consent Form for Participation in Scientific Research

Research project title: Exploring the Long-Term Impact of AI Integration on Economic Sustainability in Healthcare: A Cost-Saving Perspective

Place of research: Turku, Finland
The person responsible for the research: Huma Farid

I have been invited to participate in the above-mentioned research. I have read and understood the information given and I agree to participate in the project. I understand that participating in the research is voluntary and that I can at any point withdraw from participating in the research without giving any reason or cancel my consent without any negative consequences. I have received sufficient information about the research and how my personal data is processed. I have had the opportunity to ask questions from the researchers. With my signature, I give consent for participating in the research.

☐ Yes ☐ No

I consent that my interview can be audio-recorded
☐ Yes ☐ No

I consent that my interview can be video-recorded
☐ Yes ☐ No

I agree to be identified in the following way in the research outputs:
[Pseudonym; alternative name/code chosen for the participant by the researcher]
☐ Yes ☐ No

Impersonal attribution
[e.g., by profession: company official, firm official]
☐ Yes ☐ No

Contact Information

Name of participant: ________________
Date: ______________________________
Signature: ______________________________

Name of the interviewer: ___________________________
Date: ___________________________
Signature: ___________________________

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Appendix 3 – Privacy Notice

1. Name of the register	The Long-Term Impact of AI Integration on Economic Sustainability in Healthcare A Cost-Saving Perspective
2. Data controller	Huma Farid, huma.h.farid@utu.fi, Turku School of Economics, University of Turku, Rehtorinpellonkatu 3, 20500 Turku
3. Contact information of the responsible person	Huma Farid, huma.h.farid@utu.fi,
4. Purpose and legal basis for the processing of personal data	• The research collects views and experiences of experts on Long-Term Impact of AI Integration on Economic Sustainability in Healthcare. • The legal basis for processing personal data in the Article 6 of the EU General Data Protection Regulation is: ☒ Processing is necessary for scientific research (public interest, Point 1a of the Article 6) ☐ Data subject has given their consent to processing personal data (consent, Point 1e of the Article 6) ☐ Other, what
5. Processes personal data	The following information of the data subjects is stored in the register: Name, Email address, position, company, experiences, and views on the research topic.
6. Recipients and recipient groups of personal data	The data will not be transferred or disclosed to parties outside the researcher or his supervisors.
7. Information on transferring data to third countries	Personal data will not be disclosed to parties outside the EU or the European Economic Area.
8. Retention period of personal data or criteria for its determination	The research data will be anonymized by erasing identifiable personal and company data. Personal data is stored until 31 December 2025, after which the data is disposed of securely.
9. Rights of the data subject	• The data subject has the right to access their personal data retained by the Data Controller, the right to rectification or erasure of data, and the right to restrict or object the

	processing of data. The right to erasure is not applied in scientific or historic research purposes in so far as the right to erasure is likely to render impossible or seriously impair the achievement of the objectives of that processing. • The realization of the right to erasure is assessed on a case-by-case basis. • The data subject has the right to lodge a complaint with the supervisory authority.
10. Information on the source of personal data	To send the invitations to the interview, email addresses or the possibility of forwarding a message are used. It will only be done after a primary contact and consent to participate has been given by the subject. The other data is collected directly from those who participate in the interviews for the study.
11. Information on the existence of automatic decision-making, including profiling	The data will not be used for automatic decision-making or profiling.

Appendix 4 – Declaration on the use of AI assistance

In the creation of this thesis, I utilised generative artificial intelligence for several support tasks. The tools, their purpose, and the verification measures are detailed below. I confirm that I have used all AI tools, with the necessary care and caution, have been fully disclosed for their use in accordance with university policy and take full responsibility for all content presented in this thesis.

1. Tool: OpenAI's ChatGPT (GPT-4 Version)

Stage of use: Literature Review and Synthesis

• Summarising individual academic articles to help quickly assess their relevance

• Identifying common themes or debates within a set of research papers.

• The formatting of citations and reference lists adheres to a specific style

Stage of use: Composition, Editing, and Revision

• Proofreading of text for spelling, grammar, and punctuation errors.

• Rephrasing individual sentences or short passages to improve clarity or academic tone.

2. Tool: Grammarly

• **Stage of Use:** Composition/Editing

• **Purpose of Use**: AI-based spelling corrections and language improvements were used throughout the writing of this paper to enhance readability.

• **Verification:** I carefully proofread all suggestions and changes recommended by these tools to ensure that the original meaning of my arguments and discussion was not altered and that the academic content remained accurate. I retained final control over the text.