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Analysis of the social cost-benefit and intent to use of AI in healthcare

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Analysis of the social cost-benefit and intent to use of AI in healthcare

Directed by Professor Sung-Uk Kuh, Won-Seuk Jang

A Doctoral Dissertation
Submitted to the Department of Medical Device Engineering and Management,
the Graduate School of Yonsei University
in partial fulfillment of the requirements for the degree
of Doctor of Philosophy in
Medical Device Engineering and Management

Jun-Young Lee

June 2023

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Acknowledgements

It's been more than 10 years since I started working in digital healthcare. In my first job at NIA after graduating from my Masters in 2006, I was in charge of the u-health and telemedicine business, but I thought I would be moved to another team in a few years' time. After moving to NIPA, I was briefly in charge of RFID and ICT policy planning, but then I was reassigned to digital healthcare, starting with the Health Information Exchange (HIE) pilot. It was very rewarding when new healthcare projects using cloud and AI technologies, such as the precision medicine hospital information system, Dr. Answer, and the AI emergency medical system, which were planned with the establishment of the Digital Health Industry Team, received a lot of external response and success stories through media coverage. I think I was fortunate that the digital healthcare business I was in charge of had a strong focus on improving the healthcare system and supporting the transformation of the medical paradigm.

Working in digital healthcare, one of the things I missed was the thirst for academic and theoretical knowledge, not just practical knowledge. However, it was not an easy decision to combine work, family and study. I would like to thank my wife for giving me the courage to do a PhD when I was hesitant. As a part-time PhD student who had to combine work and study, the period of study and thesis writing was not only possible with the sacrifices of my family, but also with their active support and interest. I would like to take this opportunity to apologize and express my gratitude to my family for the few times I have neglected my studies. Thank you to my beloved wife and son Seung-won.

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giving me the opportunity to work with various experts in the field of digital healthcare. Although my graduate life is coming to an end with the completion of my PhD, the experience I gained in graduate school will be an important asset in my new life.

I would like to be the kind of person who doesn't get complacent, who doesn't regret taking on new challenges and who can grow more than I am now.

"Never regret yesterday. Life is in you today, and tomorrow is what you make of it." (L. Ron Hubbard)

June 2023

Jun-Young Lee

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ABSTRACT

Analysis of the social cost-benefit and intent to use of AI in healthcare

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Engineering and Management
The Graduate School, Yonsei University

(Directed by Professor Sung-Uk Kuh, Won-Seuk Jang)

Background

AI in healthcare is reducing medical costs and diagnosing diseases more accurately and quickly. As a result, the global market for AI in healthcare is growing rapidly, and the number of developments and approvals is increasing not only in Korea, but also in the United States and Europe. However, despite the fact that AI is proving its effectiveness in a number of studies in the medical field, the use of AI in the healthcare sector is still at a

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low level. Unlike AI products in other sectors, AI in healthcare requires not only clinical evidence but also economic analysis to prove its cost-effectiveness in order to be covered by health insurance. In addition, physician acceptance of AI technology is a key factor in enabling AI in healthcare, but there is limited research on the factors that influence this attitude. Therefore, this study aims to verify the economic feasibility of AI in healthcare through a social cost-benefit analysis of AI in healthcare and to analyse the factors that influence medical staff's use of medical AI.

Methods

The economic analysis estimates the costs and benefits of the Dr. Answer project from 2018 to 2020. For the economic evaluation of medical AI, the government funds invested in the project, the estimated price of using medical AI, and the resulting nine benefits (reduced test and treatment costs, reduced additional inspection costs, reduced treatment costs such as surgery, reduced hospitalization and caregiving costs, reduced transportation costs, income preservation benefits for patients and guardians, and reduced medical reading costs) were estimated in monetary units through a review of existing literature and analysis of secondary data.

The effects of personal innovation, facilitating conditions, functional excellence, price value, perceived ease of use and perceived usefulness on the intention to use AI in healthcare were analysed using an online survey of 109 medical staff. The moderating effect of experience in using AI in healthcare was also tested. IBM SPSS 29 was used for frequency analysis of respondents' general characteristics, and Smart PLS 4.0 was used for reliability and validity analysis of measurement items and hypothesis testing. The bootstrap method (5,000 repeated samples) was used to estimate path coefficients and test for significance.

Results

The economic analysis of medical AI showed a net benefit of KRW 341,180,251

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thousands and a benefit-cost ratio of 4.9 times, demonstrating its economic feasibility. The sensitivity analysis by adjusting the number of patients to 25% and 75% showed a net benefit of KRW 170,590,125 thousands and a benefit-cost ratio of 3.66 times when the number of patients was 25%, and a net benefit of KRW 511,770,377 thousands and a benefit-cost ratio of 5.54 times when the number of patients was 75%, demonstrating economic feasibility. The stage of the patient journey with the highest healthcare cost savings was found to be the stage of disease onset prediction, which can prevent unnecessary tests and treatments by predicting disease in advance. Breast cancer prediction (benefit KRW 62,477,977 thousands, benefit-cost ratio 5.58 times), colorectal cancer prediction (benefit KRW 44,528,502 thousands, 23.62 times), heart disease prediction (benefit KRW 37,596,545 thousands, benefit-cost ratio 3.82 times) and epilepsy seizure prediction (benefit KRW 28,634,041 thousands, benefit-cost ratio 11.74 times).

The results of the analysis of factors influencing medical staff's intention to use medical AI showed that there was no positive effect between personal innovation and perceived ease of use, price value and intention to use, and perceived ease of use and intention to use. In addition, the moderating effect of usage experience is tested on the relationship between personal innovation, facilitating conditions, functional excellence and price value on intention to use medical AI. The results show that intentions to use healthcare AI are consistent regardless of the facilitation condition for AI-experienced medical staff, whereas for inexperienced medical staff, intentions to use healthcare AI increase as the facilitation condition for receiving organizational and technical help and support in using healthcare AI increases.

Conclusion

AI in healthcare is economically feasible, with a net benefit greater than zero and a benefit-cost ratio greater than one, and is expected to make a positive contribution to

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reducing healthcare costs if widely adopted. We also found that individual innovation, facilitating conditions and functional excellence are important factors in the intention to use medical AI, and that organizational and technical help and support from hospitals and companies facilitate the use of medical AI by medical staff.

As the development and approval of medical AI increases globally, there is a need to continue to support and improve the system at a national level to improve the efficiency of the current healthcare system and promote the medical AI industry. This is expected to improve people's health, reduce the cost of medical care, and promote domestic companies in the rapidly growing global market for medical AI.

Key words : AI in Healthcare, Health Economic Evaluations, CBA(Cost Benefit Analysis), TAM(Technology Acceptance Model), PLS-SEM(Partial Least Square-Structural Equation Model)

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I. Introduction

1. Research background and needs

After the shocking match between Lee Se-dol 9 and AlphaGo, AI has become a natural part of our daily lives. As AI is applied to different industries, there are expectations and concerns that it will replace humans. One of the areas where AI is expected to take over is healthcare.

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The current healthcare system is under great pressure due to an ageing population, increasing life expectancy and growing demand for quality healthcare services. Due to the increasing number of people with chronic diseases and a rapidly ageing population, Korea's current healthcare expenditure is expected to increase rapidly from KRW 142.7 trillion in 2018 to KRW 180.6 trillion in 2021[1]. According to the Ministry of Health and Welfare, the number of outpatient visits per capita in Korea in 2020 will be 14.7 times per year, the highest among OECD countries and 2.5 times higher than the average of member countries (5.9 times)[2]. In addition, the average number of days per inpatient in Korea in 2020 will be 19.1 days, the second highest among OECD countries after Japan (28.3 days)[2].

A number of technologies, including AI, IoT and sensor technology, are being developed to address the problems of the current healthcare system and to respond quickly to changing healthcare paradigms. Among them, AI has the potential to improve the problems of the current medical system. AI is expected to help reduce medical costs and promote the medical industry by providing rapid diagnosis and personalized medical services throughout the patient journey, including prevention, diagnosis, monitoring, treatment and aftercare.

AI technology has the potential to transform healthcare by deriving new and valuable insights from the vast amounts of data generated during the delivery of healthcare services by medical staff. In recent years, the demand for medical AI technology to assist medical staff has increased due to the increasing complexity of medical data, the difficulty of diagnosis and treatment, the rising rate of misdiagnosis and the rising cost of medical care. As a result, the number of medical AI systems that have passed the approval process in various countries is constantly increasing.

As of September 2022, the total number of AI medical devices approved in Korea is 139, and the number of approvals is increasing rapidly each year since four in 2018[3]. Among them, a total of 32 AI medical devices have been designated as innovative medical devices as of March 2023[4], and four products have received deferral of new

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medical technology evaluation[5]. The number of AI medical device approvals is also increasing in the United States. Of the 521 medical AI devices approved by the FDA, 500 (96%) were 510(k) approvals, 18 were de novo approvals and 3 were premarket approvals[6]. The New Technology Add-on Payments (NTAP) program also enabled ContaCT to receive payments of up to $1,040 per patient case[7]. This was followed by approvals for AI from RapidAI, Aidoc and Avicenna AI. Europe also received approximately 220 CE-certified medical AIs, with 71 CE Class I, 120 Class IIa and 21 Class IIb approvals[8].

The global healthcare AI market is also growing rapidly. According to a Markets and Markets report, the global market for AI healthcare is expected to expand from $6.9 billion in 2021 to $67.4 billion by 2027, at a CAGR of 46.2 per cent. The report also predicts that the software-based healthcare AI market will continue to grow from 2019 onwards[9].

The prospect of AI contributing to cost savings in healthcare is also supported by a number of studies. Accenture predicts that by 2026, AI will replace the work of physicians, address approximately 20 percent of unmet clinical needs, and generate $150 billion in annual cost savings for US healthcare[10]. ABI Research predicts that AI will produce better-quality drugs, save doctors time and reduce the number of deaths, resulting in cost savings of $52 billion by 2021[11]. According to Frost & Sullivan, AI has the potential to increase patient Outcomes by 30-40% and reduce the cost of care by up to 50%[12]. McKinsey and Harvard University have suggested that widespread adoption of AI in healthcare could save the US up to $360 billion annually[13]. The National Bureau of Economic Research estimates that widespread adoption of AI could save 5-10 per cent of US healthcare spending (approximately $200-360 billion per year in 2019 dollars)[14].

Initially, medical AI was applied to medical imaging data to assist in disease diagnosis, but in recent years the range of diseases covered has expanded and it has become more useful across the entire healthcare service cycle, including prognosis, treatment and outcomes management. AI is also expected to use algorithms and machine learning to

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analyze and interpret data, provide personalized experiences and automate repetitive and tedious tasks for medical staff.

AI at the prevention/prediction stage analyses genomic, medical and lifestyle information to predict future disease. This enables individuals to respond to disease outbreaks in advance. Such AI can be used to predict various diseases such as cancer, sepsis, heart disease and adult diseases. By improving the accuracy of disease diagnosis, AI provides more effective treatments and prescriptions tailored to individual patients' disease conditions. In particular, advances in deep learning technologies for analysing pathological images and medical imaging data are enabling breakthroughs in diagnostics. AI is also helping to improve diagnostic accuracy, reduce healthcare costs and streamline medical processes by assisting doctors with diagnosis.

For example, an Israeli startup has developed an AI algorithm that can diagnose conditions such as osteoporosis, cerebral haemorrhage, malignant tissue on mammograms and coronary aneurysms with equal or greater accuracy than humans. AI has also been developed to predict CVD risk and coronary calcium scores from retinal images, and research has shown promise for using AI-based algorithms in certain carotid ultrasound applications. Another study showed that AI is much faster than humans at reading and analysing mammograms with 99% accuracy, which could lead to faster diagnosis of breast cancer and improve the cost of diagnosis. In Korea, Seoul National University Bundang Hospital used deep learning to analyse CT images to better predict kidney cancer, with an accuracy rate of around 85%[15]. Korea University An-san Hospital analysed dental X-rays to predict osteoporosis with 86% accuracy[16]. This project, which uses a huge amount of medical image data and patient data to predict diseases, is still being researched to improve diagnostic accuracy.

Some studies have shown that AI can speed up the reading of medical images. To determine the effectiveness of medical AI in real-world clinical practice, Professor U. Joseph Schoepf of the Medical University of South Carolina analysed data from 390 patients who underwent outpatient chest CT scans with AI embedded in the clinical

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workflow. The analysis showed that radiologists using AI reduced reading time by an average of 22.1 per cent compared to those without AI[17]. VUNO published a study comparing its AI-enabled gastric cancer pathology solution, VUNO Med-PathGC AITM, to six pathologists with and without medical AI and found a reduction in diagnostic time of up to 58%[18].

Although the development of medical AI technology and related research is steadily increasing, there is still a lack of research to prove the medical efficacy of AI technology. As the role of medical AI is still to assist medical staff in diagnosis, the number of health insurance companies has been slow to enter the market, making it difficult for medical AI companies to establish a clear revenue model. Unlike business models in general industries, medical AI has a complex industry structure in which the entity that uses the product (patient, doctor), the entity that decides to use the product (hospital, doctor), and the entity that pays for the product (state, insurance) may be different, making it difficult for innovative services with high barriers to entry to be accepted[19]. In addition, due to the national specificity of the single-payer insurance system, even after medical AI is licensed, it is difficult for licensed medical AI to be realistically used in the field before the peak of new medical technology, insurance coverage, and numbers. As medical AI is a rapidly developing technology, there is a limitation that there is not enough data to validate it as a new medical technology. Developing companies also have time and budget constraints to secure clinical evidence. In this situation, the cost-effectiveness analysis of medical AI through securing clinical evidence in the medical field is also limited. In addition, despite the fact that acceptance of AI technology by medical staff is a key factor in activating AI, there is a lack of research into the factors that influence this attitude.

Therefore, this study aims to verify the economic feasibility of AI in healthcare through a social cost-benefit analysis of AI in healthcare, and to analyse the factors that influence the use of AI in healthcare by medical staff. The cost-benefit analysis was conducted by estimating the costs and benefits of the Dr. Answer project from 2018 to

2020. The factor analysis of intention to use medical AI analysed the impact of personal innovation, facilitating conditions, functional excellence and price value on perceived ease of use, perceived usefulness and intention to use through an online survey of 109 medical staff. Analyses were conducted using IBM SPSS 29 and Smart PLS 4.0.

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2. Research purpose

The main objectives of this study are to examine the economic evaluation of AI in healthcare through a social cost-benefit analysis and to analyse the factors that influence medical staff's intention to use AI in healthcare.

The specific research objectives are

First, based on objective evidence from literature reviews and secondary data analysis, we define the costs and benefits of medical AI and conduct an economic analysis of 19 medical AI systems.

Second, to derive the factors influencing the intention of medical staff to use medical AI from the literature review, and to analyse the factors influencing the intention to use medical AI through a survey of medical staff and statistical analysis.

3. Method and scope of the study

The main objectives of this study are to examine the economic evaluation of AI in healthcare through a social cost-benefit analysis and to analyse the factors that influence the intention of medical staff to use AI in healthcare.

This study consists of six chapters, including an introduction. Chapter 1, Introduction, summarizes the research background and need, research objectives and methods. Chapter 2, Theoretical background, summarizes the concept of medical AI, the status of licensing and reimbursement policies by country, and existing studies on affordability and intention to use medical AI through a literature review. Chapter 3, Research Methodology, derives cost-benefit positions for the economic analysis and summarizes research hypotheses and survey questions for the intention to use analysis. Chapter 4, Results, summarizes the results of the cost-benefit analysis of 19 medical AIs and the structural equation analysis of intention to use. Chapter 5, Discussion, presents the significance and limitations of this study, and Chapter 6, Conclusion, summarizes the results of the study.

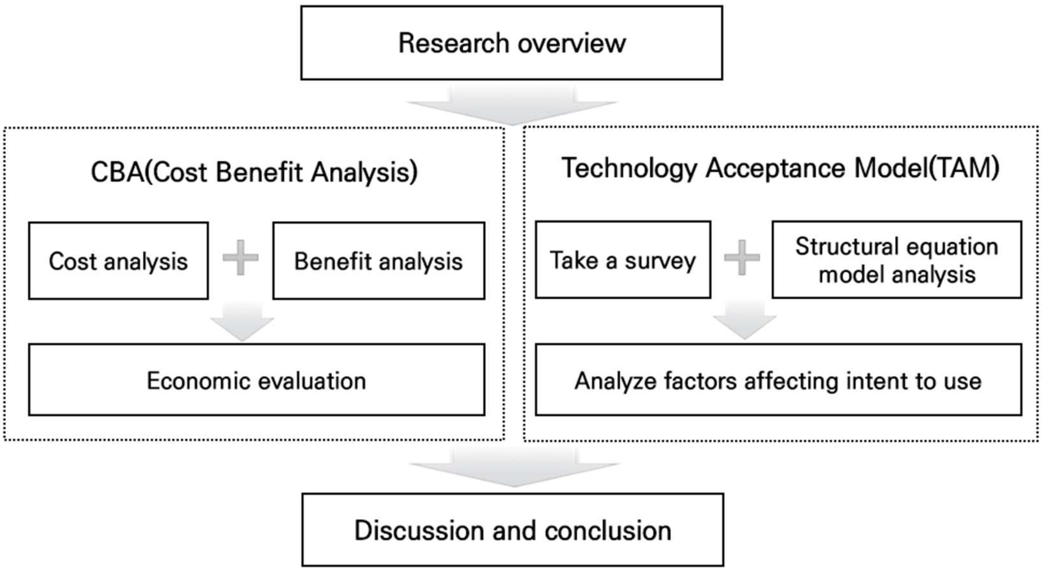

Figure 1. Research methods

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II. Theoretical background

1. AI in healthcare overview

A. AI in healthcare concepts

AI in healthcare refers to technologies developed to apply human intelligence to processes such as disease prediction, diagnosis, treatment and prognosis management. In other words, by applying AI technology to the medical field, we can improve the accuracy of measurements and create new value in processes such as predicting, diagnosing and preventing disease.

The International Medical Device Regulators Forum(IMDRF), established in 2011, defined software as a medical device (SaMD) in 2013 as "software intended for use for one or more medical purposes that is not part of a hardware medical device"[20]. As a software medical device, SaMD itself cannot replace a doctor, but SaMD can easily, quickly and continuously collect various types of valuable data that can provide essential or meaningful information for medical treatment and support to users. In addition, the functionality of existing medical devices can be enhanced through software solutions, which are faster and easier to update than hardware, and for companies using or developing SaMD, rapid feedback from users can improve product functionality and speed time to market. The Ministry of Food and Drug Safety defines medical AI as a medical device that assists medical personnel by diagnosing, managing or predicting diseases by analysing medical big data using AI. Medical big data includes a variety of medical information used to diagnose, manage, or predict diseases, from medical records or medical devices to measured biometric information, medical images, and genetic information[3]. On the other hand, there is currently no distinction between AI medical devices and non-AI medical devices globally, i.e. it is judged as a medical device or non-medical device based on the purpose of the software, not based on medical AI technology.

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In the case of medical software that uses big data and artificial intelligence (AI) technology, as defined by the Ministry of Food and Drug Safety, it is classified as a 'medical device' and a 'non-medical device', but does not distinguish between medical AI medical devices and non-medical AI medical devices. The 21st Century Cures Act, published by the US Food and Drug Administration (FDA) in December 2016, explains the reason for not classifying AI medical devices and AI non-medical devices separately as follows: "The issue is not whether AI is used, but whether the product, article, or software is classified as a medical device based on its function and purpose. Neither the United States nor the European Union (EU) specifically defines medical devices with AI technology"[21]. In summary, software medical devices with AI and big data technology can be defined as software that analyses medical images and medical information based on medical big data to diagnose, predict and treat, or provide necessary clinical information, and classified according to the type of data.

In South Korea, software was established as a separate item in August 2020 through the revision of the Regulations on Medical Device Items and Classification by Item, and was divided into 11 major categories and 90 minor categories. Of the 90 subcategories, four are classified as class 1, 71 as class 2 and 15 as class 3.[22]

Table 1. Status of software items in medical devices[22]

Large category	Medium category		small category
	E01000	Software for cardiovascular care	18
	E02000	Software for dental practices	5
	E03000	Software for ear, nose and throat practices	5
	E04000	Software for the gastroenterology and urology practice	6
	E05000	Software for medical practices	20
Software	E06000	Software for Neuroscience Practices	12
	E07000	Software for Gynaecology Practices	4
	E08000	Software for ophthalmic practices	4
	E09000	Software for orthopaedic practices	3
	E10000	Software for rehabilitation medicine practices	3
	E11000	Software for radiation oncology and radiology practices	10

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The growth of healthcare AI is directly related to the diversification of healthcare data collection. While healthcare data has traditionally been generated and accumulated within hospitals, advances in wearable devices, IoT and sensor technology are creating new sources of healthcare data outside of hospitals, exponentially increasing the variety and volume of data. At the IBM Health and Social Programs Summit in 2014, IBM classified human-generated data into three types: medical data, genomic data, and other external activity data, and announced that the size of these three types of data generated by humans in a lifetime is 0.4TB, genomic data is 6TB, and other external activity data is 1100TB, and the impact of these three types of data on human health varies by 10%, 30%, and 60%, respectively[23].

The medical data used in AI research is diverse, including medical treatment data, clinical research data, omics data, lifelog data, and public medical data. In particular, due to the characteristics of Korea's single-payer health insurance system, the NHIS(National Health Insurance Service) and the HIRA(Health Insurance Review & Assessment service) manage medical expenditures and medical histories. This provides a good environment for AI to be trained with high-quality data from individual patients, leading to improved performance in terms of prediction and analysis performed by AI. The Ministry of Health and Welfare has expanded the number of data types open to the healthcare big data platform from 31 to 57, starting in 2023.

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Table 2. Healthcare big data types[24]

Category	Types
Clinic Data	Electronic medical records, electronic health information, prescription information, admissions/discharges, medical imaging, etc.
Clinical research data	Clinical trial data on pharmaceuticals, clinical trial data on medical devices, genetic research data, research data on human derivatives, observational research data and research data that makes direct or indirect use of personal information.
Public agency data (NHIS, HIRA etc.)	Eligibility and premium data, medical history, results of health screening, information on deaths, etc.
Device-based data	Data from medical devices and patient monitoring equipment
Omics data	Genome, Transcriptome, Proteome, Metabolome, Epigenome, Lipofome etc.
Lifelog data	Weight, heart rate, blood glucose, weight, eating habits, exercise habits, medications, and behavioural and emotional data.
Apps/social media data	Data collected from health portals, physician portals, social media, etc.

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B. Status of approval of AI in healthcare

As the demand for medical AI that can diagnose and predict individual diseases at an early stage through AI analysis of various medical data increases, and as users' demand for improved healthcare quality increases due to the increasing complexity of medical data, growing difficulties in diagnosis and treatment, rising misdiagnosis rates, and rising medical costs, the number of medical AI developments and approvals to assist or replace medical personnel is increasing.

According to the Ministry of Food and Drug Safety (MFDS), the number of medical AI approvals in Korea reached 139 as of September 2022, with the number of approvals increasing rapidly year on year since the four approvals in 2018[3].

Table 3. Status of the approval of medical AI in Korea[3]

(Unit: count, as of Sept 2022)

Category		**2018**	**2019**	**2020**	**2021**	**2022.9**	**Total**
Manufacture	Permissions	3	6	14	13	8	44
	Authentication	1	4	31	20	20	76
	declaration	-	-	-	1	3	4
Import	Permissions	-	-	2	1		3
	Authentication	-	-	3	2	7	12
	declaration	-	-	-	-		-
Total		**4**	**10**	**50**	**37**	**38**	139

In the US, the number of medical AI/ML approvals is also on the rise. According to the FDA, 91 AI and ML-enabled medical devices will be cleared and approved in 2022 alone, demonstrating the rapid adoption of AI/ML technologies in the medical device sector[6].

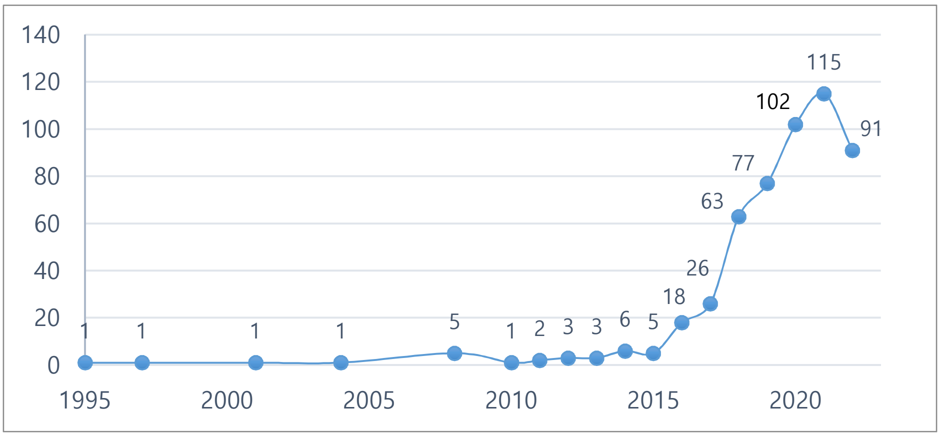

Figure 2. Number of approvals and clearances by the Food and Drug Administration per year[6]

Of the 521 FDA approvals, 392 (75%) are in radiology and 57 (11%) in cardiology, with development concentrated in radiology and cardiology. This is likely due to the wealth of trainable data available from imaging and ECG data[6].

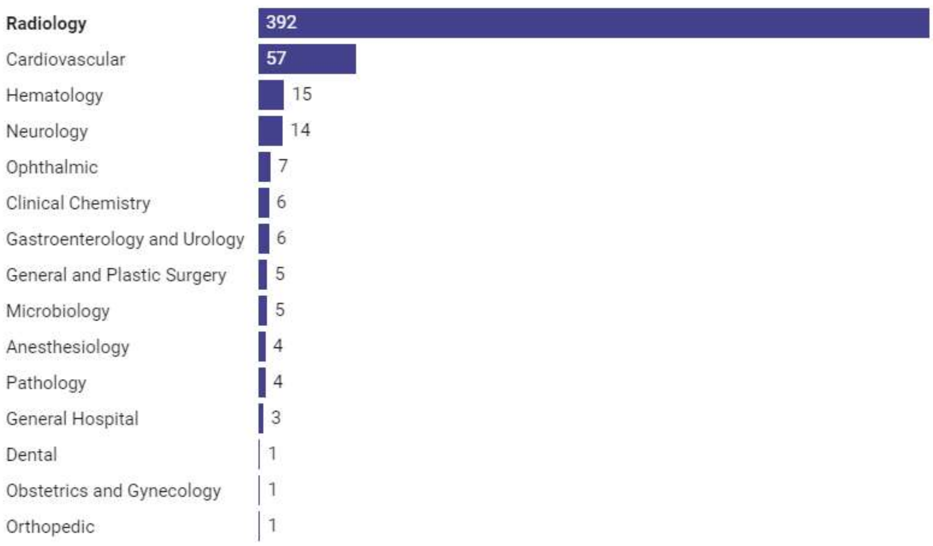

Figure 3. Number of devices by FDA panel, 1995-2022[6]

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Of the 521 AI and machine learning-enabled medical devices approved by the FDA, 96% (500) received 510(k) clearance, 18 (3%) received de novo, the FDA's more rigorous premarket approval process, and 3 received premarket approval, which is not considered high risk but has no prerequisites[6].

Table 4. Types of Food and drug administration (FDA) approvals for AI/ML-based healthcare technology are described[25]

FDA Approval Stages	**Description**
510 (k) Clearance	A 510 (k) authorization is granted to an algorithm if it is at least as secure and effective as another equivalent, commercially available algorithm. Alongside the claim, the applicant for this clearance must provide substantial proof of equivalence. It is illegal to commercialize the algorithm that is awaiting approval until it has been determined to be reasonably comparable to the other algorithm.
Premarket approval	For Class III medical devices, algorithms receive premarket approval. The safety and efficacy of the latter are assessed through more comprehensive scientific and regulatory processes since they can have a significant impact on human health. The FDA must find sufficient scientific evidence supporting the device's usefulness and safety before approving an application. The applicant can move further with product marketing after receiving approval.
de novo pathway	The de novo category is used to categorize novel medical devices with sufficient safety and efficacy and with broad controls, but in which there are no lawfully marketed equivalents. Before approving and permitting the devices to be marketed, the FDA conducts a risk-based evaluation of the device.

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The verification process for all types of equipment in Europe revolves around the CE (Conformite Europëenne) mark, which is used to indicate conformity with European health, safety and environmental protection standards and classifies equipment into four basic classes: Class I, Class IIa, Class IIb and Class III[26].

- Class III: If the decisions made by the software could cause death or irreversible deterioration of the patient's health.
- Class IIa: Software that provides information used to make decisions about diagnosis or treatment.
- Class IIb: Software decisions that could seriously affect a patient's health or require surgical intervention.
- Class I: All other software

According to an analysis of the 'AI for Radiology' website, which provides an overview of the current status of medical AI with European CE certification, there are approximately 220 medical AIs with CE certification. Of these, approximately 118 (53%) are also certified by the US FDA. In addition, there are 53 CE MDRs and 162 CE MDDs. By class, there are 71 CE Class I, 120 Class IIa, 21 Class IIb and no Class III approved medical devices[8].

The breakdown by modality and subspecialty is as follows. By modality, CT was the most popular with 87 cases, followed by MR with 72 cases and X-ray with 44 cases. The subspecialties were neuro 75, thorax 68, abdomen 25 and MSK 25[8].

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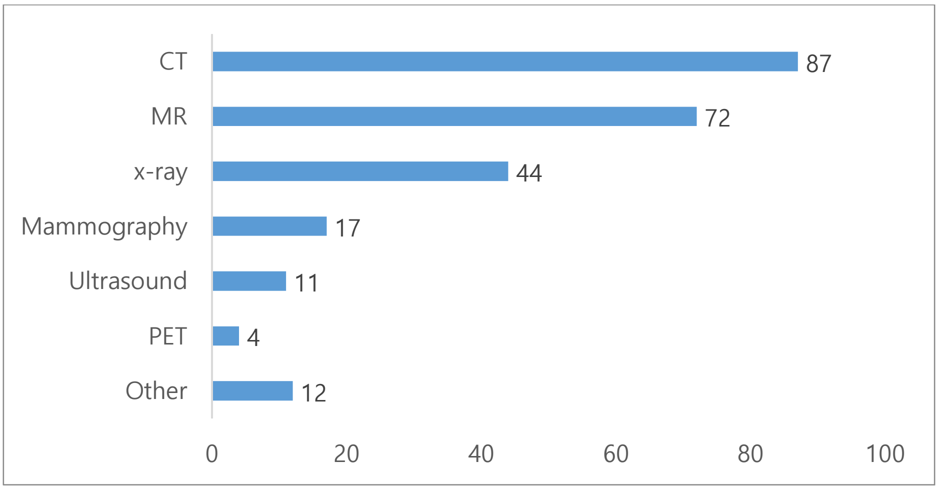

Figure 4. Permission status by modality[8]

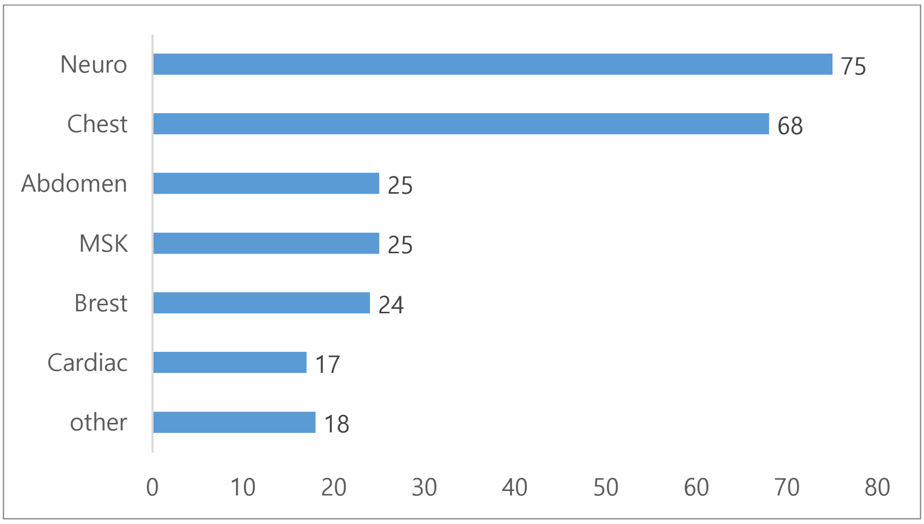

Figure 5. Permission status by Subspeciality[8]

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C. Medical AI compensation policy

Unlike the business model of most industries, healthcare AI has a complex industry structure in which the entities that use the product (patients, doctors), the entities that decide to use the product (hospitals, doctors), and the entities that pay for the product (countries, insurance companies) may all be different, creating a high barrier to entry and a difficult structure for innovative services to be accepted[19]. Therefore, countries are establishing compensation policies for healthcare AI that comprehensively consider the specifics of the medical field and the specifics of the healthcare system, such as the health insurance system.

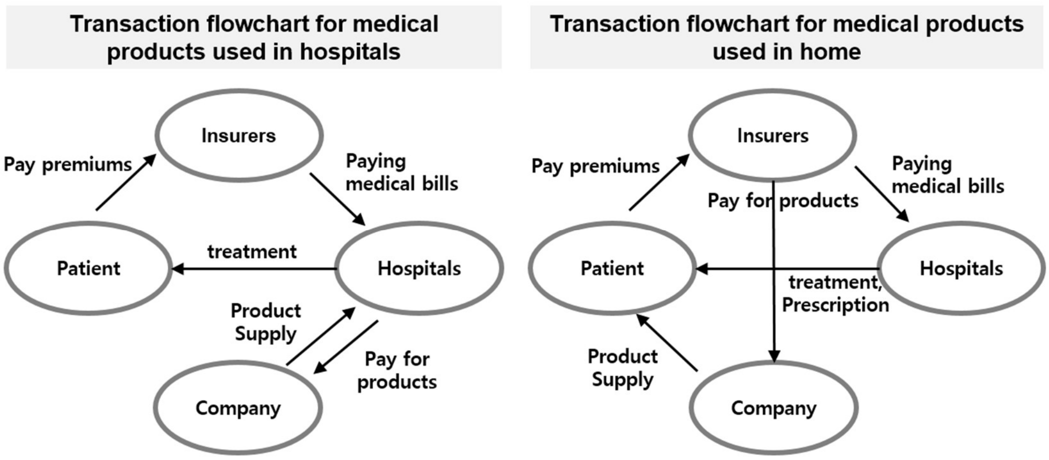

Figure 6. Transaction structure in the healthcare industry[27]

In Korea, the HIRA(Health Insurance Review & Assessment service) established the 'Guidelines for Evaluation of Medical Benefits of Innovative Medical Technologies' in the fields of radiology and pathology that apply AI-based medical technologies in 2019 and 2020, and announced a revision in October 2022 to establish an integrated review system for the designation of innovative medical devices[28].

Accordingly, the Ministry of Health and Welfare has designated 32 products as innovative medical devices to support rapid entry into the medical field by simultaneously reviewing the designation of innovative medical devices (MFDS),

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confirmation of ineligibility for medical benefits (HIRA, Health Insurance Review & Assessment service), and evaluation of innovative medical technologies (Korea Institute of Health and Medical Research), which were previously conducted sequentially by each agency. Once selected as an innovative medical device, it can be used in the medical field as a non-benefit or selective benefit for three to five years with minimal administrative measures (30 days notice)[4].

Table 5. Key companies and products designated as Innovative Medical Devices[4]

Company	Product overview
Vuno	Software that diagnoses and assists with fundus imaging abnormalities using AI technology
Heuron	Software that uses brain MRI images to diagnose and support Parkinson's disease using AI technology
Lunit	Software that diagnoses and assists with abnormalities in chest X-rays using AI technology
Corelinesoft	Software to diagnose and assist with brain haemorrhage in brain CT images using AI technology
Mediwhale	Software to analyse fundus images for cardiovascular disease risk assessment using AI technology
MedicalAi	Software that applies AI technology to the analysis of ECGs to predict the outcome of cardiac events and cardiac arrest within 24 hours.
Laonmedi	Software that uses AI technology to diagnose and assist in the treatment of sleep apnoea using the patient's CT images and biometric data.
JLK	Software that uses AI technology to help diagnose the presence and type of cerebral infarction (ischaemic stroke) lesion from brain MR images and clinical information (presence of atrial fibrillation).
Aitrics	Software that monitors inpatient EMR (19 types of electronic medical records) data to predict the risk of sepsis in the general ward, serious events and deterioration (death) in the intensive care unit.
Deepnoid	Software that uses big data and artificial intelligence (AI) technology to detect abnormalities in cerebrovascular MRA images suspected of being brain aneurysms, to help healthcare providers make diagnostic decisions.

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In 2020, the US Centers for Medicare & Medicaid Services (CMS) took an important step toward widespread adoption of AI with the first AI-related Common Procedural Terminology (CPT) codes and the first New Technology Add-on Payment (NTAP) for AI devices. In October 2020, CMS announced that ContaCT, a computed tomography (CT) scanner that uses AI-powered software, will be covered under NTAP beginning in 2021. ContaCT, which received marketing clearance from the Food and Drug Administration (FDA) in 2018, uses deep learning to analyse CT images to determine the presence or absence of blockages in large blood vessels that can lead to stroke, as well as the patient's current clinical status. The test, which has been assigned a new procedure code (4A03X5D), is reimbursed up to $1,040 per case under the fee-for-service programme[7].

Table 6. Selected AI devices that are reimbursed by US Medicare[7].

Manufacturer	Technology	Description	Payment mechanism
Digital diagnostics	IDX-DR	- Deep learning algorithm to diagnose diabetic retinopathy from fundoscopic images in the outpatient setting	CPT
viz.ai	Viz LVO	- Radiological computer-assisted triage and notification software that analyzes CT images of the brain and notifies hospital staff when a suspected large-vessel occlusion (LVO) is identified	NTAP
Rapid AI	Rapid LVO	- AI-guided medical imaging acquisition system intended to assist medical professionals in the acquisition of cardiac ultrasound images.	NTAP
Caption health	Caption guidance		NTAP
viz.ai	Viz SDH	- Radiological computer-assisted triage and notification software that analyzes CT images of the brain and notifies hospital staff when a suspected subdural hematoma is identified	NTAP
Rapid AI	Rapid aspects	- Computer-aided diagnostic device characterizing brain tissue abnormalities on brain CT images	NTAP
AIDoc	Briefcase for PE	- Radiological computer-assisted triage and notification software that analyzes CT images of the chest and notifies hospital staff when a suspected pulmonary embolism is identified	NTAP
PROCEPT BioRobotics Corporation	The AQUABEAM system	- Autonomous tissue removal robot for the treatment of lower urinary tract symptoms due to benign prostatic hyperplasia (BPH).	NTAP

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According to a research report by the HIRA(Health Insurance Review & Assessment service), which analysed the status of reimbursement for digital technologies in the healthcare systems of the United States, Japan, the United Kingdom, Germany and South Korea, as well as the guidelines and national coverage methods for payment and reimbursement standards, it was found that different methods of reimbursement for digital technologies are used depending on the healthcare system. There were cases where digital technologies were compensated in direct and indirect ways, where salary guidelines were provided, where clinical outcomes were improved through the use of AI-based software, where a surcharge was included as an item when used to reduce the workload of medical staff, and where digital applications were compensated with statutory funds by establishing legal and institutional bases[29].

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Table 7. Comparison of reimbursement for medical devices related to digital healthcare in five countries[29]

Country	Payment type	Applicable technology	Reimbursement	Benefit standard	Description
USA	Direct	- AI based software	Fee for service	- Newness - Cost thresholds - Substantial clinical improvement	- CMS decided to include ContaCT in NTAP applied fiscal year 2021 for quick stroke intervention - Maximum ,040 by each cases
Japan	Direct	- Digital pathology - Mobile application	Fee for service	- Newness - Substantial clinical improvement	- Digital pathology into medical fee schedule in Jan 2018 - Application which help to stop smoking into medical fee schedule in Dec 2021
	Indirect	- Digital system (AI, ICT, IoT)	Incentive by institute		- Evaluation item on digital system in night nursing care
UK	NA	- AI, apps, software combined medical device	NA	- Effectiveness - Economic impact : cost-consequence, budget impact, costutility	- Suggest DHT guideline - Classify DHT by function and stratify into evidence tier

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Germany	Direct	- Mobile application	Reimbursement when prescribed applications	- Safety and quality - Suitable for use - Data protection and security - Positive effect on care	- Reimburse six applications followed by Digital Health Act - Covered €116.97-€ 499.80 by each
Korea	Direct	- AI-based technology - Wearable device: ECG	Fee for service	- Diagnostic value or usefulness - Cost-effectiveness	- Guideline for AI-based technology for field of radiology and 3D print - Considerate if benefit is the better to patient than physician or institute - Selective covered on wearable ECG which patient charge
	Indirect	- Digital system	Incentive by institute	- Safety	- One of weight item for Korean New DRG payment - Uses like patient identification such as RFID

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2. The economics of AI in healthcare

A. Healthcare economic evaluation methods

There are many types of economic evaluation, depending on the types of costs and outcomes (benefits) that are measured and how they are measured, but the most common are the following four methods.

Cost-benefit analysis (CBA)

The purpose of CBA is to quantify all types of costs and benefits associated with a policy or project and express them in monetary terms; if the benefits are greater than the costs, then the policy or project should be implemented because it will improve the level of welfare of society as a whole. CBA is conceptually ideal because it expresses all costs and benefits in a single monetary measure over all time periods, and it can be used to compare a wide range of different projects.

Cost-effectiveness analysis (CEA)

CEA is a method used to select the least costly option among two or more alternatives that have different outcomes, but whose outcomes can be measured in the same unit. The aim is to rank the alternatives in order of cost per unit of outcome. However, cost-effectiveness analysis can only be used when the units of effectiveness measurement are the same, so it cannot be used to compare and analyse a large number of diseases or projects with different units of measurement, and it has the limitation that benefits are limited to one and the same outcome, so other forms of benefits may be ignored if they occur[30].

Cost-utility analysis (CUA)

As a method that can compensate for the shortcomings of CEA, CUA takes the value

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of the survival year, or the amount of utility derived from the survival year, rather than the survival year itself, as the outcome. In other words, the outcome is expressed in non-monetary terms like CEA, but explicitly expresses the quality of life during the period as a utility concept, not just the amount of life in the survival period.

Cost Minimization Analysis (CMA)

CMA is an economic evaluation method that compares only costs and can be used when the outcome of the alternatives being compared is assumed to be the same. In the past, it was presented as a type of economic evaluation, but in recent years it has not been distinguished as a separate type because it cannot resolve the uncertainty about the equivalence of the outcomes of the alternatives being compared.

Table 8. Methodology for healthcare economic analysis[31]

Methodology	Explanation	Application areas	Evaluation example
Cost Benefit Analysis	- Comparing costs and benefits in monetary terms. - It is important to put a monetary value on things like life and health.	CT, MR, Pneumoence-phalography	B/C ratio x $182/$412 = 0.44 y $795/$275 = 2.89 z $985/$850 = 1.16
Cost Effectiveness Analysis	- Compare non-monetary benefits, such as reduced disease rates benefits, such as reduced morbidity, versus monetary costs	Treatment of type diabetes	Cost/yr of vision saved x $7,080 y $3,497 z $5,281
Cost Utility Analysis	- Benefit in quality-adjusted life years (QALYs) to patient Benefit as a utility felt by the patient versus monetary costs	Screening for prostate cancer	Cost/QALY Gained x $7,080 y $3,497 z $5,281
Cost Minimization Analysis	- Determine which alternative has the lowest cost, assuming it produces the same output.	Management of high-risk pregancy	Cost over 5 years x 2.13 million $ y $ 0.99 million $ z $ 1.64 million

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B. The cost savings of AI in healthcare

Prior to 2020, when AI began to be deployed in healthcare, global research firms published a number of cost savings estimates for AI in healthcare.

Accenture (2017) predicted that by 2026, AI will replace the work of physicians and address approximately 20% of unmet clinical needs, generating $150 billion in annual cost savings for US healthcare[10]. ABI Research estimated that the commercialization of AI technology could save $52 billion by 2021 by producing better quality drugs, saving physician time, and reducing the number of deaths[11]. Frost & Sullivan estimates that AI has the potential to increase patient outcomes by 30 to 40 percent while reducing the cost of care by up to 50 percent[12]. McKinsey and Harvard University suggest that widespread adoption of artificial intelligence (AI) in healthcare could save the US up to $360 billion a year[13]. The National Bureau of Economic Research estimates that wider adoption of AI could save 5-10% of US healthcare spending, or approximately $200-360 billion per year in 2019 dollars[14].

Table 9. Breakdown of overall AI net savings opportunity within next five years using today's technology without sacrificing quality or access[14]

Stakeholder group	Total costs ($ billions)	Net savings opportunity ($ billions)	Net savings opportunity as percent of stakeholder group's total costs
Hospitals	$1,096	$60–$120	5–11%
Physician groups	$711	$20–$60	3–8%
Private payers	$1,135	$80–$110	7–10%
Public payers	$511	$30–$40	5–7%
Public payers	$817	$10–$30	1–4%
Total		$200–$360	5–10%

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C. Research on the economic analysis of domestic healthcare

In the study of the social cost-benefit analysis of setting up an emergency medical service, the direct benefits included the benefits of preventing premature deaths and the benefits of reducing the costs of outpatient and inpatient care. Indirect benefits included benefits from reduced funeral costs, benefits from reduced private death insurance costs, benefits from reduced transportation costs for outpatient visits, and benefits from reduced economic costs for carers of inpatients. The analyses estimated that the total socio-economic benefits of improving the emergency medical system from 1997 to 2004 were about KRW 6.76 trillion to KRW 7.7 trillion, depending on the scenario[32].

Table 10. Social benefits of building an emergency medical system[32]

Type		Conceptual definitions
Direct benefits	Benefits of preventing premature death	Benefits of reducing premature deaths through appropriate emergency care in emergencies
	Benefit from reduced outpatient costs	Outpatient cost savings from reducing outpatient days through urgent care.
	Benefit from reduced inpatient care costs	Inpatient cost savings from reducing hospital days through urgent care.
Indirect benefits	Benefit from reduced funeral costs	Benefits of reducing premature deaths through reduced funeral expenditure
	Benefit from lower personal death benefit costs	Savings in mortality insurance costs from preventing premature deaths
	Benefits from reduced transport costs for outpatient visits	Benefit from reducing the number of days spent in hospital and therefore the cost of transport to and from hospital.
	Economic savings for inpatient caregivers	Benefits to patient caregivers from fewer days in the hospital due to fewer lost workdays

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In the study to develop a nuisance assessment model for the ubiquitous service model, 15 benefits were proposed as individual-level benefits, service-level benefits and community-level benefits. In particular, the individual-level benefits included cost-saving benefits such as reducing medical costs (reducing outpatient medical costs and reducing inpatient medical costs), reducing nursing costs and reducing transportation costs. As a result of the analysis, the NPV was calculated to be about KRW 198 billion and the BCR was 10[33].

In the study on telemedicine policy/safety trends and development of economic evaluation system, a telemedicine economic evaluation system consisting of 21 patient-side benefit items, 4 provider-side benefit items, and 14 community/country-side benefit items was developed through the UK NICE guidelines, WHO's CHOICE survey, and review of domestic and international evaluation results[34].

The cost-benefit analysis of the Personalized Healthcare at Home project included direct benefits such as reduced medical costs, prevention of complications and reduced transportation costs, and indirect benefits such as reduced loss of productivity and prolonged life. As a result of the analysis, the total benefits of the personalized home healthcare project in 2007 were estimated to be KRW 435.6 billion and the total costs KRW 47.76 billion, resulting in a net benefit of KRW 38.8 billion and a benefit-cost ratio of 9.2 times[35].

In the policy evaluation study for the efficient operation of the mobile health care project at health centres, a cost-benefit analysis was conducted to compare and analyse the reduction in beneficiaries' medical expenses before and after the mobile health care project at health centres. Direct benefits included reductions in inpatient and outpatient medical costs, reductions in the incidence of medical costs, and reductions in transportation costs, while indirect benefits included the prevention of complications and the prevention of lost productivity. As a result of the analysis, the total benefits of the health centre mobile healthcare project for 2016-2019 were estimated at KRW 31 billion and the total costs at KRW 8.6 billion, resulting in a net benefit of KRW 22.4 billion and a benefit/cost ratio of 3.61 times[36].

The economic evaluation of the health centre visit project included the direct benefits of reduced inpatient/outpatient medical costs and reduced transportation costs, as well as the indirect benefits of reduced medical costs, prevention of complications, prolongation of life, and reduction of time costs. According to the analysis, the net benefits were KRW 198,575 million in 2012, KRW 119,176 million in 2013, KRW 123,831 million in 2014, KRW 120,189 million in 2015, KRW 131,397 million in 2016, KRW 127,753 million in 2017 and KRW 156,063 million in 2018[37].

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Table 11. Research on economic analysis of healthcare in South Korea

Name of study (year)	Target	Cost	Benefit	Economic results
Social cost-benefit analysis of building an emergency medical system[32] (2008)	Common conditions in the emergency department: trauma, acute myocardial infarction, acute stroke Acute Myocardial Infarction, Acute Stroke	Disbursements from the Emergency Medical Development Fund	<Direct benefits> Benefits from the prevention of premature death, Benefits from reduced costs of ambulatory care Benefits from reduced hospitalization costs <Indirect benefits> Reduced funeral costs Reduced costs of personal life insurance Reduced transport costs Reduced economic costs for carers	Total benefits in scenario 1 (linear change in mortality indicators) of about KRW 7.7 trillion Scenario 2 (non-linear change in mortality non-linear change in mortality indicators) of about KRW 6.8 trillion
Development of Investment Evaluation Model for Ubiquitous Health Service[33] (2008)	City of Busan's u-Health Service Model	Initial investment costs (ISP set-up, development costs, system operating environment, business management costs) Operation and maintenance costs	<Personal> Cost savings (medical, transport, nursing) Time savings (access time, waiting time) <Service Cost savings in service delivery <Community> Loss of workforce	Economic benefits - KRW 198.1 billion over 5 years Cost-benefit ratio - 10.06

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A Cost Benefit Analysis of Individual Home Visiting Health Care[35] (2010)	1,008,837 people receiving personalized home healthcare in 2007	Labour, management, training, transport, etc. entering the business.	<Direct benefits> Reduced healthcare costs Prevention of complications Reduced transport costs <Indirect benefits> Reduced loss of productivity Life extension benefit	Total benefits KRW 435.6 billion Total costs KRW 47.76 billion Net benefits KRW 3,880 billion 2,584 million Benefit-cost ratio of 9.2 times
Develop telehealth policy/security trends and economic assessment frameworks[34] (2014)	-	<Patient> Medical fees, equipment fees <provider> Investment in IT infrastructure, equipment and instrument costs, communication costs, etc. <community/country> Infrastructure investment, advertising	<Patient> Reduced readmissions, reduced outpatient use, reduced transport costs, increased working hours/earnings, etc. <Provider> More free time for doctors, more time for research and development, faster and more accurate diagnosis and treatment, etc. <Community/Country> National health expenditure, medical expenditure per capita, number of jobs, etc.	-

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Policy evaluation study for the efficient operation of mobile health services in health centres[36] (2020)	23,838 people participated in mobile health centre projects in 2016-2017	<Direct costs> Business costs of mobile healthcare (labour, business costs) Infrastructure costs Transport costs to health centres <Indirect costs> Cost of lost productivity when a person visits a health centre	<Direct benefits> Reduced inpatient/outpatient healthcare costs Reduced incidence of medical costs Reduced transport costs <Indirect benefits> Prevention of complications Benefits from prevention of productivity loss	Total benefits KRW 31 billion Total cost KRW 8.6 billion Net benefit of KRW 22.4 billion Benefit/cost ratio of 3.61 times (at a 5% discount rate)
Economic evaluation of a health visiting project[37] (2020)	Eligible for home healthcare for seven years from 2012 to 2018	<Direct costs> Outreach health business expenses (labour, training, business expenses) Newly discovered medical costs Newly discovered non-medical costs (transport) <Indirect costs> New lost productivity costs	<Direct benefits> Savings on inpatient/outpatient healthcare Transport cost savings <Indirect benefits> Reduced medical costs Prevention of complications Life extension benefits Time cost savings	<Net income> KRW 198.575 billion in 2012 KRW 119.176 billion in 2013 KRW 123,831 million in 2014 KRW 120,189 million in 2015 KRW 131,397 million in 2016 KRW 127,753 million in 2017 KRW 156,063 million in 2018 <Benefit/cost ratio> 2012 2.55 times, 2013 2.18 times, 2014 2.29 times, 2015 2.10 times, 2016 2.43 times, 2017 2.29 times, 2018 2.23 times

D. International healthcare AI economic analysis study

According to data published by the World Bank, overseas economic analysis of digital healthcare, including medical AI, focuses on cost analysis, cost-effectiveness analysis and cost-utility analysis[38].

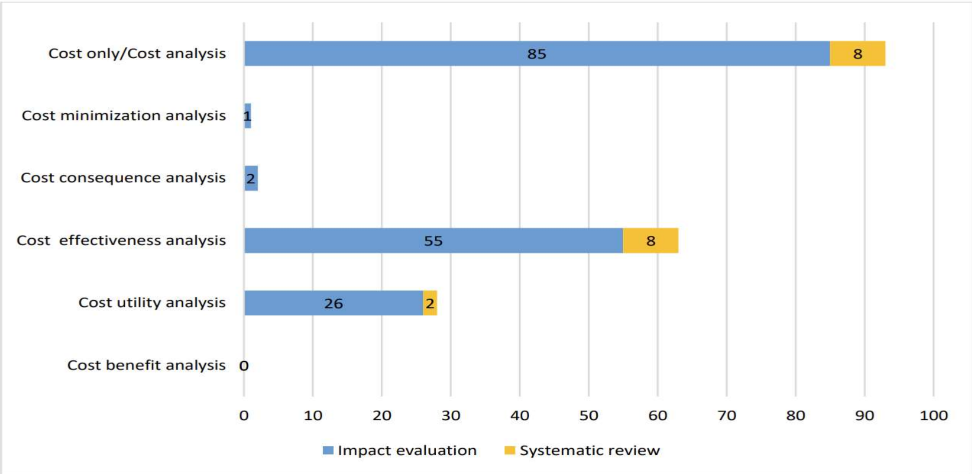

Figure 7. Economic Outcomes reporting from the DHI Evidence base[38]

Here are some studies on the economic analysis of medical AI.

Hill et al (2020) assessed the cost-effectiveness of identifying patients with atrial fibrillation using targeted screening based on machine learning (ML) risk prediction algorithms and found that the targeted screening strategy was cost-effective in the base case (Cost per QALY saved of £4,847, £5,544 compared with systematic and opportunistic screening strategies, respectively). Targeted screening using ML risk prediction algorithms has demonstrated the potential to improve the clinical and cost effectiveness of AF screening, thereby improving health outcomes through the efficient use of limited healthcare resources[39]

Risa M. Wolf et al (2020) evaluated the cost-effectiveness of detecting and treating diabetic retinopathy and its sequelae in children with type 1 diabetes (T1D) and type 2

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diabetes (T2D) using AI diabetic retinopathy screening compared with standard screening by an eye care professional (ECP). The analysis showed that in a base case scenario with 20% adherence, the use of autonomous AI was expected to result in higher average patient payments ($8.52 for T1D and $10.85 for T2D) than traditional ECP testing ($7.91 for T1D and $8.20 for T2D). However, they demonstrated that autonomous AI screening can reduce costs if at least 23% of patients are compliant with diabetic retinopathy screening[40].

F. Schwendicke et al (2021) compared the cost-effectiveness of proximal caries detection on periapical radiographs with and without AI. The analysis showed that AI had an accuracy of 0.80, which was higher than the average dentist's accuracy of 0.71, and an ICER of -13.9 euros/year, demonstrating that AI was more efficient and saved money[41].

Jesus Gomez Rossi et al (2022) compared AI with standard care for the detection of melanoma in skin photographs, dental caries in radiographs, and diabetic retinopathy in retinal fundus imaging and found that AI was associated with cost savings and an increase in years of life saved and QALYs[42].

Ziegelmayer et al (2022) used Markov simulations to evaluate the cost-effectiveness of using AI algorithms for initial screening and found that CT+AI had a negative incremental cost-effectiveness ratio (ICER) compared with CT alone, indicating lower costs and higher benefits. This shows that it is cost-effective to use AI for initial low-dose CT scans for lung cancer screening[43].

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Table 12. The state of healthcare AI economic analysis research abroad

Main author (year)	Research Purpose	Patient population	HEE type	Result
Hill et al[39] (2020)	Assess the cost-effectiveness of targeted screening using a machine learning risk prediction algorithm to identify patients with atrial fibrillation(AF).	Patients (men and women) above 50 years old eligible for Atrial Fibrillation screening	CUA	ICER (systematic) £4847/QALY (opportunistic) £5544/QALY
Wolf et al[40] (2020)	To assess the cost-effectiveness of detecting and treating diabetic retinopathy and its sequelae among children with T1D and T2D using AI diabetic retinopathy screening vs standard screening by an eye care professional (ECP).	Youths below 21 years old with Type 1 and Type 2 Diabetes	CEA	Patient payment $8.52 for T1D and $10.85 for T2D (AI), $7.91 for T1D and $8.20 for T2D (ECP)
Schwendicke et al[41] (2021)	compared the cost-effectiveness of proximal caries detection on bitewing radiographs with versus without AI.	Twelve years old individuals (men and women) with posterior permanent teeth	CEA	The ICER was −13.9 euro/y (i.e., AI saved money at higher effectiveness)

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Jesus Gomez Rossi et al[42] (2022)	To assess the cost-effectiveness of artificial intelligence (AI) for supporting clinicians in detecting and grading diseases in dermatology, dentistry, and ophthalmology.	The general US and German population aged 50 and 12 years, respectively, as well as individuals with diabetes in Brazil aged 40 years	CUA	<dermatology> AI : cost $750.35, QALYs 86.6 the control : cost $759.03, QALYs86.6 <dentistry> AI : cost €320.40, QALs 62.4 The control : cost €342.24, QALYs 60.9 <ophthalmology> AI : cost $1321, QALYs 8.42 The control : cost $1260, QALYs 8.42
Ziegelmayer et al[43] (2022)	evaluate the cost-effectiveness of an AI-based system in the context of baseline lung cancer screening.	Model input parameters were based on current literature. Age-specific risk of death was derived from the US life tables. Age at the diagnostic procedure was set to 60 years	CUA	CT+AI : $4,311, 13.76 QALYs AI : $4,378, 13.75 QALYs

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E. Research into the benefits of AI in healthcare

Omar Ali et al (2023) analysed the benefits, challenges, methods and functionalities of AI in healthcare through a systematic review of 180 papers on AI in healthcare. They concluded that AI has a significant impact on healthcare processes related to early detection and diagnosis of diseases[44].

	Patient	Healthcare Organization	Healthcare Industry
Benefits	• Automated Decision Making • Patient Monitoring • Early Diagnosis • Process Simplification	• Workflow Improvement • Cost Reduction • Fraud Detection	• Time saving • Resource optimization • Professional Training • Industry-wide data sharing & availability
Challenges	• Patient Safety	• Data Integration • Privacy & Legal Issues	• Industry-wide data Integration
Methodologies		• Multimedia processing • Textual data processing	
Functionalities	• Diagnosis • Treatment • Consultation • Monitoring	• Clinical decision making • Information Availability • Information Sharing	• IoT data collection • Medical Imaging • Remote Surgery • Research Development

Figure 8. Mapping the classification framework across the patient, healthcare organization and healthcare sector[44]

Kicky G. van Leeuwen (2022) states that AI can create value when it reduces costs or improves health outcomes, and defines the ultimate goal of AI in radiology into six categories, as shown in Figure 9[45].

Figure 9. Six objectives that can be pursued with artificial intelligence in radiology to improve efficiency and health outcomes[45]

Some studies have shown that AI can speed up the reading of medical images. To determine the effectiveness of medical AI in real-world clinical practice, Professor U. Joseph Schoepf of the Medical University of South Carolina analysed data from 390 patients who underwent outpatient chest CT scans with AI embedded in the clinical workflow. The results showed that radiologists using AI reduced reading time by an average of 22.1 per cent compared to those without AI[17].

Scans	AI-Assisted Group		Non–AI-Assisted Group		*p*	Absolute Difference (s)	Relative Difference (%)
	Mean ± SD (s)	Range (s)	Mean ± SD (s)	Range (s)			
All	328 ± 122	93–720	421 ± 175	118–897	< .001	93 (63–123)	22.1 (14.9–29.2)
Technique							
Contrast-enhanced	331 ± 139	93–674	414 ± 177	118–897	< .001	83 (38–127)	20.0 (9.2–30.7)
Noncontrast	325 ± 101	108–720	429 ± 173	156–780	< .001	104 (63–144)	24.2 (14.5–33.6)
Report categorization							
Negative	237 ± 94	93–480	321 ± 152	118–720	.001	84 (30–139)	26.2 (9.3–43.3)
Positive without new findings	339 ± 128	155–660	456 ± 171	235–780	.001	117 (41–192)	25.7 (9.0–42.1)
Positive with new findings	357 ± 114	135–720	448 ± 172	183–897	< .001	92 (54–129)	20.4 (12.2–28.8)

Note—Values in parentheses are 95% CIs. *p* values are from independent two-sample *t* tests comparing the AI-assisted and non–AI-assisted arms.

Figure 10. Mean Chest CT Interpretation Times With and Without Artificial Intelligence (AI) Assistance, Pooling Scans From All Three Readers[17]

VUNO published a study showing that its AI-enabled gastric cancer pathology solution, VUNO Med-PathGC AI™, reduced diagnostic time by up to 58% compared to six pathologists with and without medical AI[18].

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3. Intent to use AI in healthcare

B. Technology Acceptance Model (TAM)

Grounded in the Theory of Reasoned Action (TRA), the Technology Acceptance Model (TAM) was first proposed by Davis in 1986 to predict an individual's acceptance of a new innovative or information technology.

Davis describes the specific beliefs that influence the decision to adopt new technology products and services in terms of perceived usefulness and perceived ease of use. Perceived usefulness refers to the extent to which individuals perceive that using an innovation will improve their job performance, while perceived ease of use refers to the extent to which they expect to be able to use the innovation without much effort[46]. Perceived usefulness and perceived ease of use explained the relationship between attitude towards using the system, intention to use the system and actual use.

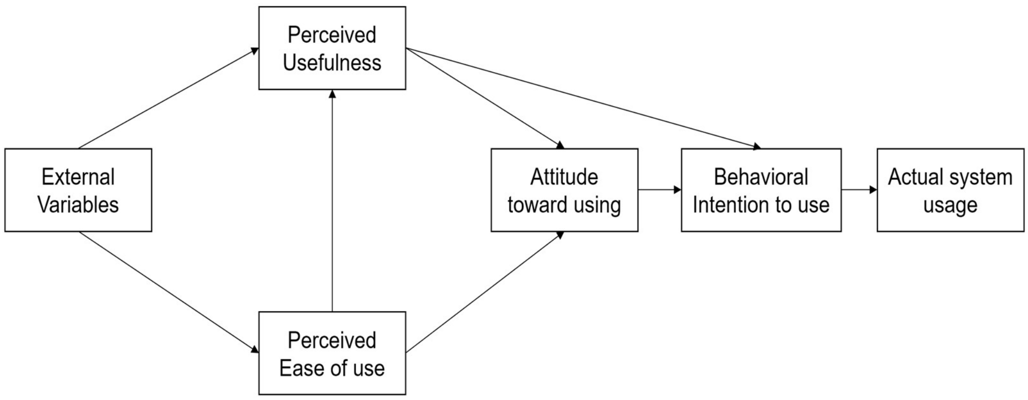

Figure 11. Technology Acceptance Model (TAM)[47]

However, Davis' TAM model has been criticized for being too simplistic and for emphasizing only the user's evaluation of the technology[48]. Therefore, Venkatesh and Davis (2000) proposed a modified technology acceptance model (TAM2) by excluding the attitude towards use variable and adding other exogenous variables that affect perceived usefulness, perceived ease of use and intention to use. Subjective norms and social image variables, which are part of social influence, are assumed to affect perceived usefulness. Venkatesh and Davis (2000) conducted a study of work systems used in organizations and assumed that subjective norms would be particularly important in organizations and adopted them as variables. They explain that the decision to adopt technology is influenced by peers or supervisors in the organization, so that behavior is driven not only by volition but also by encouragement and norms[49].

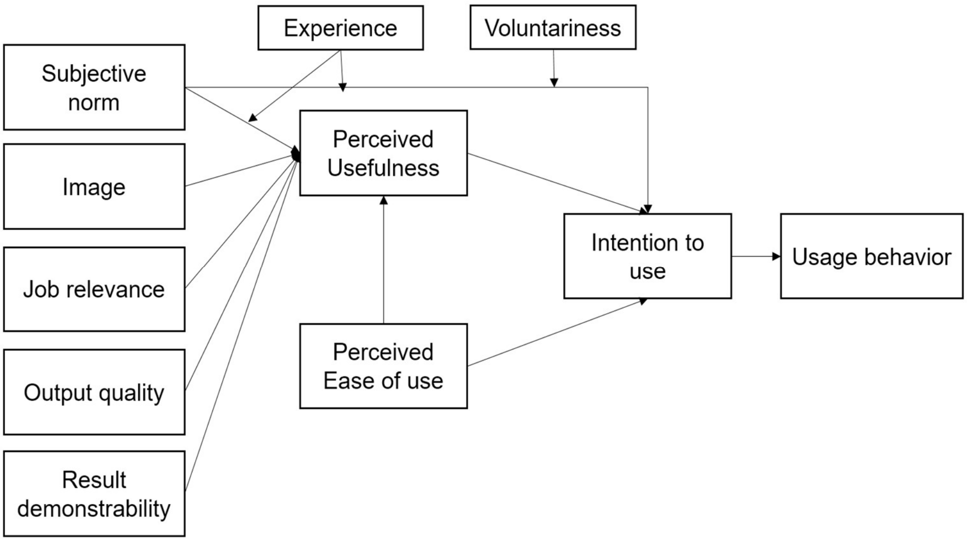

Figure 12. Modified Technology Acceptance Model (TAM2)[49]

Venkatesh et al (2003) developed the Unified Theory of Acceptance and Use of Technology (UTAUT) by adding four variables (performance expectancy, effort expectancy, social influence, and facilitating conditions) as new exogenous variables by looking at users' intention to accept technology from an integrated perspective. UTAUT is a model that integrates eight models mainly used for technology acceptance by technology users, such as the Technology Acceptance Model, the Theory of Reasoned Action, and the Theory of Planned Behavior, and has a higher explanatory power than the existing models. The components of the Unified Model of Acceptance of Technology (UTAUT) consist of three factors that influence behavioural intention (performance expectancy, effort expectancy, and social influence), one factor that influences usage

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behavior (facilitating conditions), and four control variables (gender, age, experience, and voluntariness) that have a moderating effect in the process, and these behavioural intentions determine the actual usage behavior of new information technology. In UTAUT, performance expectancy is a concept similar to perceived usefulness in TAM and refers to the extent to which an individual expects that using a new technology or product will help them do their job. Effort Expectancy, similar to Perceived ease of use in TAM, refers to the degree of ease associated with using a system. Social influence is the perceived need to use the new technology by significant others. Facilitating condition refers to beliefs about the extent to which the organizational and technical support base is in place to support the use of the new technology[50].

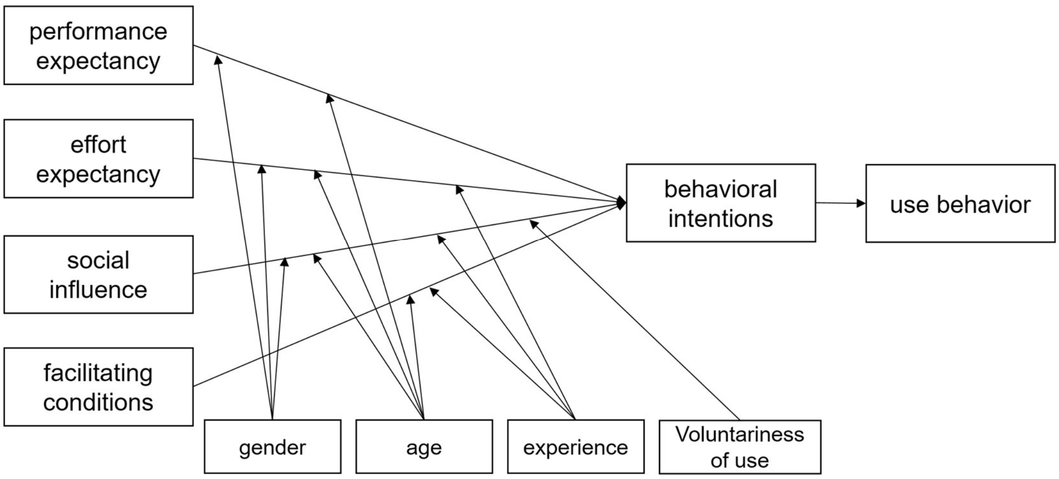

Figure 13. Unified Theory of Acceptance and Use of Technology (UTAUT)[50]

Venkatesh then presented the extended Unified Technology Acceptance Model (UTAUT 2), which adds three factors such as hedonic motivation, price value and habits as predictors of adoption intentions when adopting new technologies and products from a consumer rather than an organizational perspective. In addition, individual differences such as age, gender and experience moderate the effects of behavioural intention and technology use[51].

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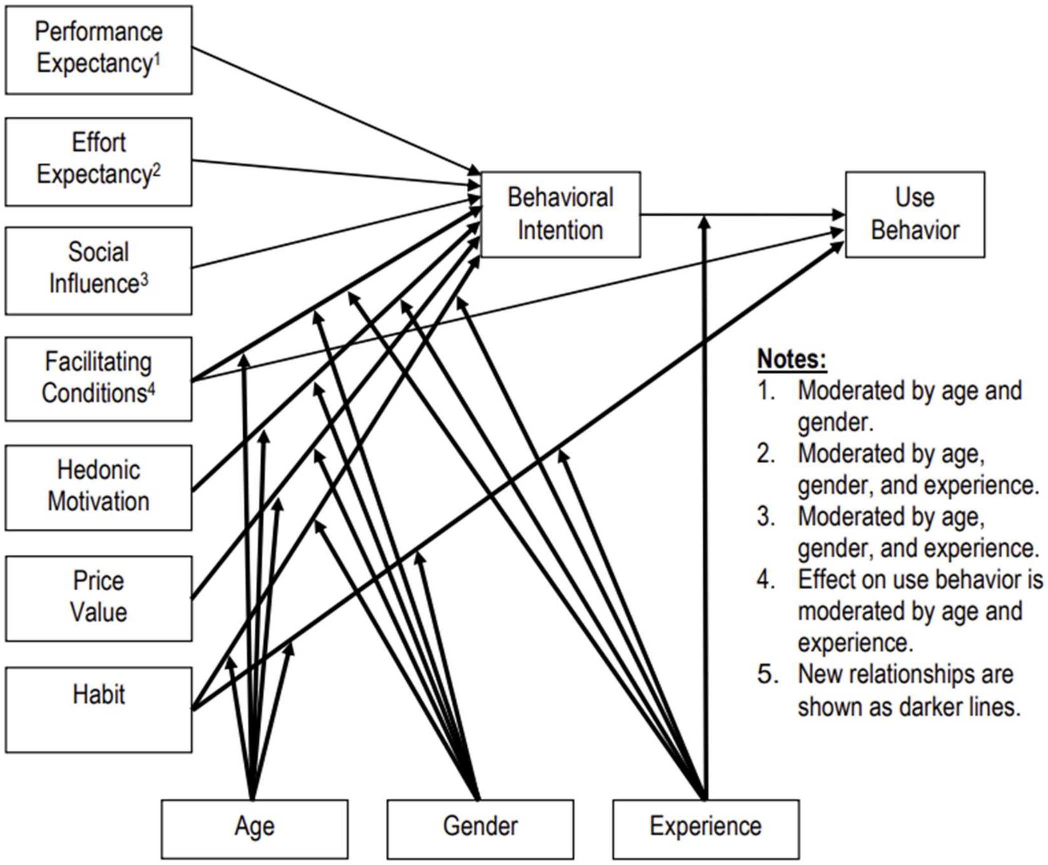

Figure 14. extended version of UTAUT(UTAUT2)[51]

The Technology Acceptance Model (TAM), proposed by Davis (1986), has been a traditional method for analysing consumers' intention to accept new innovative technologies through different stages of research. In addition to the variables of TAM, perceived usefulness, perceived ease of use and extrinsic variables, various variables based on target technology characteristics and user characteristics have been proposed and the model has been extended, and the structural causal relationships between variables have evolved in different patterns due to the development of ICT technology and artificial intelligence.

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B. Research on AI adoption intentions in South Korea

With the rapid development of AI technology and its increasing application in the medical field, many studies have been conducted on users' intention to accept and continue to use AI products and services. With the increasing market size of AI and the increasing investment in AI development by governments and related enterprises, research on users' intention to use AI products and services is recognized as an important issue. Several researchers have analysed consumers' acceptance intention of digital healthcare and medical AI products and services based on structural equation models, but there are some differences in the direct and indirect influencing factors and hypotheses of acceptance intention.

Jeon et al (2019) conducted a study on 327 members of the general population to analyse the factors influencing users' acceptance intention towards AI speakers. The results of hypothesis testing confirmed that all variables (hedonic motivation, utilitarian motivation, time pressure, users' perception of security, and experiential experience) are significant factors in users' acceptance intention towards intelligent services represented by AI speakers[52].

Yi, Hanshin et al. (2019) identified consumers' propensity to use voice-activated AI products and empirically analysed the influencing factors on usage intention. The results of the hypothesis testing show that consumer resistance to voice-activated AI products has a significant effect on usage intention, while optimism, innovativeness, discomfort, anxiety and perceived usefulness have a significance influence on perceived ease of use. However, perceived ease of use has no effect on intention to use[53].

Bae et al (2020) conducted a study to analyse consumer acceptance intentions for product and service development in the rapidly growing digital healthcare sector. The results of hypothesis testing showed that innovative characteristics of individuals can easily and quickly understand various functions of products and services, interest in health enables efficient information acquisition and use of products and services, application of latest technology in digital healthcare products, compatibility with other devices, luxurious appearance and menu design are important factors to satisfy consumer needs, and belief in quality information accumulation and provision and security enables users to quickly and easily understand and use functions[54].

Chang Seop Rhee et al (2020) conducted a study among young people in their early 20s, who are less technology averse, to analyse the influence of attitudes on intention to use AI products. They found that attitudes towards AI and perceived behavioural control significantly influenced intention to use AI products, and that attitudes towards AI were influenced by expectations of benefits from improved job performance and fears of the threat of relationship disruption[55].

Jinseok (2020) analysed the effects of health awareness, self-efficacy, cost savings, quality, accessibility and appropriateness of health services on perceived usefulness and intention to use. The results of hypothesis testing showed that health awareness and self-efficacy had a significant effect on cost savings, quality, accessibility, and appropriateness of healthcare services due to non-contact care. Cost savings and quality, accessibility and appropriateness of healthcare services had a significant effect on perceived usefulness of contactless care. Finally, perceived usefulness of contactless care had a significant effect on intention to use[56].

Seung-Yeon Choo et al (2021) conducted a study on 332 patients who had visited an obstetrics and gynaecology clinic to analyse the effect of the service value of AI medical chat bot consultation on intention to use. The results of hypothesis testing showed that the interaction between expertise and perceived usefulness was not significant when the AI chat bot provided basic advice rather than advice requiring expertise[57].

Yeong-Dae Kim et al (2021) analysed the impact of perceived value and innovation resistance factors on the intention to adopt AI platforms in the field of drug discovery. The results of hypothesis testing showed that business utility, rich knowledge discovery, and hidden pattern provision can effectively and efficiently support the drug discovery process, but the complexity of AI technology and opacity of algorithms are factors that reduce the perceived value of AI platforms. In addition, it was found that the ability to

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test and become familiar with different applications and usage environments of AI platforms, as well as the support system of receiving technical support from experts inside and outside the organization, can mitigate innovation resistance[58].

Hyuk Jin Lee et al (2022) conducted a study to explore the differences in patient adherence by type of healthcare provider (AI vs. human doctor) and the underlying causes. In Experiment 1, a cardiovascular disease scenario, they found that patient adherence was lower when the provider was an AI than when the provider was a human doctor, and that patient trust in the provider mediated this effect. Experiment 2 shows that when the physical risk is high, such as when a patient with high pain is prescribed surgery, patient adherence is lower for AI than for human doctors, whereas when the physical risk is low, such as when a patient with low pain is prescribed medication, the difference in patient adherence by provider type is not significant. Finally, Experiment 3 showed that the effect of the interaction of provider type and physical risk on patient adherence is mediated by consumer trust in the provider[59].

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Table 13. Research on AI adoption intentions in Korea

Researcher (year)	Apply to	Survey Audience	Analysis Methods	Key variables
Jeon et al[52] (2019)	AI Speaker	327 members of the general public	TAM, UTAM	- Hedonic Motivation, Utilitarian Motivation, Time Pressure, Perceived Security, Brand Awareness - Technology acceptance
Yi, Hanshin et al[53]. (2019)	Speech recognition-based AI services	252 people with experience using voice recognition AI products	TRAM	- Cost reasonableness, suitability, social impact, optimism, innovativeness, discomfort, anxiety - Resistance, perceived usefulness, perceived ease of use, intention to use
Bae et al[54] (2020)	Healthcare apps	1,000 men and women aged 65 and under nationwide	TAM	- Personal Innovativeness, Health Interest, Functional Excellence, Design Aesthetics, Price Effectiveness, Information Quality, Security Confidence - Perceived usefulness, perceived ease of use, intention to use
Chang Seop Rhee et al[55] (2020)		217 college students in their early to mid-20s	TPB	- Social quality improvement, performance improvement, human domination threat, relational disruption threat, human replacement threat, technical trust, ethical trust, attitudes towards AI, subjective norms, - Intention to use AI products

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Jinseok[56] (2020)	Virtual care		TAM	- Health awareness, self-efficacy, cost savings, quality of care, accessibility, and appropriateness - Perceived usefulness, intention to use
Seung-Yeon Choo et al[57] (2021)	AI chat bot	332 people with experience of gynaecological visits	TAM	- Independent Variables: Expertise, Reliability, Empathy, Usefulness, Ease of Use - Dependent variable: Intention to use the service - Control variables: medical administration, medical consultation
Yeong-Dae Kim et al[58] (2021)	Drug discovery areas	330 members of the general public	VAM IRM	- Perceived benefits (usability, knowledge richness), perceived costs (complexity, algorithmic opacity), resistance mitigating factors (testability, AI supportive environment), perceived value, and innovation resistance. - Intention to adopt the platform
Hyuk Jin Lee et al[59] (2022)	Patient compliance in AI healthcare	189 adults living in the US	-	- Trust, patient compliance - Covariates: healthcare provider (human, AI), physical risk (high, low)

TAM : Technology Acceptance Model
TPB : Theory of Planned Behavior
TRAM : Technology Readiness and Acceptance Model
UTAUT : Unified Theory of Acceptance and Use of Technology
VAM : Value based Adoption Model
IRM : Innovation Resistance Model

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C. Research on international AI adoption intentions

Lisa Cornelissen et al (2022) conducted a study on the drivers of healthcare professionals' acceptance of AI-driven care pathways. Parameters included age, gender and experience. Hypothesis testing revealed that expectations of health outcomes were the most important predictor of acceptance of AI-based care pathways among healthcare professionals. Patients' social influence, anxiety and innovativeness did not have a significant impact on acceptance. Gender was found to moderate the relationship between facilitators and acceptance, with identifying as male increasing the likelihood of accepting AI-based care pathways[60].

Zheng Yin et al (2022) conducted a study on factors influencing acceptance and intention to use wearable smart medical devices. The results showed that facilitating conditions have a significant impact on the use of wearable smart medical devices. Behavioural intention significantly mediated the effects of perceived risk, perceived cost, health expectancy, perceived ease of use and social influence on user behavior. Health expectancy, perceived ease of use and social influence were found to play a significant role in predicting behavioural intention. Perceived cost and perceived risk had no significant effect on behavior intention. In addition, health expectancy and perceived cost were lower among those with underlying medical conditions[61].

Stefanie Jauk et al (2021) evaluated user acceptance of a machine learning-based application to predict the risk of delirium in hospitalized patients. They have found that perceived usefulness and perceived ease of use are rated slightly positively, output quality is rated neutrally, and actual use of the system is rated slightly negatively[62].

Sandra So et al (2021) analysed the effects of perceived ease of use, perceived usefulness and subjective norms on AI acceptance among healthcare professionals. They found that perceived usefulness and subjective norms had a significant relationship with AI acceptance. They also concluded that respondents who have the most interaction with patients in clinical management are strong determinants of AI acceptance in their practice[63].

Table 14. Research on international AI adoption intentions

Researcher (year)	Apply to	Survey Audience	Analysis Methods	Key variables
Lisa Cornelissen et al[60] (2022)	Artificial Intelligence–Powered Care	67 medical professionals in the Netherlands	UTAUT	- Medical performance expectancy, Nonmedical performance expectancy, Effort expectancy, Social influence patients, Social influence medical, Facilitating conditions, Perceived trust, Anxiety, Professional identity, Innovativeness
Zheng Yin et al[61] (2022)	wearable intelligent medical devices	2,192 in China	Modified UTAUT	- Facilitating conditions, Perceived risk, Perceived cost, Health expectation, Perceived ease of use, Social influence, Feature of WIMDs - Behavioral intention, use behavior
Stefanie Jauk et al[62](2021)	Predicting Delirium in a Clinical Setting	47 nurses and physicians	TAM	- perceived ease of use, perceived usefulness, output quality and actual system use
Sandra So et al[63](2021)	personnels' perception in accepting AI in a hospital	96 healthcare personnel	TAM	- Ease of use, Perceived usefulness, Subjective norm, Intention to use by the profession

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III. Research methods

1. Social cost-benefit analysis of AI in healthcare

A. Research design

This study is a cost-benefit analysis that estimates the government funding invested in the project, the estimated price of using medical AI, and the resulting benefits in monetary terms, through a review of existing literature and analysis of secondary data to determine the economic feasibility of the Dr. Answer project conducted from 2018 to 2020.

Medical AI is a rapidly developing technology, but it is limited by the lack of sufficient data to validate it as a new medical technology. In addition, companies have limited time and budget to secure clinical evidence after approval by the Ministry of Food and Drug Safety. In this situation, it is also difficult to analyse the cost-effectiveness of medical AI using clinical evidence.

Among various economic analysis methods, this study used cost-benefit analysis, which quantifies benefits in monetary terms. Although cost-effectiveness analysis is commonly used in health care, it can only be used when the unit of effectiveness measurement is the same, so it has limitations for comparative analysis of multiple diseases with different units of measurement (National Research and Development Project Effectiveness Analysis). Cost-benefit analysis has the advantage of being able to quantify and recognize the total value of benefits and costs, and it is judged to be easier to assess the economic feasibility of all 21 medical AIs for 8 diseases, rather than specific medical AIs.

B. Subject of Study

The Dr. Answer project, the subject of the study, involved 25 large hospitals and 20 ICT companies between 2018 and March 2021, collecting a range of medical data, including treatment data and medical images, and analysing them with AI algorithms to develop 21 medical AIs for eight diseases.

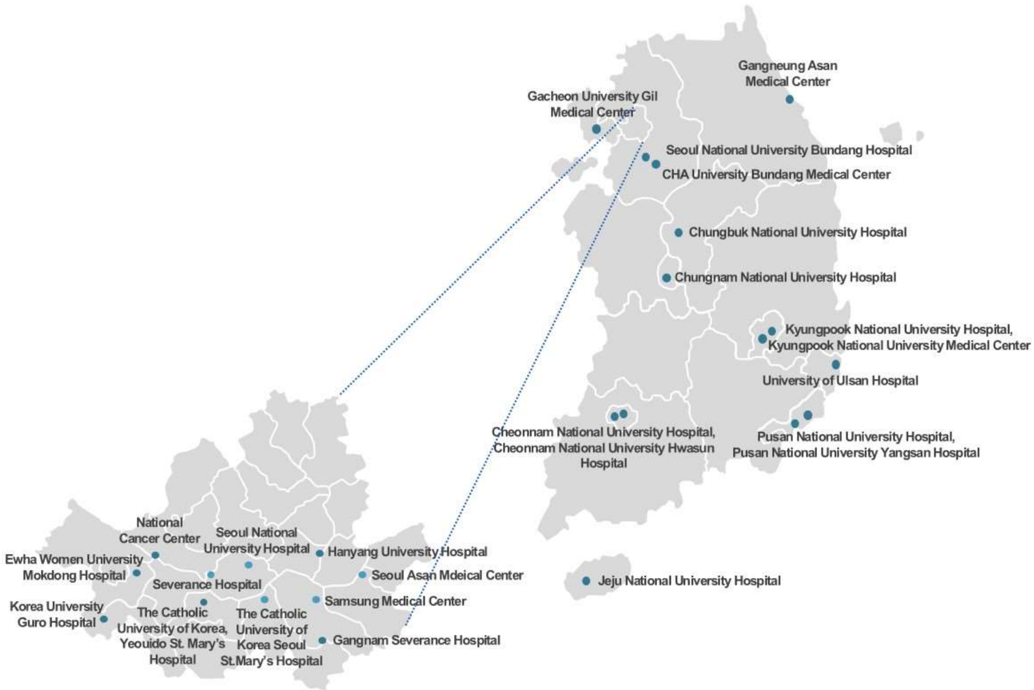

Figure 15. Hospitals participating in the Dr. Answer project

The Dr. Answer project developed algorithms based on multicentre data from 25 hospitals. The training data was extracted from medical data approved by the IRB (Institutional Review Board) of each hospital.

The training data is divided into medical data, imaging data, genomic data and lifestyle data, depending on the target disease and AI characteristics. Medical data included EMR data, medical examination data and EEG data, while imaging data included CT, MRI, endoscopy and pathological imaging data. In addition, genetic data

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were collected for colorectal cancer, developmental delay and dysplasia, and lifestyle data were collected through heart disease and colorectal cancer screening.

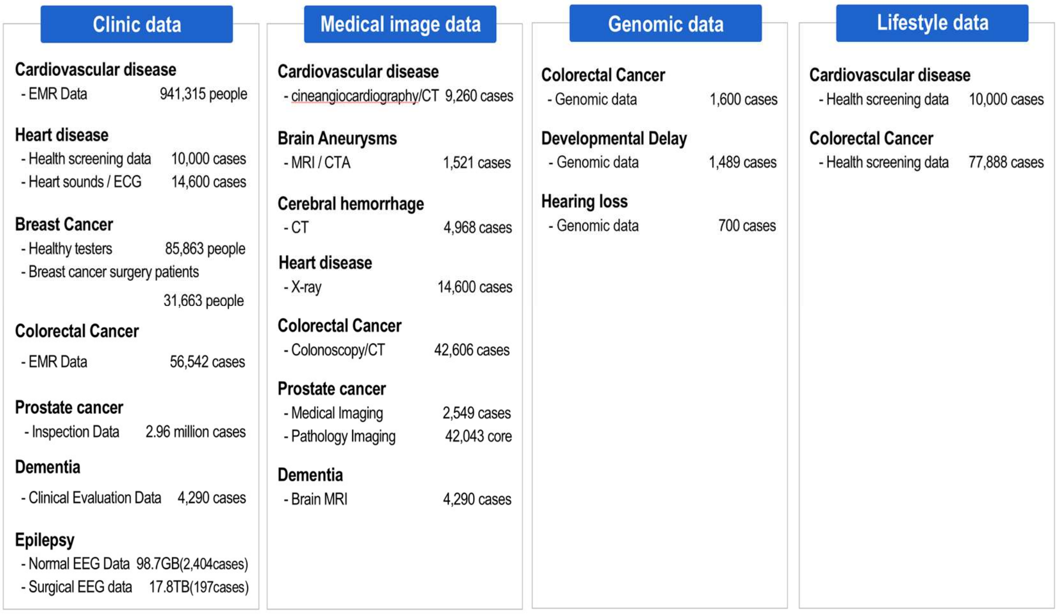

Figure 16. Dr. Answer project data types

The Dr. Answer project consists of 21 medical AIs by disease stage, including prediction, analysis/diagnosis, treatment and prognosis of eight diseases that are most closely related to healthy life expectancy in the Korean medical field.

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Table 15. Dr. Answer project AI types

Diseases	Prediction	diagnosis	Treatment	Prognosis	Visualization
Cardio-cerebrovascular		Diagnosis of coronary artery calcification score Diagnosis of brain haemorrhage Diagnosis of cerebral aneurysmal lesions		Cardiovascular disease Predicting relapse	
Heart	Predicting the onset of heart disease	Diagnosis of heart disease			Multifaceted data Blended visualizations
Breast cancer	Predicting the onset of breast cancer			Predicting breast cancer recurrence	
Colorectal cancer	Predicting the onset of colorectal cancer	Diagnosis of colorectal polyps using endoscopy	Making treatment decisions for colorectal cancer patients		
Prostate cancer		Prostate Cancer MRI imaging diagnostics Prostate cancer Histopathological diagnosis		Predicting prostate cancer recurrence	
Dementia		Dementia Early diagnosis			Automatic calculation of brain imaging values
Epilepsy	Predicting epileptic seizures	Normal cranial nerves Diagnosis			
Paediatric Rare Diseases		Developmental disorders Diagnosing genetic variants Diagnosing hearing loss genetic variants			

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(1) Cardiocerebrovascular Disease

Coronary artery calcification score diagnosis AI automatically detects the location of coronary artery calcification lesions using AI and automatically calculates the calcification score, providing fast and accurate diagnostic results that reduce time-consuming testing. Cardiovascular Disease Recurrence Prediction AI uses AI technology based on cardiovascular imaging with a large number of annual examinations to predict the risk of cardiovascular disease recurrence and provide patient management services for high-risk groups. Cerebral haemorrhage diagnosis AI detects the location of a cerebral haemorrhage based on the patient's CT image and quickly analyses the presence or absence of the haemorrhage and provides it to medical staff to help patients with cerebral haemorrhage receive appropriate treatment in a timely manner. Cerebral aneurysm lesion diagnosis AI uses patients' MRI images to analyse cerebral aneurysm lesions (location and vascular structure) to calculate quantitative figures and provide support functions for cerebral aneurysm diagnosis.

(2) Heart Disease

Heart disease prediction AI motivates healthcare by predicting the risk of developing heart disease and healthy age based on medical examination data. Heart disease diagnosis and integrated data visualization AI supports heart disease diagnosis by analysing basic examination data such as auscultatory sounds, electrocardiograms and chest X-rays.

(3) Breast cancer

Breast cancer development prediction AI is a model that predicts whether a patient will develop breast cancer in two, five and seven years and predicts the risk of developing breast cancer over the life cycle based on medical examinations, genomic test results and lifestyle data. Breast Cancer Recurrence Prediction AI is an artificial neural network model that predicts the risk of breast cancer recurrence in 2, 5 and 7 years at the time of a hospital visit during the follow-up period for patients who have undergone breast cancer

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resection surgery, using pathology, imaging, blood test results and treatment information entered in the EMR.

(4) Colorectal cancer

Endoscopy-based colorectal polyp diagnosis AI is an automated colorectal polyp detection programme based on endoscopic still images and videos using AI technology during a patient's endoscopic examination, which helps clinicians diagnose colorectal polyps to improve the miss rate. Colorectal cancer prediction AI helps reduce the likelihood of developing colorectal cancer by predicting the risk of colorectal cancer based on genomic and clinical data. Colorectal cancer treatment decision AI is a service that helps guide the treatment of colorectal cancer by inputting information such as the condition and prescription of colorectal cancer patients.

(5) Prostate Cancer

Prostate cancer recurrence prediction AI predicts the risk of post-operative metastasis and extra-prostatic invasion of prostate cancer, and visually provides surgical prognosis and treatment guidelines to improve the clarity of medical content delivery and treatment compliance. Prostate cancer MRI image diagnosis AI provides the ability to diagnose lesions in MRI images of the prostate and diagnose the location and size of the lesion, shortening pathology diagnosis time and improving efficiency. Prostate cancer histopathology diagnosis AI is used to assist pathologists in diagnosing prostate cancer by performing automated region-by-region identification of digitally scanned needle biopsy tissue slide images when examining a patient's prostate.

(6) Dementia

Dementia Early Diagnosis AI is based on AI analysis of brain MRI images of key brain regions related to cognition, and analyses the degree of volume shrinkage, etc., to detect Alzheimer's disease, a degenerative dementia, early to prevent worsening symptoms. The

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AI calculates quantitative values of key brain areas associated with dementia and provides comparative results with the standard brain area values of normal people in each age group in Korea.

(7) Epilepsy

In practice, it is difficult to see all the EEGs accumulated over 24-72 hours, which can lead to subtle EEG fluctuations being missed. Seizure prediction AI can identify all EEGs with abnormal findings and identify the seizure focus, which can improve the accuracy of epilepsy surgery. Normal cranial nerve diagnosis AI can quantitatively analyse the EEG to provide quantified information and support quantified analysis for EEG reading in hospitals.

(8) Paediatric rare diseases

Developmental Disorder Genetic Mutation Diagnosis AI provides accurate diagnosis by analyzing genetic data and interpreting results for developmentally delayed infants and young children with various phenotypes and numerous genetic mutations. Hearing Loss Genetic Mutation Diagnosis AI provides accurate diagnosis and prognosis services by combining clinical data such as genes, audiograms and Speech Cognition Assessment Scales for children with hearing loss.

C. Conceptual model of the study

In this study, we conducted an economic evaluation that considers the costs and benefits of medical AI from a societal perspective. To assess the economic feasibility of medical AI, we conducted a cost-benefit analysis assuming that medical AI is applied to patient care. The costs consisted of government funding for the development of the Doctor & Sur project and the costs of using AI, assuming that medical AI is used when a patient visits a hospital. The impact of medical AI was divided into direct benefits and indirect benefits. Direct benefits refer to the reduction in medical costs due to the prevention of unnecessary use of medical facilities through the prediction and early diagnosis of diseases by medical AI. Direct benefits include reductions in the costs of test and treatments, reductions in the costs of additional inspection, reductions in the costs of treatments such as surgery, reductions in hospitalization and caregiving costs, and reductions in transportation costs. Indirect benefits include the prevention of lost economic productivity of patients and their caregivers due to the prediction and early diagnosis of diseases, and the reduction of medical reading costs due to the reduction of reading time by AI.

The analysis is based on the year 2020, when the Dr. Answer project will end. As the Dr. Answer 2.0 project and various medical AI development projects are currently supported by the government, it was determined that the economic feasibility analysis of the project through cost-benefit analysis would be an effective resource for policy decisions if the results were presented at the end of the analyzed project.

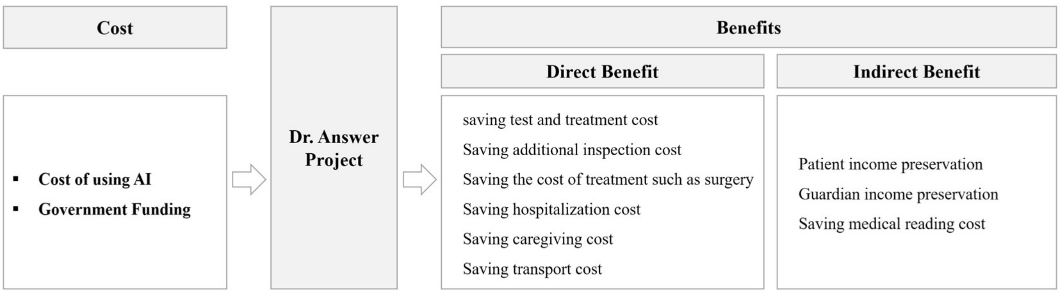

Figure 17. Framework

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For the economic analysis, out of 21 AIs, we integrated two AIs that were difficult to evaluate the economic feasibility by themselves, and conducted the analysis with 19 AIs. The AI for the visualization of multifaceted data integration for heart disease is combined with the AI for the diagnosis of heart disease, and the quantitative numbers of brain areas, which are the result of the analysis of the automatic calculation of brain image numbers, are not used alone as an AI for the analysis of the AI for the diagnosis of dementia.

Integration

Diseases	Prediction	diagnosis	Treatment	Prognosis	Visualization
Cardiocerebrovascular		Diagnosis of coronary artery calcification score Diagnosis of brain haemorrhage Diagnosis of cerebral aneurysmal lesions		Cardiovascular disease Predicting relapse	
Heart	Predicting the onset of heart disease	Diagnosis of heart disease			**Multifaceted data Blended visualisations**
Breast cancer	Predicting the onset of breast cancer			Predicting breast cancer recurrence	
Colorectal cancer	Predicting the onset of colorectal cancer	Diagnosis of colorectal polyps using endoscopy	Making treatment decisions for colorectal cancer patients		
Prostate cancer		Prostate Cancer MRI imaging diagnostics Prostate cancer Histopathological diagnosis		Predicting prostate cancer recurrence	
Dementia		Dementia Early diagnosis			**Automatic calculation of brain imaging values**
Epilepsy	Predicting epileptic seizures	Normal cranial nerves Diagnosis			
Paediatric Rare Diseases		Developmental disorders Diagnosing genetic variants Diagnosing hearing loss genetic variants			

Figure 18. Reclassifying AI for economic analysis purposes

Patient Journey refers to the entire process of understanding and treating a disease, starting with the patient's awareness of their symptoms. Based on the capabilities of the 19 AIs, the classification based on Patient Journey Coverage can be summarized into four types: predicting onset, predicting recurrence, streamlining diagnosis, and supporting treatment.

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Table 16. Four types of Patient Journeys based on functionality

Type	AI	Patient Journey Coverage				Expected effect
		Prevention	Diagnosis	Treatment	Prognosis	
onset prediction	Predicting the onset of heart disease					Reduce severity with early prediction
	Predicting the onset of breast cancer					
	Predicting the onset of colorectal cancer					
	Predicting epileptic seizures					
Recurrence prediction	Cardiovascular disease Predicting relapse					Predict risk of relapse and treat appropriately to reduce severity
	Predicting breast cancer recurrence					
	Predicting prostate cancer recurrence					
Diagnostics Efficiency	Diagnosis of coronary artery calcification score					Improve diagnostic efficiency
	Diagnosis of cerebral aneurysmal lesions					
	Diagnosis of brain haemorrhage					
	Diagnosis of heart disease					
	Diagnosis of colorectal polyps using endoscopy					
	Prostate Cancer MRI imaging diagnostics					
	Prostate cancer Histopathological diagnosis					
	Normal cranial nerves Diagnosis					
	Dementia Early diagnosis					
	Developmental disorders Diagnosing genetic variants					
	Diagnosing hearing loss genetic variants					
Treatment support	Making treatment decisions for colorectal cancer patients					Improve care efficiency

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D. Data analysis methods

(A) Selecting cost elements and Estimation methods

ⓐ Selecting cost elements

There are three types of costs: direct, indirect and intangible. Direct health care costs include doctor visits, hospital stays, medicines, dispensing fees, tests, treatments, side effects, nursing care and transport. In addition, indirect costs are the value of lost productivity due to death from illness and include the opportunity cost of lost time. Looking at the cost items in previous studies, the cost-benefit analysis of personalized home healthcare includes the costs of personnel, management, training and transport as cost items. In the study on policy evaluation for efficient operation of mobile healthcare business in health centres, mobile healthcare business cost and infrastructure construction cost were included as cost items, and in the study on telemedicine policy security trends and economic evaluation system development, medical treatment cost, equipment cost and IT infrastructure investment cost were included as cost items.

This study is not an economic analysis of medical AI after it is directly applied to patients, but a study that predicts the future economic performance of medical AI as it develops, and there are limitations in applying direct and indirect costs such as patient transportation costs, hospitalization costs, and pharmaceutical costs. Therefore, the costs in this study consisted of the government funding for the development of the Doctor & Sur project and the cost of using medical AI when a patient with a target disease visits a hospital. The cost estimation model is as follows.

$TC = Cg + Cu$

TC : Total Cost

Cg : Government Funding

Cu : Cost of using AI

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ⓑ Cost estimation methods

Government Funding

Government fundings are calculated by excluding the matching costs incurred by participating companies as government support for the Dr. Answer project and limiting it to the government support budget invested in development. Government fundings are generally composed of labour costs, R&D costs and overhead costs, each of which is a direct cost of AI development. In this study, we calculated the total input budget without breaking down the detailed items. The government funding for the development of Dr. Answer by disease is KRW 28 billion from 2018 to 2020, excluding the demonstration budget. Of this amount, KRW 23.7 billion was estimated as the government funding, excluding KRW 4.3 billion for the construction of a common platform and secretariat operating costs, which are not directly related to the development of AI.

Target patients

Excluding recurrence prediction, dementia, and rare genetic diseases in children, the number of patients targeted by AI was estimated based on the number of patients at the hospital and general hospital level in 2020 from the HIRA Bigdata Open portal operated by the HIRA(Health Insurance Review & Assessment service). For recurrence prediction AI, such as cardiovascular disease recurrence prediction, breast cancer recurrence prediction, colorectal cancer treatment decision support, and prostate cancer recurrence prediction, the targeted patients were estimated to be only patients at the general hospital level undergoing surgery with AI to support postoperative metastasis, risk of disease recurrence prediction, and surgical prognosis management. Dementia patients were assumed to be those with mild cognitive impairment, a pre-dementia stage. Patients with paediatric developmental disorders are rare disease patients under the age of 10, and patients with paediatric hearing loss are estimated by applying the incidence rate of paediatric hearing loss (0.046%) to the number of newborns (272,300) in 2020. The

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number of eligible patients for all conditions was assumed to be 50% of the number of eligible patients.

The reason for limiting the target patients to hospital level and general hospital level patients is that it is assumed that medical AI will be actively used at the hospital level and above, and that the use of medical AI will support the level of care at the hospital level and general hospital level.

Medical AI pricing

Currently, there are four medical AI products that can be used in medical institutions without payment under the new medical technology moratorium in Korea. In the United States, there are also medical AI products that are paid for under the New Technology Add-on Payments (NTAP), but there are limitations to replicating the US medical AI pricing system. In addition, several companies in Korea apply medical AI to hospitals, but the pricing policies of these AI are not disclosed, and there are differences in the prices applied to each hospital. Therefore, to estimate the price of each AI, we estimated the price of AI based on the cost of CT, MRI, PET, etc. tests by disease and estimated 10% of the cost as the price of AI. The price for each disease was estimated based on the price at a university hospital in Korea.

The AI for predicting recurrence of heart disease was estimated based on the price of similar domestic products that predict heart disease based on medical examination data, and the AI for child developmental disorder and hearing loss was estimated based on the cost of genomic diagnosis using human genome information and AI technology from domestic companies.

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(B) Selecting a benefit item and Estimation methods

ⓐ Selecting a benefit item

The basic model for the estimation of the total benefits is as follows.

$TB = B_{\text{Cardiocerebrovascular}} + B_{\text{Heart}} + B_{\text{Breast cancer}} + B_{\text{Colorectal cancer}} + B_{\text{Prostate cancer}} + B_{\text{Dementia}} + B_{\text{Epilepsy}} + B_{\text{Paediatric Rare Diseases}}$

Bi = DB(saving test and treatment cost, Saving additional inspection cost, Saving the cost of treatment such as surgery, Saving hospitalization cost, Saving caregiving cost, Saving transportation cost) + IB(Patient income preservation, Guardian income preservation, Saving medical reading cost)

TB : Total benefit

Bi : Benefit of specific AI(i= Cardiocerebrovascular, Heart, Breast cancer, Colorectal cancer, Prostate cancer, Dementia, Epilepsy, Paediatric Rare Diseases)

DB : Direct Benefit, IB : Indirect Benefit

TTB : saving test and treatment cost

AIB : Saving additional inspection cost

TSB : Saving the cost of treatment such as surgery

HB : Saving hospitalization cost

CB : Saving caregiving cost

TB : Saving transportation cost

PIB : Patient income preservation

GIB : Guardian income preservation

MRB : Saving medical reading cost

To select the benefits to be used in this study, we reviewed the economic analysis of digital health services and the economic analysis of AI medical devices. The previous studies divided benefits into direct and indirect benefits and conducted cost-benefit analyses. The direct benefits in the previous studies included medical costs saving and transportation costs saving, while the indirect benefits consisted of productivity losses and time cost savings. In addition, the benefits of using medical AI have been investigated as cost reduction, early detection, personalized diagnosis, process simplification, time savings and reduced reading time.

Based on the results of previous studies, this study selected nine benefits as benefits from the use of medical AI: direct benefits include saving on test and treatment costs, saving on additional inspection costs, saving on treatment costs such as surgery, saving on hospitalization costs, saving on caregiving costs and saving on transportation costs. Indirect benefits include patient income preservation, guardian income preservation and saving on medical reading costs. The benefits of this study are shown in <Table 17>.

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Table 17. Benefit items

Healthcare cost-benefit studies	Study on benefits of AI in healthcare
Reduce healthcare costs Prevent complications Reduce outpatient medical costs Reduce medical costs Reduce hospitalization costs Reduce nursing costs Reduce readmission costs Reduced transport costs Economic savings for carer Increased working hours/earnings Increased working hours/productivity Reduced lost productivity Increased speed and accuracy of diagnosis and treatment	Cost Reduction Early detection Personalized diagnostics Process Simplification Workflow Improvement Time Saving Shorter reading time Improved diagnostic accuracy

Type	This study
Direct benefits	saving test and treatment cost Saving additional inspection cost Saving the cost of treatment such as surgery Saving hospitalization cost Saving caregiving cost Saving transportation cost
Indirect benefits	Patient income preservation guardian income preservation Saving medical reading cost

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The economic analysis was evaluated by calculating the applied benefits according to the level of patient journey impact based on basic statistical data. The economic analysis was divided into onset prediction, recurrence prediction, diagnosis and treatment, depending on the Patient Journey Impact and the characteristics of medical AI by disease. In addition, to avoid overestimating the benefits, a conservative assessment was made by applying the benefits differently according to the functional characteristics of the medical AI. In estimating costs and benefits, the economic feasibility of the project is based on the actual commercialization model, so we applied the principle of estimating benefits as low as possible and costs as high as possible to conduct a conservative review.

First, the outbreak prediction AI was calculated only in terms of transportation cost saving benefits and patient income preservation benefits, assuming that unnecessary hospital visits and treatments are avoided by predicting diseases in advance through medical AI. It was assumed that the concept of predicting disease in advance does not generate the direct benefits of reduced costs of test and medical treatment, reduced costs of additional inspection, reduced costs of treatment such as surgery, and reduced costs of hospitalization and caregiving. In addition, onset prediction AI is AI that predicts the onset of a disease by analyzing the patient's genomic information, EMR data and lifestyle information in an integrated manner, assuming that no separate medical image reading is performed.

Recurrence prediction AI is AI that predicts the recurrence of a disease after surgery and was estimated to reduce the benefit of secondary surgery and hospitalization. Accordingly, it was calculated as a direct benefit by reducing treatment costs such as surgery, hospitalization and caregiving costs, and as an indirect benefit by reducing transportation costs and preserving the income of patients and guardian. Recurrence prediction AI is also assumed to be AI that predicts recurrence based on integrated analysis of patient genomic information, EMR data and lifestyle data, and does not require separate reading of medical images.

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For AI that supports diagnosis and treatment, we applied different benefits according to the characteristics of each disease. Because a visit to a medical facility is essential for diagnosis, the benefit of reducing transportation costs was applied generally, while the benefit of reducing reading costs was applied to diseases that are diagnosed through medical image reading, such as cardiac CT and MRI.

The application status of benefit items by detailed medical AI is as follows <Table 18>.

Table 18. Benefit application status

Benefit	onset prediction	Recurrence prediction	Diagnostics											Treat ment
			Coronary artery	Brain aneur-ysms	Cerebral haemo-rrhage	Heart	Colonosc opy	Prostate cancer imaging	Prostate cancer pathology	Demen-tia	Normal cranial nerves	Develop-mental disability	Hear-ing loss	Color-ectal cancer
saving test and treatment cost			◎	◎	◎							◎	◎	
Saving additional inspection cost						◎				◎				
Saving the cost of treatment such as surgery		◎					◎							◎
Saving hospitalization cost		◎												
Saving caregiving cost		◎												
Saving transportation cost	◎	◎	◎	◎	◎	◎	◎	◎ ◎	◎	◎	◎	◎	◎	

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Patient income preservation	◎	◎	◎	◎	◎	◎	◎	◎	◎	◎		
Guardian income preservation		◎									◎	◎
Saving medical reading cost			◎	◎	◎	◎		◎	◎	◎		

onset prediction : Heart disease prediction, breast cancer prediction, colorectal cancer prediction, epileptic seizure prediction

Recurrence prediction : Cardiovascular disease recurrence prediction, breast cancer recurrence prediction, prostate cancer recurrence prediction

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ⓑ **Methods for estimating benefit items**

Direct benefits

The benefit of saved test and treatment costs refers to the reduction in the cost of the patient's own test, diagnosis, surgery, hospitalization, etc. due to the use of the medical AI, or the reduction in the cost of medical treatment to confirm test results, although the same test is performed. It was estimated on the basis of the number of patients and the cost of follow-up treatment for each medical AI.

The benefit of saved additional inspection costs means that the rate of additional and secondary tests is reduced by the use of medical AI. It was estimated by applying the number of patients and test costs.

The benefit of saved treatment costs such as surgery refers to the reduction in the rate of surgeries and treatments performed due to the use of medical AI. It is applied to the case of recurrence prediction AI to predict recurrence after surgery for cardiovascular, breast, colorectal and prostate cancer. It was estimated by the number of patients and per capita savings for each medical AI. The per capita savings were calculated using the per capita medical costs of senior general hospitals and general hospitals.

The hospitalization cost savings benefit refers to the number of hospital days reduced by the use of medical AI and the corresponding hospital cost savings. It was estimated from the number of patients, the number of days reduced and the cost of hospitalization.

The caregiving cost savings benefit refers to the amount paid to hire paid caregivers when patients use medical facilities for treatment, rehabilitation, etc. It is estimated from the number of patients and days of hospitalization avoided, the proportion of inpatients using carers and the average daily cost of carers.

The transportation savings benefit is the amount of money saved when a patient uses transport to visit a healthcare facility, such as for outpatient treatment. It basically refers to the cost of transportation used to receive medical treatment, such as outpatient and hospital care. It is estimated using the number of patients and the average daily cost of

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transportation. For the relapse prediction AI, caregiver transportation costs were estimated using the number of patients, the number of days with fewer visits, the proportion of inpatients without caregivers, and the average daily transportation cost.

Indirect benefits

Income preservation benefits for patients and guardian are defined as the costs associated with the avoided loss of economic productivity due to reduced hospitalization and treatment time as a result of the reduced likelihood of severe disability due to the prevention, early diagnosis and treatment of disease through the use of health information technologies. Loss of economic productivity includes absence from work due to illness and those who return to work but are unable to work at their pre-illness level of productivity due to illness. The patient income preservation benefit is calculated differently when using AI for onset prediction and diagnosis and AI for relapse prediction. For onset prediction and diagnosis AI, the number of patients, average hourly wage and outpatient treatment time (4 periods) are used to estimate benefits. Relapse prediction AI was estimated using the number of patients, days of reduced hospitalization, average hourly wage, and 8 hours to prevent loss of patient productivity due to the effect of reducing hospitalization costs due to surgery, etc. AI was estimated using the number of patients, days of reduced hospitalization, average hourly wage, and 8 hours to prevent loss of patient productivity due to the effect of reducing hospitalization costs due to surgery, etc. The guardian income preservation benefit was calculated for the relapse prediction AI only and was estimated using the number of patients, number of days of reduced hospitalization, proportion of inpatients without a caregiver, average hourly wage, and 8 hours.

Medical reading cost saving benefit refers to the cost savings from reduced reading time and improved reading accuracy by using AI to read CT, MRI, etc. by a radiologist. It was estimated by applying the number of patients, the reading time saved and the average hourly wage of radiologists and pathologists.

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Table 19. Benefit formula

Type	Benefit items	Formula
Direct benefits	saving test and treatment cost	- (number of patients) × (cost of return visits)
	Saving additional inspection cost	- (number of patients) × (cost of test)
	Saving the cost of treatment such as surgery	- (number of patients) × (cost per patient saved)
	Saving hospitalization cost	- (number of patients) × (number of days with fewer visits) × (average cost per day)
	Saving caregiving cost	- (number of patients) × (days of reduced visits) × (percentage of inpatients using caregivers) × (average daily caregiver cost)
	Saving transportation cost	- Outbreak prediction, diagnosis: (number of patients) × (transportation cost) - Recurrence prediction: (number of patients) × (number of days with fewer visits) × (inpatient of inpatients not using caregivers) × (transportation cost)
Indirect benefits	Patient income preservation	- Outbreak prediction, diagnosis: (number of patients) × (hourly average wage) × (4 hours) - Recurrence prediction: (number of patients) x (number of days with fewer visits) × (hourly average wage) × (8 hours)
	guardian income preservation	- (number of patients) × (days of reduced care) × (percentage of inpatient caregivers unused) × (average hourly wage) × (8 hours)
	Saving medical reading cost	- (number of patients served) × (reading time saved) × (average hourly wage of radiologists and pathologists)

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Benefit assumptions

Re-visits were estimated at KRW 13,320 per visit to a general hospital in 2020[64]. Transportation costs were estimated at KRW 8,250 per visit to a convalescent rehabilitation centre in the second phase of the pilot project[65]. The average hourly wage of patients was estimated to be KRW 19,316 per hour in 2020, as published by Statistics Korea's National Indicator System. The cost of hospitalization was estimated at KRW 135,940 for a three-bed room in a first-class care unit in a senior general hospital[66]. Outpatient treatment was estimated at 4 hours. The rate of caregiver use was estimated to be 7.6%, as reported in the 2020 Healthcare Experience Survey[67], and the rate of caregiver non-use was estimated to be 92.4%. The average daily cost of a caregiver was estimated to be KRW 85,579 from the 2020 Healthcare Experience Survey[67]. The average hourly wage of radiologists and the average hourly wage of pathologists were estimated by dividing the 2020 annual salaries of radiologists (KRW 318,648,194) and pathologists (KRW 315,355,638) by 12 months and 209 hours based on the Healthcare Workforce Survey published by the Ministry of Health and Welfare[68]. The reduction in reading time for medical images was estimated by applying AI to a study that showed a 22.1% reduction in reading time for chest CT[17] and a 58% reduction in reading time for gastric cancer pathology images[18].

Table 20. Benefit assumptions

Benefit metrics	Benefit	Source
Revisit costs	KRW 13,320	Decomposition of health insurance payments by provider payment characteristics
Transportation costs	KRW 8,250	Evaluation of the effectiveness of the second phase of the pilot project on the number of rehabilitation medical institutions and research on ways to improve it
Average patient hourly rate	KRW 19,316	Office for National Statistics National Indicator System
Hospitalization costs	KRW135,940	Hospitalization in a three-bedded room at an advanced general hospital
Outpatient treatment time	4 hours	Assumptions
Caregiver usage rate	7.6%	2020 Healthcare Experience Survey
Caregiver unused rate	92.4%	Assuming a 7.6% caregiver usage rate
Average daily care costs	KRW 85,579	2020 Healthcare Experience Survey
Average hourly wage for radiologists	KRW127,053	Health Workforce Survey
Average hourly wage for pathologists	KRW125,740	Health Workforce Survey
Reduced medical reading time	22.1%	Impact of Artificial Intelligence Assistance on Chest CT Interpretation Times: A Prospective Randomized Study
Reduced medical reading time for pathology images	58%	A Prospective Validation and Observer Performance Study of a Deep Learning Algorithm for Pathologic Diagnosis of Gastric Tumors in Endoscopic Biopsies

E. Sensitivity analysis

As this study estimated the benefits assuming 50% of the target patients as the impact of the medical AI project, we set the percentage of target patients to 25% and 75% to compensate for the uncertainty, and examined the resulting net benefits and benefit-cost ratios.

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2. Intent to use AI in healthcare

A. Research model and hypothesis

1) Research model

This study modified and applied the Technology Acceptance Model (TAM) and the Extended Unified Technology Acceptance Model (UTAUT2) to examine the factors influencing healthcare professionals' intention to use AI medical devices as the development and use of medical AI increases. Based on previous studies, four factors were selected as influencing the intention to use AI medical devices: personal innovation, facilitating conditions, functional excellence and price value. These factors were expected to have a significant effect on perceived usefulness and perceived ease of use, and perceived usefulness and perceived ease of use were expected to have a significant effect on determining intention to use. In addition, we expected that personal innovation, facilitating conditions, functional excellence, and price value would have a direct and significant effect on intention to use, and designed a research model in which medical staff's experience in using medical AI would act as a moderating effect. The research model of this study is shown in <Figure 19>.

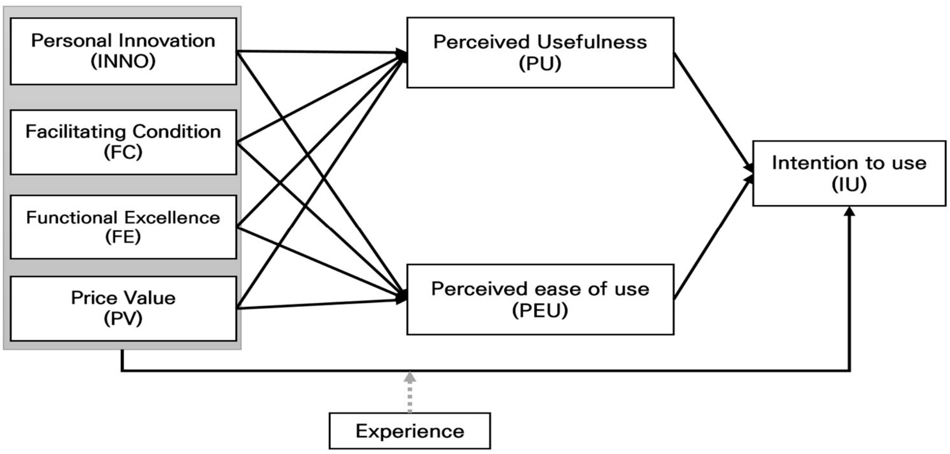

Figure 19. Research models

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2) Research hypothesis

It can be assumed that doctors using AI in healthcare in this nascent market have a positive and proactive attitude towards the new technology, which can be explained by their personal innovation. High innovativeness is characterized by a positive attitude towards uncertain risk and proactivity in adopting new technologies[69]. The innovativeness of consumers using new services can be explained by their proactive and positive attitude and low tolerance for uncertainty in using products and services, which makes it easier to understand their functions and master them faster[70]. We hypothesize that personal innovation will positively influence perceived usefulness, perceived ease of use and intention to use healthcare AI. Therefore, we hypothesize that personal innovation will positively influence perceived usefulness, perceived ease of use, and intention to use.

H1-1. Personal innovation will have a positive effect on perceived usefulness.
H1-2. Personal innovation will have a positive effect on perceived ease of use.
H1-3. Personal innovation will have a positive effect on intention to use.

Facilitating conditions refer to the extent to which people believe that the organizational and technical foundations are in place to support the use of a new system. Thompson et al (1991) defined facilitating conditions as objective factors that create an environment that makes it easier to perform a behavior[71]. Venkatesh et al. (2003) defined enabling conditions as the extent to which individuals believe that organizational and technological infrastructure exists to support the use of a system, and that employees will find it easier to use a system if the existing technological infrastructure is user-friendly and supports employees' use of the system[50]. A study by Zheng Yin et al (2022) also found that facilitating conditions had a significant impact on the use of wearable smart medical devices[61]. When using the new technology of healthcare AI, the belief that organizational and technical help is available to use the technology will reduce the initial anxiety of using a new technology. It was therefore hypothesized that facilitation

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conditions would positively influence perceived usefulness, perceived ease of use and intention to use.

H2-1. Facilitation conditions will have a positive effect on perceived usefulness.
H2-2. Facilitation condition will have a positive effect on perceived ease of use.
H2-3. Facilitation condition will have a positive effect on intention to use.

Functional excellence in medical AI can be described as fast and accurate diagnosis, reducing the time to read medical images, and providing comprehensive information for diagnosis and treatment. Functional excellence has a significant impact on the usefulness and usability of products and services[72], and studies have shown that the functional excellence of digital healthcare products makes users believe that they are useful and perceive them as convenient to use. There are also many previous studies on the functional excellence of medical AI, such as accurately predicting diseases such as kidney cancer and osteoporosis, and reducing the time to read medical images by 22.1%[17]. As a result, the better the functional excellence of medical AI, the higher the belief in and satisfaction with medical AI. Therefore, it is expected that the functional excellence of medical AI will have a positive impact on perceived usefulness, perceived ease of use and intention to use.

H3-1. Functional excellence will have a positive effect on perceived usefulness.
H3-2. Functional excellence will have a positive effect on perceived ease of use.
H3-3. Functional excellence will have a positive effect on Intention to Use.

The price value of a product or service is an important factor in determining a user's intention to adopt. Venkatesh(2012) states that consumers have a higher sense of responsibility due to the direct cost of using the technology, and the lower the cost, the more intensive the use of the technology[51]. Furthermore, price value is defined as the consumer's trade-off between the perceived benefits of an application and the monetary cost of using the application[51]. Therefore, a positive relationship between the value of a product and service and intention to use is established when users perceive the benefits of using the product and service to be higher and more important than the monetary cost. Affordability, value for money and price competitiveness with existing products will play an important role in user acceptance and use of the technology[51]. The perceived value of the price and the level of satisfaction with the price will influence the perceived usefulness and ease of use of the product or service, which will ultimately have a significant impact on the decision to use it. Therefore, it is expected that the price value of medical AI will have a positive effect on perceived usefulness, perceived ease of use and intention to use. However, as the pricing policy of medical AI can be set in conjunction with the government system, such as the number of health insurance premiums, it was considered as an expectation of value for money.

H4-1. Price value will have a positive effect on perceived usefulness.
H4-2. Price value will have a positive effect on perceived ease of use.
H4-3. Price value will have a positive effect on intention to use.

The Technology Acceptance Model (TAM), first proposed by Davis, is a model that predicts an individual's acceptance of an innovative technology based on the theory of reasoned action. In other words, TAM is a theoretical model that explains that the antecedent variables, perceived usefulness and perceived ease of use, form a causal relationship with the user's attitude, and the user's attitude influences behavioural intention, which in turn influences actual use[47]. Perceived usefulness refers to the extent to which individuals perceive that using a particular information technology can improve their job performance, while perceived ease of use refers to the extent to which individuals expect to use a particular information technology easily and without much mental and physical effort. It has been found that intention to use a new information technology is determined by perceived usefulness and perceived ease of use, which are antecedents of the technology acceptance model, and that the effect of external variables on intention to use is mediated by perceived usefulness and perceived ease of use. This means that the higher the perceived usefulness and ease of use of a new technology, the more positive the attitude towards using the technology, which in turn influences the intention to use the technology. Therefore, the research hypotheses regarding perceived usefulness, perceived ease of use and intention to use are as follows

H5. perceived ease of use will have a positive effect on intention to use.
H6. perceived usefulness will have a positive effect on intention to use.

User experience refers to all the experiences a user may have in the various interactions between the user and the technology. In the UTAUT2 proposed by Venkatesh (2012), experience can moderate the relationship between facilitating conditions, hedonic motivation, price-value, habit and behavioural intention[51]. Alba and Hutchinson (1987) found that more experience leads to greater familiarity with the technology and a knowledge structure that facilitates user learning, which can reduce users' dependence on external support[73]. Notani (1998) found that users with less experience or familiarity rely more on facilitating conditions[74]. User experience is not only the moment-to-moment experience that a user has while using a technology, but it is also influenced by prior knowledge, expectations, etc. to change attitudes and feelings towards the technology, forming a comprehensive user experience. In terms of the relationship between experience and satisfaction, the higher the quality of the experience in terms of system, information and service, the higher the customer satisfaction. In the case of medical AI, which is still in its infancy, the use experience of medical staff will have a great influence on the intention to use medical AI in the future. Therefore, it is assumed that the use experience of medical AI will be a static moderator between personal innovation, facilitating conditions, functional excellence, price value and intention to use.

H7. Use experience will positively moderate the relationships between personal innovation, facilitating conditions, functional excellence, price value, and intention to use.

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B. Research design

1) Sample selection and data collection

The main subjects of the survey were medical staff, including those who have used medical AI and those who have never used it. The medical staff conducted an online survey using the Google platform for medical staff in departments where medical AI can be applied, such as internal medicine, surgery, and rehabilitation medicine.

2) Questionnaire construction (operational definition)

In this study, the questionnaire was modified to fit medical AI by reviewing the variables used in technology acceptance model theory and previous studies and the detailed items to measure them. The questionnaire items used to measure the latent variables are shown in <Table 22>. All questions were asked on a 5-point Likert scale, with 1 being strongly disagree, 3 being agree and 5 being strongly agree. The operational definitions and questionnaire construction for each hypothesis are as follows.

Table 21. Operational definition by variable

Factor	Operational definition	Number of questions	Reference
Personal Innovation (INNO)	The extent to which clinicians are willing to adopt innovations in AI in the healthcare sector ahead of others.	3	53,54,60
Facilitating Conditions (FC)	The belief that the organizational and technical foundations are in place to support the use of AI in healthcare.	3	54,58,60,61
Functional Excellence (FE)	The extent to which AI in the healthcare sector provides accurate diagnoses, reduces reading times and provides comprehensive information for diagnosis and treatment.	4	54,62
Price Value (PV)	The extent to which you are of the opinion that AI in healthcare is reasonably priced and that the product will be of value.	3	53,54,58

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Perceived Usefulness (PU)	The extent to which you believe the use of AI in healthcare can help you improve outcomes for your intended use.	3	54,57,58,62,63
Perceived ease of use (PEU)	The belief that the use of AI in healthcare will not be a major undertaking	3	53,54,57,61-63
Intention to Use (IU)	Current and future use of AI in healthcare	3	52-54,56-58,63

Table 22. Configure the questionnaire

Factor	Questionnaire items
Personal Innovation (INNO)	- I am curious about AI medical devices. - I am interested in using AI medical devices. - I try to use AI medical devices before others.
Facilitating Conditions (FC)	- I will have access to specialized training on AI medical devices. - I will have access to expert help if I have difficulty using the AI medical device. - I will receive detailed instructions on how to use the AI medical device..
Functional Excellence (FE)	- AI medical devices will enable faster and more accurate diagnosis. - AI medical devices will reduce the time needed to read medical images. - AI medical devices will reduce diagnosis and treatment time. - AI medical devices will provide comprehensive and sufficient information for diagnosis and treatment.
Price Value (PV)	- AI medical devices will be affordable. - AI medical devices will be good value for money. - AI medical devices will be significantly more competitive than similar products.
Perceived Usefulness (PU)	- AI medical devices will improve care. - AI medical devices will improve work performance. - The results or information presented by AI medical devices will be useful.
Perceived ease of use (PEU)	- AI medical devices will be easy to use. - AI medical devices will be clear and easy to use. - It will not take long to get used to AI medical devices.
Intention to Use (IU)	- I think I need an AI medical device. - I intend to continue using AI medical devices. - I intend to recommend AI medical devices to other healthcare providers.

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3) Data analysis method

This study is a factor analysis of medical staff's intention to use AI medical devices, and the analysis was conducted using IBM SPSS 29 and Smart PLS. 4.0 programs. PLS-SEM is a principal components-based model, which has the advantage of obtaining latent variable values based on observations and can be analysed even with relatively small sample sizes. As the sample size of this study is rather small (109 cases), it is appropriate to use PLS-SEM for this study.

The analyses were carried out as follows.

First, the general characteristics of the respondents were summarized in terms of the number of respondents and percentages through frequency analysis using IBM SPSS 29.

Second, Cronbach's alpha value was tested to analyse the reliability and validity of the measurement items using Smart PLS (Partial Least Square) 4.0, and the structural model was evaluated.

Thirdly, Smart PLS (Partial Least Square) 4.0 was used to test the research hypotheses, indirect effects and moderating effects.

Finally, all statistical significance was set at 0.05.

IV. Research results

1. Social Cost-Benefit analysis

A. Cost analysis

(1) Cost calculation

The government funding for the development of Dr. Answer by disease was calculated as the development budget, excluding the demonstration budget, from 2018 to 2020. Of the KRW 28 billion development support budget, KRW 23.7 billion was calculated as the government funding, excluding KRW 4.3 billion for the common platform construction and secretariat operation costs that are not directly related to the development of AI. The government funding is shown in <Table 23>.

Except for recurrence prediction, dementia, and paediatric rare genetic diseases, the target patients for AI were estimated from the number of hospital-level and general hospital-level patients as of 2020 in the HIRA Bigdata Open portal operated by the HIRA(Health Insurance Review & Assessment service). The target patients for recurrence prediction AI, such as cardiovascular disease recurrence prediction, breast cancer recurrence prediction, and prostate cancer recurrence prediction, were estimated only for general hospital-level patients because it is an AI that determines whether a patient will have a recurrence after surgery, and the target patients for dementia were estimated by applying a 15% probability of transitioning to dementia among patients with mild cognitive impairment, which is a pre-dementia stage[75]. Paediatric developmental disabilities were estimated based on the number of rare disease patients under the age of 10 years published by the Korea Disease Control and Prevention Agency (KDCA)[76]. The number of people with paediatric hearing loss was estimated by applying the incidence of paediatric hearing loss (0.46%) to the number of newborns in 2020 (272,300), based on

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an incidence rate of 4.6 per 1,000 newborns[77]. The number of eligible patients for all conditions was assumed to be 50% of the number of eligible patients. The number of eligible patients by AI is shown in <Table 24>

There are currently four medical AI products that can be used without payment for a limited time under the new medical technology moratorium in Korea. In the US, there are medical AI products that are paid for under the New Technology Add-on Payments (NTAP), but there are limitations in applying the pricing system of US medical AI. In addition, several companies in Korea apply medical AI to hospitals, but their pricing policies are not disclosed, and there are differences in the prices applied to each hospital. Therefore, to estimate the price of each AI, we estimated the price of the AI based on the cost of CT, MRI, PET, etc. tests by disease and estimated 10% of the cost as the price of the AI. The price for each disease was estimated based on the price at a university hospital in Korea. The AI for heart disease recurrence prediction was estimated based on the price of domestic similar products that predict heart disease based on medical examination data, and the AI for child developmental disorders and hearing loss was estimated based on the cost of genomic diagnosis using human genome information and AI technology from domestic companies. In addition, the recurrence prediction AI is an AI that predicts the recurrence of diseases using EMR data, check-up data and lifestyle data, and the price was estimated by applying the cost of PET scans taken by surgical patients after surgery. The price estimates for each AI are shown in <Table 25>.

Table 23. Government funding for Dr. Answer development (unit : KRW thousands)

Diseases	AI	Government funding
Cardiocerebrovascular	Diagnosis of coronary artery calcification score	854,655
	Cardiovascular disease Predicting relapse	854,655
	Diagnosis of cerebral aneurysmal lesions	1,184,820
	Diagnosis of brain haemorrhage	1,184,820
Heart	Predicting the onset of heart disease	1,186,790
	Diagnosis of heart disease	1,186,790
Breast cancer	Predicting the onset of breast cancer	1,282,245
	Predicting breast cancer recurrence	1,282,245
Colorectal cancer	Predicting the onset of colorectal cancer	920,462
	Diagnosis of colorectal polyps using endoscopy	920,462
	Making treatment decisions for colorectal cancer patients	920,462
Prostate cancer	Prostate Cancer MRI imaging diagnostics	986,508
	Prostate cancer Histopathological diagnosis	986,508
	Predicting prostate cancer recurrence	986,508
Dementia	Dementia Early diagnosis	2,965,498
Epilepsy	Predicting epileptic seizures	1,531,337
	Normal cranial nerves Diagnosis	1,531,337
Paediatric Rare Diseases	Developmental disorders Diagnosing genetic variants	1,483,474
	Diagnosing hearing loss genetic variants	1,483,474
Common platform development and secretariat operating costs		4,266,948

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Table 24. Number of patients targeted by each of the AI

Diseases	AI	Target disease	Number of patients
Cardio-cerebrovascular	Diagnosis of coronary artery calcification score	PCI percutaneous coronary intervention, coronary artery bypass grafting, percutaneous coronary stenting	36,069
	Cardiovascular disease Predicting relapse	Myocardial infarction	28,176
	Diagnosis of cerebral aneurysmal lesions	Obstruction and narrowing of cerebral arteries that do not cause cerebral infarction	13,203
	Diagnosis of brain haemorrhage	Intracerebral haemorrhage	21,883
Heart	Predicting the onset of heart disease	Angina pectoris	173,092
	Diagnosis of heart disease	Echocardiogram	97,111
Breast cancer	Predicting the onset of breast cancer	Malignant neoplasms of the breast	42,062
	Predicting breast cancer recurrence	Breast cancer surgery	3,590
Colorectal cancer	Predicting the onset of colorectal cancer	Colorectal cancer	38,543
	Diagnosis of colorectal polyps using endoscopy	Colonoscopy	427,836
	Making treatment decisions for colorectal cancer patients	Colorectal cancer surgery	2,746
Prostate cancer	Prostate Cancer MRI imaging diagnostics	Prostate cancer	20,940
	Prostate cancer Histopathological diagnosis	Prostate cancer	20,940
	Predicting prostate cancer recurrence	Prostate cancer surgery	378
Dementia	Dementia Early diagnosis	15% probability of dementia progression in people with mild cognitive impairment	20,703
Epilepsy	Predicting epileptic seizures	Epilepsy	26,491
	Normal cranial nerves Diagnosis	Epilepsy	26,491
Paediatric Rare Diseases	Developmental disorders Diagnosing genetic variants	Pervasive Developmental Disorders (under 10)	514
	Diagnosing hearing loss genetic variants	Apply childhood hearing loss incidence rates	626

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Table 25. Estimated price by AI (unit : KRW)

Diseases	AI	modality	Price	AI Cost
Cardio-cerebrovascular	Diagnosis of coronary artery calcification score	Heart CT	366,590	36,659
	Cardiovascular disease Predicting relapse	Whole-body PET	1,704,190	170,419
	Diagnosis of cerebral aneurysmal lesions	Brain CT	218,240	21,824
	Diagnosis of brain haemorrhage	Brain MRI	609,500	60,950
Heart	Predicting the onset of heart disease	Health screening data, etc.	-	50,000
	Diagnosis of heart disease	Echocardiography	200,000	20,000
Breast cancer	Predicting the onset of breast cancer	Genetic testing (BRCA2 Gene)	2,358,360	235,836
	Predicting breast cancer recurrence	Whole-body PET	1,704,190	170,419
Colorectal cancer	Predicting the onset of colorectal cancer	Genetic testing (BRAF test)	250,220	25,022
	Diagnosis of colorectal polyps using endoscopy	Colonoscopy	238,450	23,845
	Making treatment decisions for colorectal cancer patients	Whole-body PET	1,704,190	170,419
Prostate cancer	Prostate Cancer MRI imaging diagnostics	Prostate MRI	609,500	60,950
	Prostate cancer Histopathological diagnosis	Pathological biopsy for prostate cancer	118,870	11,887
	Predicting prostate cancer recurrence	Whole-body PET	1,704,190	170,419
Dementia	Dementia Early diagnosis	Brain MRI	632,500	63,250
Epilepsy	Predicting epileptic seizures	Electroencephalography (EEG)	342,520	34,252
	Normal cranial nerves Diagnosis	Electroencephalography (wakefulness EEG)	130,860	13,086
Paediatric Rare Diseases	Developmental disorders Diagnosing genetic variants	Genetic testing	-	1,000,000
	Diagnosing hearing loss genetic variants	Genetic testing	-	1,000,000

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The cost of using AI in healthcare was calculated by multiplying the number of patients covered by each of the 19 AIs by a price estimated at 10% of the cost of the test.

Table 26. Cost of using AI (unit : KRW)

Diseases	AI	Number of patients	Cost	Cost of using AI
Cardio-cerebrovascular	Diagnosis of coronary artery calcification score	36,069	36,659	1,322,253,471
	Cardiovascular disease Predicting relapse	28,176	170,419	4,801,725,744
	Diagnosis of cerebral aneurysmal lesions	13,203	21,824	288,142,272
	Diagnosis of brain haemorrhage	21,883	60,950	1,333,768,850
Heart	Predicting the onset of heart disease	173,092	50,000	8,654,600,000
	Diagnosis of heart disease	97,111	20,000	1,942,220,000
Breast cancer	Predicting the onset of breast cancer	42,062	235,836	9,919,733,832
	Predicting breast cancer recurrence	3,590	170,419	611,804,210
Colorectal cancer	Predicting the onset of colorectal cancer	38,543	25,022	964,422,946
	Diagnosis of colorectal polyps using endoscopy	427,836	23,845	10,201,749,420
	Making treatment decisions for colorectal cancer patients	2,746	170,419	467,970,574
Prostate cancer	Prostate Cancer MRI imaging diagnostics	20,940	60,950	1,276,293,000
	Prostate cancer Histopathological diagnosis	20,940	11,887	248,913,780
	Predicting prostate cancer recurrence	378	170,419	64,418,382
Dementia	Dementia Early diagnosis	20,703	63,250	1,309,464,750
Epilepsy	Predicting epileptic seizures	26,491	34,252	907,369,732
	Normal cranial nerves Diagnosis	26,491	13,086	346,661,226
Paediatric Rare Diseases	Developmental disorders Diagnosing genetic variants	514	1,000,000	514,000,000
	Diagnosing hearing loss genetic variants	626	1,000,000	626,000,000

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(2) Results of the cost analysis

The total cost was estimated at KRW 69,534,563 thousands, including KRW 45,801,512 thousands for AI use and KRW 23,733,051 thousands for government support. The costs for each disease and detailed AI are shown in <Table 27>.

Table 27. Cost analysis results (unit : KRW thousands)

Diseases	AI	Cost of using AI	Government Funding	Total
Cardio-cerebrovascular	Diagnosis of coronary artery calcification score	1,322,253	854,655	2,176,908
	Cardiovascular disease Predicting relapse	4,801,726	854,655	5,656,381
	Diagnosis of cerebral aneurysmal lesions	288,142	1,184,820	1,472,962
	Diagnosis of brain haemorrhage	1,333,769	1,184,820	2,518,589
Heart	Predicting the onset of heart disease	8,654,600	1,186,790	9,841,390
	Diagnosis of heart disease	1,942,220	1,186,790	3,129,010
Breast cancer	Predicting the onset of breast cancer	9,919,734	1,282,245	11,201,979
	Predicting breast cancer recurrence	611,804	1,282,245	1,894,049
Colorectal cancer	Predicting the onset of colorectal cancer	964,423	920,462	1,884,885
	Diagnosis of colorectal polyps using endoscopy	10,201,749	920,462	11,122,211
	Making treatment decisions for colorectal cancer patients	467,971	920,462	1,388,433

Prostate cancer	Prostate Cancer MRI imaging diagnostics	1,276,293	986,508	2,262,801
	Prostate cancer Histopathological diagnosis	248,914	986,508	1,235,422
	Predicting prostate cancer recurrence	64,418	986,508	1,050,926
Dementia	Dementia Early diagnosis	1,309,465	2,965,499	4,274,964
Epilepsy	Predicting epileptic seizures	907,370	1,531,337	2,438,707
	Normal cranial nerves Diagnosis	346,661	1,531,337	1,877,998
Paediatric Rare Diseases	Developmental disorders Diagnosing genetic variants	514,000	1,483,474	1,997,474
	Diagnosing hearing loss genetic variants	626,000	1,483,474	2,109,474
	Total	45,801,512	23,733,051	69,534,563

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B. Benefit analysis

(1) Cardiocerebrovascular disease

The benefits of AI for the diagnosis of coronary artery calcification were estimated as the sum of the benefits of saved test and treatment costs, the benefits of saved transportation costs, the benefits of patient income preservation, and the benefits of saved medical reading costs. The number of patients was estimated to be 36,069, which is 50% of the patients who underwent PCI percutaneous coronary intervention, coronary artery bypass grafting, and percutaneous coronary stenting in hospitals and general hospitals in 2020 from the HIRA Bigdata Open portal operated by the HIRA(Health Insurance Review & Assessment service). The test and treatment cost saving benefit and transportation cost saving benefit were calculated by multiplying the number of eligible patients (36,069) by the revisit cost (KRW 13,320) and transportation cost (KRW 8,250). The patient income preservation benefit was calculated by multiplying the average hourly wage (KRW 19,316) by the assumption that outpatient treatment takes half a day (4 hours). The medical reading cost savings benefit was calculated by multiplying the average hourly wage of a radiologist (KRW 127,053) by the assumption of a 22.1% reduction in reading time with the use of AI. As a result of the analysis, the benefit of AI for coronary artery calcification diagnosis was calculated to be KRW 4,577,614,645. The detailed benefits are KRW 480,439,080 in test and treatment cost savings, KRW 297,569,250 in transportation cost savings, KRW 2,786,835,216 in patient income preservation, and KRW 1,012,771,099 in medical reading cost savings.

The benefits of AI for cardiovascular disease recurrence prediction were estimated as the sum of the benefits of saved the cost of treatment such as surgery, the benefits of saved hospitalization costs, the benefits of saved caregiving costs, the benefits of saved transportation costs, the benefits of patient income preservation, and the benefits of guardian income preservation. The number of patients was estimated at 28,176, or 50% of the myocardial infarction patients who visited general hospitals in 2020, from the HIRA

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Bigdata Open portal operated by the HIRA(Health Insurance Review & Assessment service). The benefit of saved the cost of treatment such as surgery, was calculated by multiplying the number of eligible patients (28,176) by the per capita cost savings (KRW 368,637) when treated in a general hospital compared to a superior general hospital, and the benefit of reducing hospitalization costs was calculated by multiplying the number of eligible patients (28,176) by the number of hospitalization days (0.88 days) and the average hospitalization cost per day for a three-bed room in a superior general hospital as of December 2019 (KRW 135,940). The caregiving cost savings benefit was calculated as the product of the number of days saved (0.88), the proportion of inpatients using caregivers (7.6%), and the average daily nursing cost (KRW 85,579) for the target patients (28,176). The transportation cost savings benefit was calculated as the product of the number of patients (28,176), the number of days saved (0.88), the proportion of inpatients without caregivers (92.4%), and the transportation cost (KRW 8,250). The patient income preservation benefit was calculated by multiplying the number of eligible patients (28,176) by the number of hospital days saved (0.88 days), the average hourly wage in 2020 (KRW 19,316) and the assumption that a hospital visit lasts 8 hours. The guardian income preservation benefit was calculated by multiplying the number of eligible patients (28,176) by the number of days of reduced hospitalization (0.88 days), the proportion of inpatients without caregivers (92.4%), the average hourly wage (KRW 19,316) and eight hours assuming a hospital stay of one day. As a result of the analysis, the benefit of AI for predicting recurrence of cardiovascular disease was calculated to be KRW 21,479,421,657. The detailed benefits are KRW 10,386,716,112 in saving the costs of treatment such as surgery, KRW 3,370,615,987 in hospitalization costs saving, KRW 161,265,999 in caregiving costs saving, KRW 189,011,370 in transportation costs saving, KRW 3,831,503,217 in patient income preservation and KRW 3,540,308,972 in guardian income preservation.

The benefits of AI for the diagnosis of cerebral aneurysm lesions were estimated as the sum of the benefits of saved test and treatment costs, the benefits of saved transportation

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costs, the benefits of patient income preservation and the benefits of saved medical reading cost. The number of eligible patients was estimated by the HIRA Bigdata Open portal operated by the HIRA(Health Insurance Review & Assessment service) to be 13,203, or 50 per cent of patients with obstruction and stenosis of cerebral arteries without cerebral infarction who visited hospitals and general hospitals in 2020. The test and treatment cost saving and transportation cost saving benefits were calculated by multiplying the number of target patients (13,203) by the Revisit cost (KRW 13,320) and transportation cost (KRW 8,250). The patient income preservation benefit was calculated by multiplying the average hourly wage (KRW 19,316) by the assumption that outpatient treatment takes half a day (4 hours). The medical reading cost savings benefit was calculated by multiplying the average hourly wage of a radiologist (KRW 127,053) by the assumption of a 22.1% reduction in reading time with the use of AI. As a result of the analysis, the benefit of AI for diagnosing brain aneurysm lesions is KRW 1,675,628,550. The detailed benefits are KRW 175,863,960 in test and treatment costs saving, KRW 108,924,750 in transportation costs saving, KRW 1,020,116,592 in patient income preservation, and KRW 370,723,248 in medical reading costs savings.

The benefits of AI for the diagnosis of cerebral haemorrhage were estimated as the sum of the benefits of saved test and treatment costs, the benefits of saved transportation costs, the benefits of patient income preservation, and the benefits of saved medical reading costs. The number of patients was estimated to be 21,883, which is 50% of the patients with intracerebral haemorrhage who will visit clinics and general hospitals in 2020. The test and treatment costs saving and transportation costs saving benefits were calculated by multiplying the target number of patients (21,883) by the costs of Revisit cost (KRW 13,320) and transportation cost (KRW 8,250). The patient income preservation benefit was calculated by multiplying the average hourly wage (KRW 19,316) by the assumption that outpatient treatment takes half a day (4 hours). The medical reading costs saving benefit was calculated by multiplying the average hourly wage of a radiologist (KRW 127,053) by the assumption of a 22.1% reduction in reading time with the use of AI. As a result of the analysis, the benefit of AI for cerebral haemorrhage diagnosis was calculated to be KRW 2,777,230,899. The detailed benefits are KRW 291,481,560 in test and treatment costs saving, KRW 180,534,750 in transportation costs saving, KRW 1,690,768,112 in patient income preservation and KRW 614,446,477 in medical reading costs saving.

Table 28. Cardiocerebrovascular disease benefits (unit : KRW)

	Evaluation metrics	Benefit	Calculations
Diagnosis of coronary artery calcification score	saving test and treatment cost	480,439,080	Number of patients (36,069) x Revisit cost (KRW 13,320)
	Saving transportation cost	297,569,250	Number of patients (36,069) x Transportation cost (KRW 8,250)
	patient income preservation	2,786,835,216	Number of patients (36,069) x average patient hourly rate(KRW 19,316) x 4 hours
	Saving medical reading cost	1,012,771,099	Number of patients (36,069) x Reading time saved per case(22.1%) x Average radiologist hourly wage(KRW 127,053)
	Total	4,577,614,645	
Cardiovascular disease Predicting relapse	Saving the cost of treatment such as surgery	10,386,716,112	Number of patients (28,176) × Savings per per son (KRW 368,637)
	Saving hospitalization cost	3,370,615,987	Number of patients (28,176) × Days of hospita lization reduced (0.88 days) x Hospitalization cost (KRW 135,9400)
	Saving caregiving cost	161,265,999	Number of patients (28,176) × Days of hospita lization reduced (0.88 days) × Percentage of h ospitalized patients using caregivers (7.6%) × Average daily care cost (KRW 85,579)
	Saving transportation cost	189,011,370	Number of patients (28,176) × Reduction in h ospitalization days (0.88 days) × Percentage of hospitalized patients not using caregivers (92. 4%) × Average daily transportation cost (KR W 8,250)

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	patient income preservation	3,831,503,217	Number of patients (28,176) × Days of reduced hospitalization (0.88 days) × Average hourly wage (KRW 19,316) x 8 hours
	guardian income preservation	3,540,308,972	Number of patients (28,176) × Reduction in hospitalization days (0.88 days) × Percentage of hospitalized patients not using caregivers (92.4%) × Average hourly wage (KRW 19,316) x 8 hours
	Total	21,479,421,657	
Diagnosis of cerebral aneurysmal lesions	saving test and treatment cost	175,863,960	Number of patients (13,203) × Revisit cost (KRW 13,320)
	Saving transportation cost	108,924,750	Number of patients (13,203) × transportation cost (KRW 8,250)
	patient income preservation	1,020,116,592	Number of patients (13,203) × average patient hourly rate(KRW 19,316) × (4 hours)
	Saving medical reading cost	370,723,248	Number of patients (13,203) x Reading time saved per case (22.1%) x Average hourly wage for radiologists (KRW 127,053)
	Total	1,675,628,550	
Diagnosis of brain haemorrhage	saving test and treatment cost	291,481,560	Number of patients (21,883) × Revisit cost (KRW 13,320)
	Saving transportation cost	180,534,750	Number of patients (21,883) × transportation cost (KRW 8,250)
	patient income preservation	1,690,768,112	Number of patients (21,883) × average patient hourly rate(KRW 19,316) × (4 hours)
	Saving medical reading cost	614,446,477	Number of patients (21,883) × Reading time saved per case (22.1% hours) × Average radiologist hourly wage(KRW 127,053)
	Total	2,777,230,899	

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(2) Heart disease

The benefits of AI predicting the onset of heart disease were estimated as the sum of the benefits of saved transportation costs and the benefits of patient income preservation. The number of eligible patients was estimated to be 173,092, or 50% of angina patients visiting hospitals and general clinics in 2020, from the HIRA Bigdata Open portal operated by the HIRA(Health Insurance Review & Assessment service). The transportation cost saving benefit was calculated by multiplying the number of patients (173,092) by the number of days of reduced visits (2.54 days) and the transportation cost (KRW 8,250), and the patient income preservation benefit was calculated by multiplying the number of days of reduced visits (2.54 days) by the average hourly wage (KRW 19,316), assuming that outpatient treatment takes half a day (4 hours). As a result of the analysis, the benefits of AI for heart disease prediction were calculated to be KRW 37,596,544,792. The detailed benefits are KRW 3,627,142,860 in transportation costs saving and KRW 33,969,401,932 in patient income preservation.

The benefits of AI for heart disease diagnosis were estimated as the sum of the benefits of saved additional inspection costs, the benefits of saved transportation costs, the benefits of patient income preservation, and the benefits of saved medical reading costs. The number of eligible patients was estimated by the HIRA Bigdata Open portal operated by the HIRA(Health Insurance Review & Assessment service) to be 97,111, or 50% of patients who underwent echocardiography in hospitals and general hospitals in 2020. The additional inspection cost saving benefit was calculated by multiplying the number of patients (97,111) by the cost of a hospital-level stress echocardiography test (KRW 195,550) in 2020. The transportation cost saving benefit was calculated by multiplying the number of patients (97,111) by the transportation cost (KRW 8,250), and the patient income preservation benefit was calculated by multiplying the average hourly wage (KRW 19,316) by the assumption that outpatient treatment takes half a day (4 hours). The medical reading cost saving benefit was calculated by multiplying the average hourly wage of a radiologist (KRW 127,053) based on a 22.1% reduction in reading time with the use of AI. The benefits of AI for heart disease diagnosis were calculated to be KRW 30,021,158,002. The detailed benefits are KRW 18,990,056,050 in additional inspection costs saving, KRW 801,165,750 in transportation costs saving, KRW 7,503,184,304 in patient income preservation, and KRW 2,726,751,898 in medical reading cost saving.

Table 29. Heart disease benefits (unit : KRW)

	Evaluation metrics	Benefit	Calculations
Predicting the onset of heart disease	Saving transportation cost	3,627,142,860	Number of patients (173,092) × Days of hospitalization reduced (2.54 days) × Transportation cost (KRW 8,250)
	patient income preservation	33,969,401,932	Number of patients (173,092) × Days of hospitalization reduced (2.54 days) × Average patient hourly wage(KRW 19,316)x (4 hours)
	Total	37,596,544,792	
Diagnosis of heart disease	Saving additional inspection cost	18,990,056,050	Number of patients (97,111) × cost of echocardiogram (KRW 195,550)
	Saving transportation cost	801,165,750	Number of patients (97,111) × Transport cost (KRW 8,250)
	patient income preservation	7,503,184,304	Number of patients (97,111) × Time spent per visit (4 hours) × Average patient hourly wage(KRW 19,316)
	Saving medical reading cost	2,726,751,898	Number of patients (97,111) × Reading time saved per case (22.1%) × Radiographer Hourly Rate Average wage (KRW 127,053)
	Total	30,021,158,002	

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(3) Breast cancer

The benefits of AI for predicting the onset of breast cancer were estimated as the sum of the benefits of saved transportation costs and the benefits of patient income preservation.

The number of eligible patients was estimated to be 42,062, or 50% of patients with malignant neoplasms of the breast who visited hospitals and general hospitals in 2020, from the HIRA Bigdata Open portal operated by the HIRA(Health Insurance Review & Assessment service). The transportation cost saving benefit was calculated by multiplying the number of patients (42,062) by the number of days of reduced visits (17.37 days) and transportation costs (KRW 8,250), and patient income preservation benefit was calculated by multiplying the number of days of reduced visits (17.37 days) by the average hourly wage (KRW 19,316), assuming that outpatient treatment takes half a day (4 hours). As a result of the analysis, the benefit of AI for breast cancer prediction is KRW 62,477,977,007. The detailed benefits are KRW 6,027,589,755 in transportation costs saving and KRW 56,450,387,252 in patient income preservation.

The benefits of AI for breast cancer recurrence prediction were estimated as the sum of the benefits of saved treatment costs such as surgery, the benefits of saved hospitalization costs, the benefits of saved caregiving costs, the benefits of saved transportation costs, the benefits of patient income preservation, and the benefits of guardian income preservation. The number of patients was estimated to be 3,590, or 50% of the patients who underwent breast cancer surgery at general hospitals in 2020, from the HIRA Bigdata Open portal operated by the HIRA(Health Insurance Review & Assessment service). In terms of the effect of reducing the cost of surgery and other treatments, we estimated that there would be no effect of reducing the cost of care, as the per capita cost of care at general hospitals and hospitals (KRW 7,316,192) was higher than the per capita cost of care at senior general hospitals (KRW 7,125,652). The hospitalization cost saving benefit was calculated as the product of the number of hospitalization days saved (1.58 days) and the average daily hospitalization cost (KRW 135,940) for 3,590 patients. The caregiving cost

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saving benefit was calculated as the product of the number of days saved per patient (3,590), the percentage of inpatients using nurses (7.6%), and the average daily nursing cost (KRW 85,579). The transportation cost saving benefit was calculated as the product of the number of eligible patients (3,590), the number of days reduced (1.58), the proportion of inpatients without a carer (92.4%), and the average daily transportation cost (KRW 8,250). The patient income preservation benefit was calculated by multiplying the number of eligible patients (3,590) by the number of days saved (1.58), the average hourly wage (KRW 19,316) and an 8-hour working day. The guardian income preservation benefit was calculated by multiplying the number of patients (3,590) by the number of days with fewer visits (1.58 days), the percentage of inpatients without caregivers (92.4%), the average hourly wage (KRW 19,316), and 8 hours per day. As a result of the analysis, the benefit of AI for breast cancer recurrence prediction was calculated to be KRW 2,537,622,460. The detailed benefits are KRW 771,078,868 in hospitalization costs saving, KRW 36,892,011 in caregiving costs saving, KRW 43,239,181 in transportation costs saving, KRW 876,513,722 in patient income preservation, and KRW 809,898,679 in guardian income preservation

Table 30. Breast Cancer Disease Benefits (unit : KRW)

	Evaluation metrics	**Benefit**	**Calculations**
Predicting the onset of breast cancer	Saving transportation cost	6,027,589,755	Number of patients served (42,062) × Days saved (17.37) × Transportation costs (KRW 8,250)
	Patient income preservation	56,450,387,252	Number of patients (42,062) × Days saved (1 7.37 days) × Time spent per visit (4 hours) × Average patient hourly wage(KRW 19,316)
	Total	62,477,977,007	

Predicting breast cancer recurrence	Saving the cost of treatment such as surgery	0	Fees in higher general hospitals are higher than in general hospitals No savings because the cost of treatment is higher than in a general hospital
	Saving hospitalization cost	771,078,868	Number of patients (3,590) × Reduction in hospitalization days (1.58 days) × Hospitalization cost (KRW 135,940)
	Saving caregiving cost	36,892,011	Number of patients (3,590) × Caregiver utilization rate (7.6%) × Reduction in hospitalization days (1.58 days) × Average daily caregiver cost (KRW 85,579)
	Saving transportation cost	43,239,181	Number of patients (3,590) × Guardian care rate (92.4%) × Reduced hospitalization days (1.58 days) × Transportation cost (KRW 8,250)
	Patient income preservation	876,513,722	Number of patients (3,590) × Reduced hospitalization days (1.58 days) × Average patient hourly wage(KRW 19,316) × (8 hours)
	guardian income preservation	809,898,679	Number of patients (3,590) × Guardian care ratio (92.4%) × Reduction in hospitalization days (1.58 days) × Average hourly wage for chaperones (KRW 19,316) × (8 hours)
	Total	2,537,622,460	

(4) Colorectal cancer

The benefits of AI in predicting the development of colorectal cancer were estimated as the sum of the benefits of saved transportation costs and the benefits of patient income preservation. The number of target patients was estimated to be 38,543, or 50% of the patients who received colorectal cancer treatment at hospitals and general hospitals in 2020 from the HIRA Bigdata Open portal operated by the HIRA(Health Insurance Review & Assessment service). The transportation cost saving benefit was calculated by multiplying the number of patients (38,543) by the number of days of reduced visits (13.51 days) and transportation costs (KRW 8,250), and the benefit of patient income preservation was calculated by multiplying the number of days of reduced visits (13.51

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days) by the average hourly wage (KRW 19,316), assuming that outpatient treatment takes half a day (4 hours). As a result of the analysis, the benefits of AI for outbreak prediction were calculated to be KRW 44,528,502,038. The detailed benefits are KRW 4,295,906,423 in transportation costs saving and KRW 40,232,595,616 in patient income preservation.

The benefits of AI for endoscopic colorectal polyp diagnosis were estimated as the sum of the benefits of saved the cost of treatment such as surgery, and the benefits of saved transportation costs. The number of patients was estimated at 427,836, which is 50% of the patients who underwent colonoscopy in hospitals and general hospitals in 2020, according to the HIRA Bigdata Open portal operated by the HIRA(Health Insurance Review & Assessment service). The cost of treatment such as surgery saving benefit was calculated by multiplying the number of patients (427,836) by the polyp detection rate at colonoscopy (20%), the probability of progression to colorectal cancer at 10 years (8%), and the average cost savings of colorectal cancer surgery per person (KRW 2,040,088). The transportation cost saving benefit was calculated as the product of the number of patients (427,836) and the average daily transportation cost (KRW 8,250). As a result of the analysis, the benefit of AI for endoscopic colorectal polyp diagnosis was calculated at KRW 17,494,816,433. The detailed benefits were KRW 13,965,169,433 in the cost of treatment such as surgery saving, and KRW 3,529,647,000 in transportation costs saving.

The benefits of AI decision support for colorectal cancer treatment were estimated as the sum of the benefits of saved the cost of treatment such as surgery, the benefits of saved transportation costs, and the benefits of patient income preservation. The number of patients was estimated to be 2,746, or 50% of the patients who underwent colorectal cancer surgery at general hospitals in 2020, from the HIRA Bigdata Open portal operated by the HIRA(Health Insurance Review & Assessment service). The cost of treatment such as surgery saving benefit was calculated as the number of target patients (2,746) multiplied by the amount of surgery cost savings per person (KRW 2,040,088). The transportation cost saving benefit was calculated by multiplying the number of patients

(2,746) by the number of days of reduced visits (4.44 days) and transportation costs (KRW 8,250), and the benefit of patient income preservation was calculated by multiplying the number of days of reduced visits (4.44 days) by the average hourly wage (KRW 19,316), assuming that outpatient treatment takes half a day (4 hours). As a result of the analysis, the benefits of AI for colorectal cancer treatment decision support were calculated to be KRW 6,644,688,859. The detailed benefits were calculated as KRW 5,602,081,648 in the cost of treatment such as surgery saving, KRW 100,585,980 in transportation costs saving, and KRW 942,021,231 in patient income preservation.

Table 31. Colorectal Cancer Disease Benefits (unit : KRW)

	Evaluation metrics	Benefits	Calculations
Predicting the onset of colorectal cancer	Saving transportation cost	4,295,906,423	Number of patients (38,543) × Days of hospitalization reduced (13.51 days) × Transportation cost (KRW 8,250)
	Patient income preservation	40,232,595,616	Number of patients (38,543) × Number of days with fewer visits (13.51 days) × Average patient hourly Wage (KRW 19,316) × (4 hours)
	Total	44,528,502,038	
Diagnosis of colorectal polyps using endoscopy	Saving the cost of treatment such as surgery	13,965,169,433	Number of patients (427,836) × colorectal cancer polyp detection rate (20%) × probability of colorectal cancer after 10 years (8%) × Saving money on colorectal cancer surgery (KRW 2,040,088)
	Saving transportation cost	3,529,647,000	Number of patients (427,836) × Transportation cost (KRW 8,250)
	Total	17,494,816,433	
Making treatment decisions for colorectal cancer patients	Saving the cost of treatment such as surgery	5,602,081,648	Number of patients served(2,746)×Saving money on colorectal cancer surgery(KRW 2,040,088)
	Saving transportation cost	100,585,980	Number of patients (2,746) × Days of reduced visits (4.44 days) × Transportation costs (KRW 8,250)
	Patient income preservation	942,021,231	Number of patients (2,746) × Days of reduced visits (4.44 days) × Average patient hourly Wage(KRW 19,316) × (4 hours)
	Total	6,644,688,859	

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(5) Prostate cancer

The benefits of AI for prostate cancer MRI image diagnosis were estimated as the sum of the benefits of saved test and treatment costs, the benefits of saved transportation costs, the benefits of patient income preservation, and the benefits of saved medical reading costs. The number of patients was estimated to be 20,940, which is 50% of the patients treated for prostate cancer in hospitals and general hospitals in 2020 in the HIRA Bigdata Open portal operated by the HIRA(Health Insurance Review & Assessment service). The test and treatment cost saving benefit and transportation cost saving benefit were calculated by multiplying the target patients (20,940) by the Revisit cost (KRW 13,320) and transportation cost (KRW 8,250). The patient income preservation benefit was calculated by multiplying the average hourly wage (KRW 19,316) by the assumption that outpatient treatment takes half a day (4 hours). The medical reading cost saving benefit was calculated by multiplying the average hourly wage of a radiologist (KRW 127,053) by the assumption of a 22.1% reduction in reading time with the use of AI. As a result of the analysis, the benefit of AI for prostate cancer MRI image diagnosis is KRW 2,657,552,210. The detailed benefits are KRW 278,920,800 in test and treatment costs saving, KRW 172,755,000 in transportation costs saving, KRW 1,617,908,160 in patient income preservation, and KRW 587,968,250 in medical reading costs saving.

The benefits of histopathology-based diagnostic AI were estimated as the sum of the benefits of saved test and treatment cost, the benefits of saved transportation cost, the benefits of patient income preservation, and the benefits of saved medical reading cost. The number of patients was estimated to be 20,940, which is 50% of the patients treated for prostate cancer in hospitals and general hospitals in 2020 in the HIRA Bigdata Open portal operated by the HIRA(Health Insurance Review & Assessment service). The test and treatment cost saving benefit and transportation cost saving benefit were calculated by multiplying the target patients (20,940) by the Revisit cost (KRW 13,320) and transportation cost (KRW 8,250). The patient income preservation benefit was calculated by multiplying the average hourly wage (KRW 19,316) by the assumption that outpatient

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treatment takes half a day (4 hours). The medical reading cost saving benefit was calculated by multiplying the average hourly wage of a pathologist (KRW 125,740) by the assumption that the pathology reading time was reduced by 58% with the use of AI. As a result of the analysis, the benefit of AI for histopathology-based diagnosis was calculated to be KRW 3,596,721,408. The detailed benefits are KRW 278,920,800 in test and treatment costs saving, KRW 172,755,000 in transportation costs saving, KRW 1,617,908,160 in patient income preservation, and KRW 1,527,137,448 in medical reading costs saving.

The benefits of AI for prostate cancer recurrence prediction were calculated as the sum of the benefits of saved the cost of treatment such as surgery, the benefits of saved hospitalization cost, the benefits of saved caregiving cost, the benefits of saved transportation cost, the benefits of patient income preservation, and the benefits of guardian income preservation. The number of patients was estimated to be 378, or 50% of the patients who underwent prostate cancer surgery at general hospitals in 2020, from the HIRA Bigdata Open portal operated by the HIRA(Health Insurance Review & Assessment service). The benefits of the cost of treatment such as surgery were calculated by multiplying the number of patients (378) by the cost per person saved (KRW 1,321,843), and the hospitalization cost saving benefit was calculated by multiplying the number of patients (378) by the number of hospitalization days saved (1.68 days) and the average hospitalization cost per day (KRW 135,940). The caregiving cost saving benefit was calculated as the product of the number of days saved per patient (378), the proportion of inpatients using nurses (7.6%), and the average daily nursing cost (KRW 85,579). The transportation cost saving benefit was calculated as the product of the number of patients (378), the number of days saved (1.68), the proportion of inpatients without carers (92.4%) and the average daily transportation cost (KRW 8,250). The patient income preservation benefit was calculated by multiplying the number of patients (378) by the number of days of reduced hospitalization (1.68 days), the average hourly wage (KRW 19,316) and an 8-hour day. The guardian income preservation benefit was calculated by multiplying the number of patients (378) by the number of days of reduced hospitalization (1.68 days), the proportion of inpatients without caregivers (92.4%), the average hourly wage (KRW 19,316) and 8 hours per day. As a result of the analysis, the benefit of AI for prostate cancer recurrence prediction was calculated to be KRW 783,760,135. The detailed benefits are KRW 499,656,654 in treatment costs saving such as surgery, KRW 86,327,338 in hospitalization costs saving, KRW 4,130,303 in caregiving costs saving, KRW 4,840,910 in transportation costs saving, KRW 98,131,461 in patient income preservation and KRW 90,673,470 in guardian income preservation.

Table 32. Prostate cancer disease benefits (unit: KRW)

	Evaluation metrics	Benefits	Calculations
Prostate Cancer MRI imaging diagnostics	saving test and treatment cost	278,920,800	Number of patients (20,940) × Revisit cost (KRW 13,320)
	Saving transportation cost	172,755,000	Number of patients (20,940) × Transportation cost (KRW 8,250)
	Patient income preservation	1,617,908,160	Number of patients (20,940) × Time spent per visit (4 hours) × Number of visits (1) × Average patient hourly Wage (KRW 19,316)
	Saving medical reading cost	587,968,250	Number of patients (20,940) × Reading time saved (22.1%) × Average hourly wage of radiologists (KRW 127,053)
	Total	2,657,552,210	
Prostate cancer Histopathological diagnosis	saving test and treatment cost	278,920,800	Number of patients (20,940) × Revisit cost (KRW 13,320)
	Saving transportation cost	172,755,000	Number of patients (20,940) × Transportation cost (KRW 8,250)
	Patient income preservation	1,617,908,160	Number of patients (20,940) × Time spent per visit (4 hours) × Average patient hourly Wage (KRW 19,316)
	Saving medical reading cost	1,527,137,448	Number of patients (20,940) × Time saved (58%) × Average hourly wage of pathologists (KRW 125,740)
	Total	3,596,721,408	

Predicting prostate cancer recurrence	Saving the cost of treatment such as surgery	499,656,654	· Number of patients (378) × Savings (KRW 1,321,843)
	Saving hospitalization cost	86,327,338	Number of patients (378) × Days of hospitalization r educed (average 1.68 days) × Hospitalization cost (K RW 135,940)
	Saving caregiving cost	4,130,303	Number of patients (378) × Caregiver utilization rate (7.6%) × Days of hospitalization reduced (average 1 .68 days) × Average caregiver cost per day (KRW 83,745)
	Saving transportation cost	4,840,910	Number of patients (378) × Guardian care ratio (92.4 %) × Days of hospitalization reduced (average 1.68 days) × Transportation cost (KRW 8,250)
	Patient income preservation	98,131,461	Number of patients (378) × Days of reduced hospital ization (average 1.68 days) × Average hourly wage (KRW 19,316)
	guardian income preservation	90,673,470	Number of patients (378) × Guardian care ratio (92.4 %) × Days of hospitalization reduced (average 1.68 days) × Average daily wage (KRW 19,316)
	Total	783,760,135	

(6) Dementia

The benefits of AI for early diagnosis of dementia were calculated as the sum of the benefits of saved additional inspection costs and the benefits of saved transportation costs. The number of patients was estimated at 20,703 by applying 50% of the number of mild cognitive impairment diagnoses in 2019 (276,045) announced by the HIRA(Health Insurance Review & Assessment service) in 2020 and the probability of progression to dementia among patients with mild cognitive impairment (15%). The additional inspection cost saving benefit was calculated by multiplying the number of patients (20,703) by the average cost of the Amylodi PET test (KRW 1,250,000), and the transportation cost saving benefit was calculated by multiplying the number of patients (20,703) by the transportation cost (KRW 8,250). As a result of the analysis, the benefits of AI for early diagnosis of dementia were calculated to be KRW 26,049,549,750. The detailed benefits were calculated as KRW 25,878,750,000 in additional inspection costs saving and KRW 170,799,750 in transportation costs saving.

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Table 33. Dementia Disease Benefits (unit : KRW)

Evaluation metrics	Benefits	Calculations
Saving additional inspection cost	25,878,750,000	Number of patients (20,703) × Amyloid PET test cost (KRW 1,250,000)
Saving transportation cost	170,799,750	Number of patients (20,703) × Transportation cost (KRW 8,250)
Total	26,049,549,750	

(7) Epilepsy

The benefits of AI for predicting epileptic seizures were estimated as the sum of the benefits of saved transportation costs and the benefits of patient income preservation. The number of eligible patients was estimated to be 26,491, or 50% of the patients treated for epilepsy in hospitals and general clinics in 2020, according to the HIRA Bigdata Open portal operated by the HIRA(Health Insurance Review & Assessment service). The transportation costs saving benefit was calculated by multiplying the number of patients (26,491) by the number of days of reduced visits (12.64 days) and transportation costs (KRW 8,250), and the benefit of patient income preservation was calculated by multiplying the number of days of reduced visits (12.64 days) by the average hourly wage (KRW 19,316), assuming that outpatient treatment takes half a day (4 hours). As a result of the analysis, the benefit of AI for predicting epileptic seizures was calculated to be KRW 28,634,041,367. The detailed benefits were KRW 2,762,481,480 in transportation costs saving and KRW 25,871,559,887 in patient income preservation.

The benefits of AI for normal cranial nerve diagnosis were estimated as the sum of the benefits of saved transportation costs, the benefits of patient income preservation, and the benefits of medical reading costs. The number of target patients was estimated to be 26,491, which is 50% of the patients treated for epilepsy in hospitals and general hospitals in 2020 in the HIRA Bigdata Open portal operated by the HIRA(Health

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Insurance Review & Assessment service). The transportation cost saving benefit was calculated by multiplying the number of patients (26,491) by the transportation cost (KRW 8,250), and the patient income preservation benefit was calculated by multiplying the average hourly wage (KRW 19,316), assuming that outpatient treatment takes half a day (4 hours). The medical reading cost saving benefit was calculated by multiplying the average hourly wage of a radiologist (KRW 127,053) based on a 22.1% reduction in reading time with the use of AI. As a result of the analysis, the benefit of AI for normal cranial nerve diagnosis was calculated to be KRW 3,009,184,560. The detailed benefits are KRW 218,550,750 in transportation costs saving, KRW 2,046,800,624 in patient income preservation, and KRW 743,833,186 in medical reading costs saving.

Table 34. Epilepsy Disease Benefits (unit : KRW)

	Evaluation metrics	Benefits	Calculations
Predicting epileptic seizures	Saving transportation cost	2,762,481,480	Number of patients (26,491) × Days of reduced hospital visits (12.64 days) × Transportation costs (KRW 8,250)
	Patient income preservation	25,871,559,887	Number of patients (26,491) × Number of days with fewer visits (12.64 days) × Average hourly wage (KRW 19,316) × (4 hours)
	Total	28,634,041,367	
Normal cranial nerves Diagnosis	Saving transportation cost	218,550,750	Number of patients (26,491) × Transportation cost (KRW 82,250)
	Patient income preservation	2,046,800,624	Number of patients (26,491) × Average hourly wage (KRW 19,316) x 4 hours
	Saving medical reading cost	743,833,186	Number of patients (26,491) × Time saved (22.1%) × Average hourly wage of radiologists (KRW 127,053)
	Total	3,009,184,560	

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(8) Paediatric rare diseases

The benefits of AI for diagnosing genetic mutations in developmental disorders were estimated as the sum of the benefits of saved test and treatment cost, the benefits of saved transportation cost and the benefits of guardian income preservation. The number of eligible patients was estimated to be 514, which represents 50% of all rare disease patients under the age of 10 in 2020. The test and treatment cost saving benefit was calculated by assuming that the average number of medical visits and the average medical cost of KRW 5,500,000 per visit would be reduced to one visit through the use of AI. The transportation cost saving benefit was calculated as the product of the number of patients (514), the number of patients accompanied by a caregiver (2), the number of hospital visits reduced (7), and the transportation cost (KRW 8,250). The guardian income preservation benefit was calculated by multiplying the number of reduced hospital visits (7) by the average hourly wage (KRW 19,316), assuming that outpatient treatment takes half a day (4 hours). As a result of the analysis, the benefits of AI for diagnosing genetic mutations in developmental disorders were calculated to be KRW 20,126,362,872. The detailed benefits are KRW 19,789,000,000 in test and treatment costs saving, KRW 59,367,000 in transportation costs saving, and KRW 277,995,872 in guardian income preservation.

The benefits of AI for the diagnosis of genetic mutations in hearing loss were estimated as the sum of the benefits of saved test and treatment cost, the benefits of saved transportation cost and the benefits of guardian income preservation. The number of eligible patients was estimated at 626, which is 50% of 1,252 or 0.46% of the 272,300 newborns in 2020, as the incidence of childhood hearing loss is 4.6 per 1,000 newborns. The test and treatment cost saving benefit was calculated assuming that the average number of visits and the average treatment cost of KRW 5,500,000 per visit are reduced to one visit by using AI. The transportation cost saving benefit was calculated as the product of the number of patients (626), the number of patients accompanied by a caregiver (2), the number of hospital visits reduced (7), and the transportation cost (KRW

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8,250). The guardian income preservation benefit was calculated by multiplying the number of reduced hospital visits (7) by the average hourly wage (KRW 19,316), assuming that outpatient treatment takes half a day (4 hours). As a result of the analysis, the benefit of AI for genetic mutation diagnosis of hearing loss was calculated to be KRW 24,511,873,848. The detailed benefits are KRW 24,101,000,000 in test and treatment costs saving, KRW 72,303,000 in transportation costs saving, and KRW 338,570,848 in guardian income preservation.

Table 35. Paediatric Rare Disease Benefit (unit : KRW)

	Evaluation metrics	Benefits	Calculations
Developmental disorders Diagnosing genetic variants	saving test and treatment cost	19,789,000,000	Number of patients (514) × Reduced test fees until diagnosis Minutes (KRW 5,500,000 x 8 times - KRW 5,500,000 x 1 time)
	Saving transportation cost	59,367,000	Number of patients (514) × number of visitors (2) × number of visits (7) × transportation cost (KRW 8,250)
	Guardian income preservation	277,995,872	Number of patients (514) × Time spent per visit (4 hours) × Number of visits (7) × Hourly wage (KRW 19,316)
	Total	20,126,362,872	
Diagnosing hearing loss genetic variants	saving test and treatment cost	24,101,000,000	Number of patients (626) × Reduced test fees until diagnosis Minutes (KRW 5,500,000 x 8 times – KRW 5,500,000 x 1 time)
	Saving transportation cost	72,303,000	Number of patients (626) × number of visitors (2) × number of visits (7) × transportation cost (KRW 8,250)
	Guardian income preservation	338,570,848	Number of patients (626) × Time spent per visit (4 hours) × Number of visits (7) × Hourly wage (KRW 19,316)
	Total	24,511,873,848	

* 1. assumption of parental presence, 2. assumption of reduction in diagnoses from an average of 8 to 1

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C. Results of the cost-benefit analysis

The economic analysis of 19 medical AIs in 8 diseases showed a net benefit of KRW 341,180,251 thousands and a benefit-cost ratio of 4.9 times. Looking at the benefits and benefit-cost ratios for each disease, we found that Cardiocerebrovascular disease (benefit of KRW 30,509,896 thousands, benefit-cost ratio of 2.58 times), heart disease (benefit of KRW 67,617,703 thousands, benefit-cost ratio of 5.21 times), breast cancer (benefit of KRW 65,015,599 thousands, benefit-cost ratio of 4.96 times), colorectal cancer (benefit of KRW 68,668,007 thousands, benefit-cost ratio of 4. 77 times), prostate cancer (benefit of KRW 7,038,034 thousands, benefit-cost ratio 1.55 times), dementia (benefit of KRW 26,049,549 thousands, benefit-cost ratio 6.09 times), epilepsy (benefit of KRW 31,643,226 thousands, benefit-cost ratio 7.33 times) and paediatric rare genetic diseases (benefit of KRW 44,638,237 thousands, benefit-cost ratio 10.87 times). The results of the economic analysis are shown in <Table 36>.

D. Sensitivity Analysis

To reflect the uncertainty in the effectiveness of the project, a sensitivity analysis was conducted for 25% and 75% of eligible patients. The results of the analysis showed that when the number of eligible patients was 25%, the benefit was KRW 170,590,125 thousands and the cost-benefit ratio was 3.66 times. For 75% of eligible patients, the benefit was KRW 511,770,377 thousands and the cost-benefit ratio was 5.54 times. The results of the sensitivity analysis are shown in <Table 37>.

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Table 36. Synthesis of economic analysis (unit : KRW thousands)

	Cardio-cerebrovascular disease	**Heart disease**	**Breast Cancer**	**Colorectal Cancer**	**Prostate cancer**	**Dementia**	**Stroke**	**Pediatric Rare Diseases**	**Total**
Saving test and treatment cost	947,785	-	-	-	557,842	-	-	43,890,000	45,395,626
Saving additional inspection cost	-	18,990,056	-	-	-	25,878,750	-	-	44,868,806
Saving the cost of treatment such as surgery	10,386,716	-	-	19,567,251	499,657	-	-	-	30,453,624
Saving hospitalization cost	3,370,616	-	771,079	-	86,327	-	-	-	4,228,022
Saving caregiving cost	161,266	-	36,892	-	4,130	-	-	-	202,288
Saving transportation cost	776,040	4,428,309	6,070,829	7,926,139	350,351	170,800	2,981,032	131,670	22,835,169
Patient income preservation	9,329,223	41,472,586	57,326,901	41,174,617	3,333,948	-	27,918,361	-	180,555,635
Guardian income preservation	3,540,309	-	809,899	-	90,673	-	-	616,567	5,057,448
Saving medical reading cost	1,997,941	2,726,752	-	-	2,115,106	-	743,833	-	7,583,632

Benefit total	**30,509,896**	**67,617,703**	**65,015,599**	**68,668,007**	**7,038,034**	**26,049,550**	**31,643,226**	**44,638,237**	**341,180,251**
Cost of using AI	7,745,890	10,596,820	10,531,538	11,634,143	1,589,625	1,309,465	1,254,031	1,140,000	45,801,512
Government Funding	4,078,950	2,373,581	2,564,490	2,761,386	2,959,523	2,965,498	3,062,675	2,966,948	23,733,052
Cost Total	**11,824,840**	**12,970,401**	**13,096,028**	**14,395,529**	**4,549,148**	**4,274,963**	**4,316,706**	**4,106,948**	**69,534,564**
Cost-Benefit	**18,685,055**	**54,647,302**	**51,919,571**	**54,272,478**	**2,488,885**	**21,775,124**	**27,326,520**	**40,531,289**	**271,645,687**
B/C	**2.58**	**5.21**	**4.96**	**4,77**	**1.55**	**6.09**	**7.33**	**10.87**	**4.9**

Table 37. Results of the sensitivity analysis (unit : KRW thousands)

		Cardio-cerebrovascular disease	Heart disease	Breast Cancer	Colon Cancer	Prostate cancer	Dementia	Stroke	Pediatric Rare Diseases	Total
25% assumption	Benefit Total	15,254,947	33,808,851	32,507,799	34,334,003	3,519,016	13,024,774	15,821,612	22,319,118	170,590,125
	Cost of using AI	3,872,945	5,298,410	5,265,769	5,817,071	794,812	654,732	627,015	570,000	22,900,756
	Government Funding	4,078,950	2,373,580	2,564,490	2,761,385	2,959,523	2,965,498	3,062,674	2,966,947	23,733,051
	Cost Total	7,951,895	7,671,990	7,830,259	8,578,457	3,754,335	3,620,230	3,689,690	3,536,947	46,633,807
	Cost-Benefit	**7,303,052**	**26,136,860**	**24,677,540**	**25,755,546**	**(235,319)**	**9,404,544**	**12,131,922**	**18,782,170**	**123,956,317**
	B/C	**1.92**	**4.41**	**4.15**	**4.00**	**0.94**	**3.60**	**4.29**	**6.31**	**3.66**
75% assumption	Benefit Total	45,764,843	101,426,554	97,523,399	103,002,010	10,557,050	39,074,324	47,464,838	66,957,355	511,770,377
	Cost of using AI	11,618,835	15,895,230	15,797,307	17,451,214	2,384,437	1,964,197	1,881,046	1,710,000	68,702,268
	Government Funding	4,078,950	2,373,580	2,564,490	2,761,385	2,959,523	2,965,498	3,062,674	2,966,947	23,733,051
	Cost Total	15,697,785	18,268,810	18,361,797	20,212,600	5,343,961	4,929,695	4,943,721	4,676,947	92,435,320
	Cost-Benefit	**30,067,057**	**83,157,743**	**79,161,601**	**82,789,410**	**5,213,089**	**34,144,629**	**42,521,117**	**62,280,407**	**419,335,057**
	B/C	**2.92**	**5.55**	**5.31**	**5.10**	**1.98**	**7.93**	**9.60**	**14.32**	**5.54**

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2. Intent to use analysis

A. Basic statistical analysis

1) General status of respondents

In this study, questionnaires were collected from healthcare professionals to analyse the factors that influence their intention to use AI medical devices. The survey was conducted online through Google Forms for about two weeks from 8 May to 19 May 2023.

A total of 114 questionnaires were collected, and 109 questionnaires were used in the analysis, excluding five that were incomplete. To analyse the demographic characteristics of the respondents, we conducted a frequency analysis using IBM SPSS 29. The characteristics of the respondents are presented in <Table 38>.

Of the total respondents, 80 (73.4%) were male, with 29 (26.6%) female, 25 (22.9%) in their 30s, 63 (57.8%) in their 40s, 18 (16.5%) in their 50s and 3 (2.8%) in their 60s. Regarding whether or not they had used AI medical devices, 56 respondents (51.4%) had and 53 respondents (48.6%) had not. The medical specialties of the respondents were internal medicine 24 (22.0%), rehabilitation 23 (21.1%), ophthalmology 15 (13.8%), emergency medicine 6 (5.5%), radiology 5 (4.6%), family medicine 5 (4.6%), psychiatry 5 (4.6%), surgery 4 (3. 7%), neurology and neurosurgery 4 (3.7%), paediatrics 2 (1.8%), obstetrics and gynaecology 2 (1.8%), urology 2 (1.8%), pathology 1 (0.9%), nuclear medicine 1 (0.9%), dermatology 1 (0.9%), radiation oncology 1 (0.9%), and 8 (7.3%) who did not specify a specialty. Regarding work experience, 15 (13.8%) had less than 5 years, 15 (13.8%) had 5-10 years, 28 (25.7%) had 10-15 years, 26 (23.9%) had 15-20 years, and 25 (22.9%) had more than 20 years.

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Table 38. General status of respondents

		Respondents (people)	Percentage (%)
All		109	100
Gender	Male	80	73.4
	female	29	26.6
Age	30s	25	22.9
	40s	63	57.8
	50	18	16.5
	60s	3	2.8
Enabled	Experienced	56	51.4
	No experience	53	48.6
Medical specialties	Internal Medicine	24	22.0
	Department of Rehabilitation	23	21.1
	Ophthalmology	15	13.8
	Emergency Medicine	6	5.5
	Department of Radiology	5	4.6
	Family Medicine	5	4.6
	Psychiatry	5	4.6
	Surgical	4	3.7
	Neurology/Neurosurgery	4	3.7
	Pediatrics	2	1.8
	Gynecology	2	1.8
	Urology	2	1.8
	Pathology	1	0.9
	Nuclear Medicine	1	0.9
	Dermatology	1	0.9
	Department of Radiation Oncology	1	0.9
	Others	8	7.3
Years of service	Less than 5 years	15	13.8
	5-10 years	15	13.8
	10-15 years	28	25.7
	15-20 years	26	23.9
	20+ years	25	22.9

2) Descriptive statistics for each variable

The descriptive statistics of the questions for each variable, based on the 5-point scale of the variables used in this study, are as follows: means and standard deviations.

Table 39. The average value per question of a variable

Variables	Survey items	Average	Standard deviation
Personal Innovation (INNO)	- I am curious about AI medical devices.	4.48	0.740
	- I am interested in using AI medical devices.	4.44	0.686
	- I try to use AI medical devices before others.	4.03	1.023
Facilitating Conditions (FC)	- I will have access to specialised training on AI medical devices.	3.92	0.862
	- I will have access to expert help if I have difficulty using the AI medical device.	3.91	0.866
	- I will receive detailed instructions on how to use the AI medical device..	3.73	0.939
Functional Excellence (FE)	- AI medical devices will enable faster and more accurate diagnosis.	3.68	0.932
	- AI medical devices will reduce the time needed to read medical images.	4.08	0.914
	- AI medical devices will reduce diagnosis and treatment time..	3.91	0.898
	- AI medical devices will provide comprehensive and sufficient information for diagnosis and treatment.	3.73	0.899
Price Value (PV)	- AI medical devices will be affordable.	2.76	0.971
	- AI medical devices will be good value for money.	3.11	0.906
	- AI medical devices will be significantly more competitive than similar products.	2.83	0.928
Perceived Usefulness (PU)	- AI medical devices will improve care.	4.04	0.652
	- AI medical devices will improve work performance.	4.06	0.664
	- The results or information presented by AI medical devices will be useful.	4.06	0.606
Perceived ease of use (PEU)	- AI medical devices will be easy to use.	3.51	0.823
	- AI medical devices will be clear and easy to use.	3.42	0.810
	- It will not take long to get used to AI medical devices.	3.34	0.929
Intention to Use (IU)	- I think I need an AI medical device.	4.22	0.712
	- I intend to continue using AI medical devices.	4.28	0.692
	- I intend to recommend AI medical devices to other healthcare providers.	4.03	0.897

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Among the items in the personal innovation variable, 'I am curious about AI medical devices' was the highest at 4.48, followed by 'I find the use of AI medical devices interesting' at 4.44, and 'I try to use AI medical devices before others' at 4.03.

The facilitating factors variables were 'I would be able to get professional training related to the AI medical device' at 3.92, 'I would be able to get expert help if I had difficulties using the AI medical device' at 3.91, and 'I would be able to get detailed instructions on how to use the AI medical device' at 3.73.

The highest score was 4.08 for "AI medical devices will reduce the time it takes to read medical images", followed by 3.91 for "AI medical devices will reduce the time it takes to diagnose and treat", 3.73 for "AI medical devices will provide comprehensive enough information to diagnose and treat", and 3.68 for "AI medical devices will enable quick and accurate diagnosis".

The highest score for the price/benefit variable was 3.11 for 'AI medical devices will provide good value for money'. The price variables for AI medical devices are lower than the other variables, with 2.83 for 'AI medical devices will be very competitive with similar products' and 2.76 for 'AI medical devices will be reasonably priced'.

The perceived usefulness variables were 4.06 for 'AI medical devices will improve work performance' and 'The results or information presented by AI medical devices will be useful', and 4.04 for 'AI medical devices will help with medical treatment'.

For the perceived ease of use variable, "AI medical devices will be easy to use" was the highest at 3.51. "Operating the functions of the AI medical device will be clear and simple" was 3.42, and "I will not need a long time to get used to the AI medical device" was 3.34.

Finally, for the intention to use variable, "I intend to use AI medical devices continuously" was the highest at 4.28. "I think I need an AI medical device" was 4.22 and "I would recommend an AI medical device to other healthcare providers" was 4.03.

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B. Analysis results

1) Analyse the reliability and validity of measures

Before the PLS structural equation model (PLS-SEM) can evaluate the structural model, the measurement model describing the latent variables must be validated. To validate the measurement model, reliability and validity analyses were conducted for each latent variable.

Reliability is a concept that determines how consistent the results are when survey respondents respond repeatedly[78]. In this study, both Cronbach's alpha and composite reliability (CR) analyses were conducted to analyse reliability. In general, exploratory studies are considered reliable when Cronbach's alpha is 0.70 or higher[79], and Composite Reliability (CR) generally applies the same criteria as Cronbach's alpha, which is 0.70 or higher[80]. Validity is a concept that determines how accurately a researcher has measured the concept they are trying to measure[78]. Validity analysis is divided into convergent and discriminant validity, where convergent validity is based on measurement reliability at the level of individual indicator variables and average variance extracted (AVE) at the level of latent variables. Measure reliability, also known as commonality, is calculated by squaring the factor loadings and is generally considered reliable if it is greater than 0.5[80].

The results of the analysis showed that the external loadings of the observed variables ranged from a low of 0.708 to a high of 0.933, which adequately explained the latent variables. Cronbach's alpha is also above 0.7 for all variables, indicating that reliability is not a problem. In addition, the conceptual reliability, composite reliability (rho_a) and composite reliability (rho_c) are both above 0.8 and the average variance extracted (AVE) value is above 0.7, indicating that they are internally consistent in reliability and convergent validity.

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Table 40. Factor analysis and reliability analysis

Latent variables	Observation variables	Outer loadings	Cronbach's alpha	CR (rho_a)	CR (rho_c)	AVE
Personal Innovation (INNO)	INNO 1	0.869	0.839	0.847	0.903	0.756
	INNO 2	0.904				
	INNO 3	0.834				
Facilitating Conditions (FC)	FC 1	0.859	0.847	0.847	0.907	0.765
	FC 2	0.877				
	FC 3	0.888				
Functional Excellence (FE)	FE 1	0.891	0.855	0.890	0.902	0.700
	FE 2	0.834				
	FE 3	0.898				
	FE 4	0.708				
Price Value (PV)	PV 1	0.749	0.791	0.840	0.876	0.704
	PV 2	0.904				
	PV 3	0.855				
Perceived Usefulness (PU)	PU 1	0.907	0.879	0.884	0.925	0.805
	PU 2	0.909				
	PU 3	0.876				
Perceived ease of use (PEU)	PEU 1	0.932	0.880	0.929	0.924	0.803
	PEU 2	0.926				
	PEU 3	0.826				
Intention to Use (IU)	IU 1	0.912	0.913	0.918	0.945	0.852
	IU 2	0.933				
	IU 3	0.924				

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Discriminant validity was determined using Fornell-Larcker and HTMT values.

The Fornell-Larcker criterion is recognised as a more conservative method than the cross-factor loading method, and discriminant validity is considered to be achieved when the square root of the average variance extracted (AVE) of a latent variable is greater than the highest of the correlation coefficients with the remaining latent variables. A discriminant validity analysis is considered valid if the AVE of each variable is greater than 0.5. As shown in <Table 41>, the square roots of the diagonal AVE values are all greater than the correlation coefficients between the variables, indicating discriminant validity.

Table 41. Fornell-Larcker criterion analysis results

	FC	FE	INNO	IU	PU	PEU	PV
FC	**0.875**						
FE	0.437	**0.836**					
INNO	0.250	0.278	**0.870**				
IU	0.470	0.512	0.558	**0.923**			
PU	0.432	0.509	0.378	0.617	**0.897**		
PEU	0.348	0.426	0.260	0.397	0.455	**0.896**	
PV	0.224	0.467	0.308	0.378	0.400	0.428	**0.839**

※ The diagonal values are the square root of the AVE. The values below the diagonal are the correlation values between the latent variables.

Using the HTMT value to assess discriminatory power is considered to be a superior discriminatory power method compared to the Fornell-Larcker criterion method and the cross-validation method. If the HTMT value is generally less than 0.9 and strictly less than 0.85, it is considered to be discriminatory. As shown in <Table 42>, all values are below 0.85, indicating that discriminant validity is assured.

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Table 42. HTMT analysis results

	FC	FE	INNO	IU	PU	PEU	PV
FC							
FE	0.513						
INNO	0.286	0.307					
IU	0.532	0.559	0.630				
PU	0.498	0.575	0.435	0.686			
PEU	0.399	0.462	0.288	0.421	0.495		
PV	0.253	0.535	0.389	0.423	0.452	0.499	

2) Structural model evaluation

In the PLS structural equation model, the structural model was assessed for multicollinearity, coefficient of determination (R^2), predictive relevance (Q^2) and effect size (f^2).

Firstly, the internal VIF values were checked to assess multicollinearity and it was found that there was no multicollinearity among the research variables in the structural model, as the internal VIF values ranged from 1.159 to 1.678 among the proposed latent variables, all of which were less than 5. The coefficient of determination (R^2) refers to the explanatory power of exogenous latent variables on endogenous latent variables, and in consumer behaviour research, if the R^2 value of an endogenous variable is above .20, the predictive ability is considered to be very high. In this study, the R^2 values were checked and all were found to have an explanatory power of 0.2 or more. Predictive fit (Q^2) assesses whether the structural model has a predictive fit for a given endogenous latent variable. If the structural model has a Q^2 greater than 0 for a given endogenous latent variable, it has a good predictive fit, and if it is less than 0, it does not have a good predictive fit. In this study, all endogenous latent variables have Q^2 values greater than 0, so the structural model has a good predictive fit.

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Table 43. R^2 and Q^2 analysis results

	R-square	R-square adjusted	Q^2predict
Intention to Use	0.563	0.537	0.449
Perceived Usefulness	0.377	0.354	0.324
Perceived ease of use	0.284	0.256	0.220

The effect size (f^2) assesses how much the exogenous latent variable contributes to the R^2 of the endogenous latent variable. An f^2 of 0.02 is considered a small effect size, 0.15 is considered a medium effect size, and 0.35 is considered a large effect size. After checking the effect size (f^2), all of them were found to be above f^2=0.02, except for personal innovation → perceived usefulness (f^2=0.007), perceived ease of use → intention to use (f^2=0.001), and price value → intention to use (f^2=0.001).

Table 44. Inner VIF and f^2 analysis results

	Inner VIF	f-square
FC → IU	1.371	0.045
FC → PU	1.264	0.064
FC → PEU	1.264	0.036
FE → IU	1.671	0.037
FE → PU	1.516	0.084
FE → PEU	1.516	0.037
INNO → IU	1.221	0.215
INNO → PU	1.159	0.052
INNO → PEU	1.159	0.007
PU → IU	1.678	0.132
PEU → IU	1.458	0.001
PV → IU	1.459	0.001
PV → PU	1.337	0.030
PV → PEU	1.337	0.077

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C. Results of hypothesis testing

(1) Results of hypothesis testing

To test the hypotheses of this study, PLS analysis was performed using Smart PLS version 4.0. The bootstrap method (5,000 repeated samples) was used for path coefficient estimation and significance testing, and a one-tailed test was applied. It is generally recommended to perform bootstraps for 5,000 iterations[80].

PLS is concerned with predictions between concepts, and bootstrapping is a technique for predicting parameters. Bootstrapping is a non-parametric method for assessing sampling error in data obtained from data without the assumption of a probability distribution, and is used to derive t-values through path analysis. The value of the path coefficient (original sample) represents the ratio of the change in the dependent variable to the change in the independent variable, and the standard deviation represents the standard error of the sample mean distribution, which indicates the precision and stability of the parameter estimate. Finally, whether the hypothesis is accepted or rejected is expressed by the t-value, which is calculated by dividing the path coefficient value by the standard deviation. A t-value of 1.96 or more is significant at a significance level of 0.05, a t-value of 2.58 or more is significant at a significance level of 0.01, and a t-value of 3.30 or more is significant at a significance level of 0.001. The hypothesis testing results of the research model are shown in <Table 45>.

Facilitating conditions positively influenced intention to use (β=0.164, p<0.035), perceived usefulness (β=0.225, p<0.007) and perceived ease of use (β=0.181, p<0.023). Functional excellence has a positive effect on intention to use (β=0.165, p<0.026), perceived usefulness (β=0.282, p<0.001) and perceived ease of use (β=0.200, p<0.024). Personal innovation has a positive effect on intention to use (β=0.338, p<0.000) and perceived usefulness (β=0.194, p<0.010), but not on perceived ease of use (β=0.076, p<0.199). Price value benefits have a positive effect on perceived usefulness (β=0.158, p<0.032) and perceived ease of use (β=0.271, p<0.001), but not on intention to use

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(β=0.022, p<0.375). Finally, perceived usefulness has a positive effect on intention to use (β=0.312, p<0.004), but perceived ease of use has no significant effect on intention to use (β=0.030, p<0.365).

Table 45. Hypothesis testing results(Path Analysis)

	Original sample	Sample mean	Standard deviation	T statistics	P values	Result
FC → IU	0.164	0.171	0.090	1.818	**0.035**	**Accept**
FC → PU	0.225	0.225	0.092	2.442	**0.007**	**Accept**
FC → PEU	0.181	0.180	0.091	1.989	**0.023**	**Accept**
FE → IU	0.165	0.163	0.085	1.939	**0.026**	**Accept**
FE → PU	0.282	0.290	0.094	2.998	**0.001**	**Accept**
FE → PEU	0.200	0.203	0.101	1.980	**0.024**	**Accept**
INNO → IU	0.338	0.340	0.062	5.446	**0.000**	**Accept**
INNO → PU	0.194	0.189	0.083	2.333	**0.010**	**Accept**
INNO → PEU	0.076	0.077	0.090	0.844	0.199	Reject
PV → IU	0.022	0.026	0.070	0.320	0.375	Reject
PV → PU	0.158	0.163	0.085	1.852	**0.032**	**Accept**
PV → PEU	0.271	0.274	0.090	3.003	**0.001**	**Accept**
PU → IU	0.312	0.310	0.117	2.656	**0.004**	**Accept**
PEU → IU	0.030	0.028	0.087	0.346	0.365	Reject

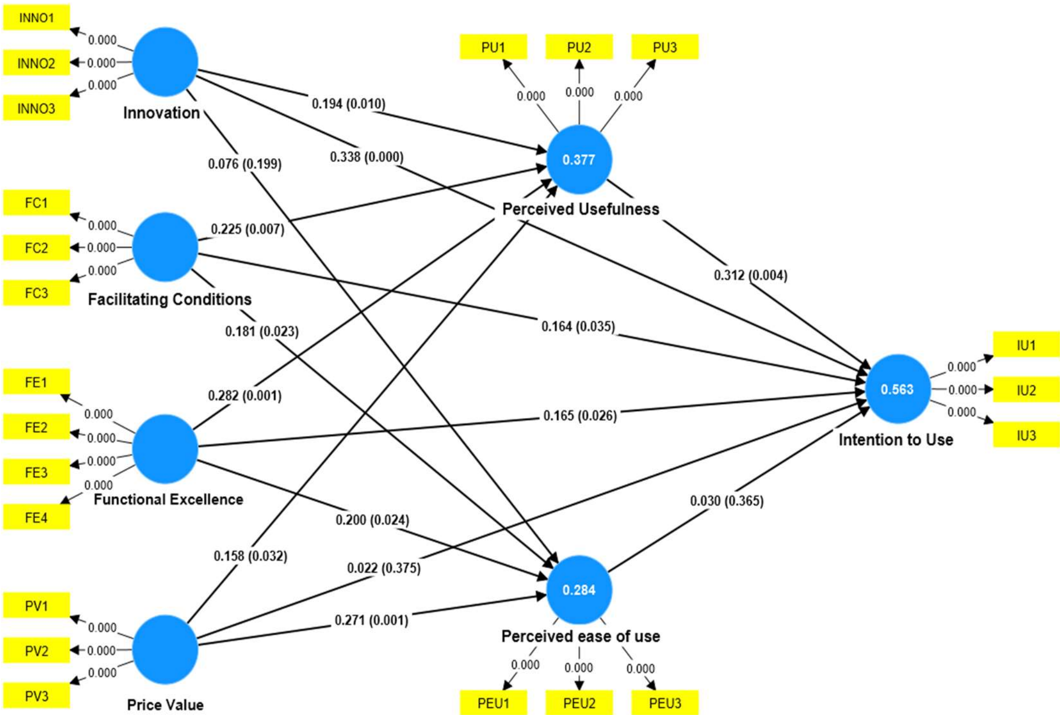

Figure 20. Hypothesis testing results (Path Analysis)

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(2) Indirect Effect Verification Results

<Table 46> is the result of estimating the indirect effect in this research model, and the specific analysis results are as follows.

Functional excellence has a significant indirect effect on intention to use via perceived usefulness (β=0.088, p=0.020). Personal innovation has a significant indirect effect on intention to use via perceived usefulness (β=0.061, p=0.046). Facilitating conditions had a significant indirect effect on intention to use via perceived usefulness (β=0.070, p=0.048). The other factors had no indirect effect.

Table 46. Indirect effect validation results

	Original sample	Sample mean	Standard deviation	T statistics	P values
FE→PU→IU	0.088	0.088	0.043	2.064	**0.020**
INNO→PU→IU	0.061	0.059	0.036	1.688	**0.046**
FC→PU→IU	0.070	0.071	0.042	1.660	**0.048**
FC→PEU→IU	0.005	0.003	0.018	0.310	0.378
INNO→PEU→IU	0.002	0.004	0.011	0.203	0.420
FE→PEU→IU	0.006	0.007	0.021	0.292	0.385
PV→PV→IU	0.049	0.050	0.033	1.492	0.068
PV→PEU→IU	0.008	0.008	0.026	0.319	0.375

(3) Moderation effect test results

In this study, we tested the moderating effect of usage experience on the relationship between personal innovation s, facilitating conditions, functional excellence and price value on usage intention among the paths in the research model. The results are presented in <Table 47>. Specifically, we found a moderating effect of experience in the path between facilitating conditions and intention to use (P=0.048). On the other hand, there was no moderating effect of experience on the paths between personal innovation, functional excellence, price value and intention to use.

<Figure 21> shows the moderating effect of experience on the path between facilitating conditions and intention to use. It can be seen that the intention to use medical AI is constant regardless of the facilitation conditions, while the intention to use medical AI increases as the facilitation conditions for receiving help and support in using medical AI increase.

Table 47. Moderation effect verification results

	Original sample	Sample mean	Standard deviation	T statistics	P values
FC → IU	-0.020	-0.011	0.149	0.132	0.448
FC → PU	0.225	0.225	0.092	2.442	**0.007**
FC → PEU	0.181	0.180	0.091	1.989	**0.023**
FE → IU	0.269	0.256	0.115	2.341	**0.010**
FE → PU	0.282	0.290	0.094	2.998	**0.001**
FE → PEU	0.200	0.203	0.101	1.980	**0.024**
INNO → IU	0.309	0.314	0.123	2.513	**0.006**
INNO → PU	0.194	0.189	0.083	2.333	**0.010**
INNO → PEU	0.076	0.077	0.090	0.844	0.199
PU → IU	0.324	0.317	0.113	2.875	**0.002**
PEU → IU	0.039	0.045	0.086	0.459	0.323
PV → IU	-0.016	-0.010	0.081	0.194	0.423
PV → PU	0.158	0.163	0.085	1.852	**0.032**
PV → PEU	0.271	0.274	0.090	3.003	**0.001**
EXP → IU	-0.079	-0.065	0.145	0.543	0.294
EXP x FC → IU	0.302	0.302	0.182	1.660	**0.048**
EXP x FE → IU	-0.157	-0.142	0.188	0.837	0.201
EXP x INNO → IU	0.010	0.004	0.156	0.065	0.474
EXP x PV → IU	0.131	0.128	0.165	0.791	0.214

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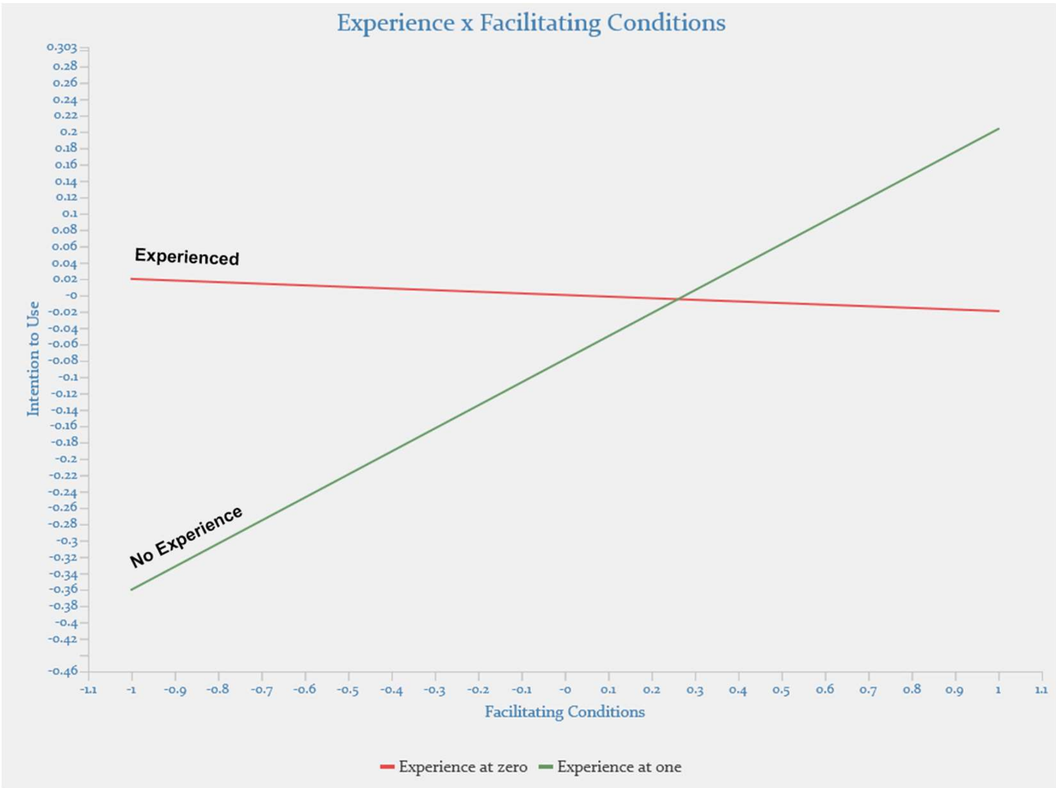

Figure 21. Moderation Effect Graph

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V. Discussion

1. Discussion on the results

This study analyses the social cost-benefit of AI in healthcare and examines the factors that influence physicians' intentions to use AI in healthcare. Here's a look at each study

A. Social cost-benefit analysis of AI in healthcare

In this study, a cost-benefit analysis was conducted to analyse the economic feasibility of medical AI, using the case of the Dr. Answer project developed between 2018 and 2020. The economic evaluation was calculated in the form of net benefits and benefit-cost ratios using the estimated cost and benefit items, and sensitivity analyses (25%, 75%) were performed to compensate for the uncertainty of the analysis.

The estimated cost of using medical AI was calculated by multiplying the price of medical AI by the number of patients for each medical AI with the price of similar products at a major hospital in Korea, which was estimated to be 10% of the cost of testing for each disease. The total cost of this study was estimated at KRW 69,534,563 thousands, of which KRW 45,801,512 thousands was the estimated cost of using medical AI and KRW 23,733,051 thousands was the government funding.

In this study, nine benefit items were derived from the literature review, including cost-benefit studies of medical services and benefit studies of medical AI. The direct benefits consisted of saved test and treatment costs, saved additional test costs, saved treatment costs such as surgery, saved hospitalization costs, saved caregiving costs and saved transportation costs. The indirect benefits consisted of patient income preservation, guardian income preservation and saved medical reading cost. In order to avoid overestimation of benefits, the analysis of benefits distinguished between prediction of onset, prediction of recurrence and diagnosis. In estimating costs and benefits, the

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economic feasibility of the project is based on the actual marketing model, so we applied the principle of estimating benefits as low as possible and costs as high as possible to be conservative.

The economic analysis of medical AI showed a net benefit of KRW 341,180,251 thousands and a benefit-cost ratio of 4.9 times. By disease, colorectal cancer, heart disease, breast cancer and paediatric rare diseases were found to be the most effective in reducing medical costs. Looking at the benefits and benefit-cost ratios for each disease, colorectal cancer (benefit KRW 68,668,007 thousands, benefit-cost ratio 4.77 times), heart disease (benefit KRW 67,617,703 thousands, benefit-cost ratio 5.21 times), breast cancer (benefit KRW 65,015,600 thousands, benefit-cost ratio 4. 96 times), paediatric rare diseases (benefit KRW 44,638,237 thousands, benefit-cost ratio 10.86 times), epilepsy (benefit KRW 31,643,226 thousands, benefit-cost ratio 7.33 times), Cardiocerebrovascular diseases (benefit KRW 30,509,896 thousands, benefit-cost ratio 2. 58 times), dementia (benefit KRW 26,050,116 thousands, benefit-cost ratio 6.09 times) and prostate cancer (benefit KRW 7,038,034 thousands, benefit-cost ratio 1.55 times).

Through AI, the medical cost reduction effect of onset prediction was high. Breast cancer prediction (benefit KRW 62,477,977 thousands, benefit-cost ratio 5.58 times), colorectal cancer prediction (benefit KRW44,528,502 thousands, 23.62 times), heart disease prediction (benefit KRW 37,596,545 thousands, benefit-cost ratio 3.82 times), and epilepsy seizure prediction (benefit KRW 28,634,041 thousands, benefit-cost ratio 11.74 times). It can be seen that outbreak prediction has a high benefit in terms of reducing medical costs by predicting diseases in advance to prevent unnecessary tests and medical treatment. In the case of diagnostic AI, it can be seen that AI with the concept of disease prediction can reduce medical costs in the case of colonoscopy diagnosis (benefit of KRW 17,494,816 thousands, benefit-cost ratio 1.57 times) and early diagnosis of dementia (benefit of KRW 26,049,549 thousands, benefit-cost ratio 6.09 times). In addition, medical AI is expected to drastically reduce diagnosis time, considering that rare genetic diseases in children require more than eight diagnoses over an average of five

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years to be accurately diagnosed.

The number of diseases for which medical AI is being applied is increasing, and research is also being conducted at home and abroad to reduce costs. Considering that various demonstration projects to support the application of medical AI in hospitals are underway in Korea, the impact of medical AI on reducing medical costs is expected to be greater than it actually is.

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B. Research on intention to use AI in healthcare

This study was conducted for about two weeks, from 8 May to 19 May 2023, using an online method among medical staff to analyse the factors that influence their intention to use medical AI. A total of 114 questionnaires were collected and the results of 109 questionnaires were used for analysis, excluding 5 questionnaires that could not be completed.

This study tested 14 hypotheses about whether four variables - personal innovation, facilitating conditions, functional excellence, and perceived usefulness and perceived ease of use - have a significant impact on medical staff's intention to use medical AI. Eleven of the hypotheses were accepted and the remaining three were rejected.

Personal innovation was found to have a significant effect on perceived usefulness and intention to use healthcare AI, but not on perceived ease of use. This means that individual curiosity and early adopter tendencies are important factors in perceiving the benefits of using healthcare AI as a new technology, such as convenience and effectiveness of care, but are not important factors in facilitating understanding and adoption of healthcare AI use. In other words, personal innovation is a factor that makes people feel that healthcare AI is necessary and convenient for medical care, but it is limited in terms of feeling that they can easily and quickly understand the functions of healthcare AI.

Facilitating conditions were found to have a significant effect on perceived usefulness, perceived ease of use and intention to use healthcare AI. This suggests that the level of facilitating conditions is an important factor in the use of healthcare AI, as it relates to the belief that the technology can help with the use of healthcare AI, malfunctions, or inexperience.

Functional excellence was found to have a significant impact on perceived usefulness, perceived ease of use and intention to use. Unlike general digital healthcare products used by individuals, medical AI plays an important role in supporting and assisting medical staff in healthcare institutions. Therefore, it is essential to continuously verify the

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accuracy of the algorithms from the development process to the approval stage by the Ministry of Food and Drug Safety. In addition, the subjective and objective evaluation of medical AI functions from the perspective of medical staff using it in practice is also an important factor, and such functional excellence makes medical staff believe that medical AI is useful and convenient to use, which ultimately leads to its use. Accordingly, the better the functioning of medical AI, the higher the perceived usefulness, perceived ease of use and willingness to use it in medical practice.

Price value was found to have a significant effect on perceived usefulness and perceived ease of use, but not on intention to use. Medical AI can only be used in hospitals if it is covered by health insurance. As of September 2022, 139 medical AIs have been approved by the Ministry of Food and Drug Safety, but only four are currently eligible for non-payment under the new medical technology moratorium. Various demonstration projects are currently being promoted by the government, but the demonstration projects are not for hospitals to purchase medical AIs, but for the government to help medical institutions with the implementation costs of using medical AIs. Therefore, there are limitations for medical staff to compare whether the price of medical AI is reasonable compared to the function of medical AI, whether the value of the product is high, and whether it is more competitive than existing products. Considering that it is not easy for AI to be used in the medical field unless there is separate compensation for medical AI, the correlation between price value and intention to use medical AI is not high in the current situation.

Perceived usefulness has a significant effect on intention to use, but perceived ease of use has no significant effect on intention to use. Perceived usefulness is the belief that healthcare AI will help with care, improve performance and provide useful information. As there are many studies on perceived usefulness of healthcare AI, it can be concluded that the perceived usefulness of healthcare AI is very high, which has a positive effect on intention to use. Perceived ease of use is the belief that healthcare AI will be easy to use, clear and simple to operate. Although previous studies have shown that easy

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understanding of product and service functions and convenience have a positive effect on intention to use, it is assumed that medical AI will be used for patient care, as opposed to products and services that provide personal pleasure and enjoyment. Therefore, it can be seen that the ease of understanding and convenience of using medical AI are not important factors in determining intention to use.

Finally, we tested the moderating effect of experience on the relationship between personal innovation, facilitating conditions, functional excellence and price value on intention to use and found that facilitating conditions had a moderating effect on experience. Alba and Hutchinson (1987) also found that more experience leads to greater familiarity with the technology and a knowledge structure that facilitates user learning, which can reduce user dependence on external support[73]. It is expected that doctors with experience of using medical AI will have no fear of using medical AI, whereas doctors without experience will have fear factors such as unexpected errors when using medical AI. Therefore, inexperienced medical staff may be able to reduce their anxiety about using medical AI by strengthening the facilitating conditions to receive help and support from hospitals and technical staff when using medical AI.

2. Limitations of the research

Firstly, this study is of practical importance because it objectifies the economic impact of AI medical devices. However, there are also some limitations to the social cost-benefit analysis of medical AI. In order to estimate costs and benefits accurately, sophisticated estimation methods and a wealth of reliable data are essential. However, not only are data on the price and effectiveness of medical AI still scarce, but their use is also very limited. Therefore, the limitations of this study due to data constraints are as follows.

First, the per capita transportation costs, average hourly wage, medical cost savings and hospital days saved, which were estimated using secondary data sources in the benefit analysis, have the limitation that there is uncertainty in the benefits by using indirect methods such as citing the results of previous studies or secondary data. In the case of transport costs, the costs may vary depending on the residence of the patient and guardian, and there may also be differences depending on the mode of transport. This study assumes that transport costs are the same for all, despite differences in residence and mode of transport, and uses transport costs from secondary sources to inform the analysis. The hourly wage of patients and caregivers may also vary depending on their income level, but this study used the average hourly wage published by Statistics Korea for the analysis. Therefore, for an accurate analysis of the economic impact of medical AI in the future, it will be necessary to elaborate the benefits by creating more specific impact indicators.

Second, to avoid overestimating the benefits of each medical AI, this study minimizes the benefits and applies them differently according to onset prediction, relapse prediction and diagnosis. However, the benefits will vary depending on the patient's situation, such as disease status and postoperative course. For example, even if the onset of a disease is predicted in advance by medical AI, patients may incur additional medical tests, treatment costs such as surgery, and hospitalization costs. However, this study was limited in its ability to take into account all the factors of benefit depending on the patient's health

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situation. Although this study estimated the benefits of using 19 medical AIs, it is possible to extend the use to additional or related diseases depending on the patient's health status and the characteristics of the medical AI. Therefore, if the benefits of application are expanded and the benefits of other diseases are considered, the actual social benefits of using medical AI are expected to be very large.

Third, there is no specific pricing system for medical AI, so we estimated the cost of use by using figures and the prices of some similar products. There are many limitations in estimating the price of medical AI, as the use of medical AI in medical institutions is not high at present. There are also limitations in applying the prices of medical AI covered by the US NTAP due to the differences in the medical systems in Korea and the US. In addition, companies' pricing systems for medical AI vary from hospital to hospital and country to country, even for the same medical AI, and it is difficult to calculate a clear price due to differences in application methods. Further research and guidance is needed on the billing system for medical AI in Korea. It is also necessary to determine whether the actual medical costs are reduced or increased, and whether the clinical improvement effect is outstanding, after a certain period (2-3 years) after applying separate compensation for innovative digital technologies, such as the case of the United States, which applies fee-for-service as a conventional method and adds a supplemental payment to the established existing fee, and re-determine whether to pay (or add a supplemental payment) by integrating it into the basic fee (including recalculation)[29].

Next, there are limitations to the analysis of factors influencing the use of medical AI by medical staff.

First, due to the small sample size of the survey, it was not possible to analyse the differences in factors affecting the intention to use medical AI according to the characteristics of the medical staff (gender, age, medical department, years of service, etc.). Depending on the characteristics of the medical staff using medical AI, the important usage factors may differ and the specific requirements may differ accordingly. In future studies, it is necessary to analyse the influencing factors on the intention to use medical AI by the characteristics of the medical staff, and to conduct further research on the intention to use medical AI by gender, medical department, years of service, etc.

Second, this study was not able to analyse the factors that influence the intention to use medical AI, such as the concerns that medical staff may have when using medical AI, security issues for personal medical information, and legal restrictions. According to a survey of medical staff conducted by the Korea Healthcare Industry Promotion Agency, the top three concerns regarding the adoption of digital healthcare were the risk of errors and medical accidents (65.2%), the protection/security of personal medical information (16.5%), and healthcare-related legal regulations (7.2%). Future research needs to analyse the concerns of healthcare professionals[81].

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VI. Conclusion

This study examines the economic feasibility of medical AI through a social cost-benefit analysis and analyses the factors that influence physicians' intentions to use AI.

The economic analysis of medical AI was conducted by reviewing existing literature and analyzing secondary data to confirm the economic feasibility. The time of the economic analysis was 2020, the end of the project, and the analysis period was one year. The economic feasibility was assessed by estimating the input costs and benefits of the project from a societal perspective. To avoid overestimating the benefits, a conservative assessment was made by applying differential benefits according to the functional characteristics of each of the 19 medical AIs. In estimating costs and benefits, the economic feasibility of the project is based on the actual commercialization model, so we applied the principle of estimating benefits as low as possible and costs as high as possible to ensure a conservative review. The results of the cost-benefit analysis are as follows.

First, the costs were estimated as the development costs and the expected costs of using medical AI. The government funding for the development of Dr. Answer was KRW 28 billion from 2018 to 2020, excluding the demonstration budget, and KRW 23.7 billion, excluding KRW 4.3 billion for the development of a common platform and business operation costs not directly related to the development of medical AI. The estimated cost of using medical AI for each disease is based on the number of MRI, CT and PET scans, and 10% of this number is estimated as the price of medical AI. The estimated price was used because the current billing system for medical AI is not established and there are not many actual cases of its use in hospitals. Accordingly, the total cost was estimated to be KRW 69,534,563 thousands.

Second, when we look at the benefits and benefit-cost ratios for each disease, we find that Cardiocerebrovascular disease (benefit KRW 30,509,896 thousands, benefit-cost ratio of 2.58 times), heart disease (benefit KRW 67,617,703 thousands, benefit-cost ratio

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of 5.21 times), breast cancer (benefit KRW 65,015,599 thousands, benefit-cost ratio of 4.96 times), colorectal cancer (benefit KRW 68,668,007 thousands, benefit-cost ratio of 4.77 times), prostate cancer (benefit KRW 7,038,034 thousands, benefit-cost ratio of 1.55 times), dementia (benefit KRW 26,049,549 thousands, benefit-cost ratio of 6.09 times), epilepsy (benefit KRW 31,643,226 thousands, benefit-cost ratio of 7.33 times) and rare genetic diseases in children (benefit KRW 44,638,237 thousands, benefit-cost ratio of 10.87 times).

Third, the cost-benefit analysis showed a net benefit of KRW 341,180,251 thousands and a benefit-cost ratio of 4.9 times, demonstrating economic feasibility. When the number of eligible patients was adjusted to 25% and 75%, the net benefit was KRW 170,590,125 thousands and the cost-benefit ratio was 3.66 times, and the net benefit was KRW 511,770,377 thousands and the cost-benefit ratio was 5.54 times.

We then used Smart PLS 4.0 to analyze the factors influencing physicians' intention to use AI. We analyzed the association between variables using a structural equation model. The results of the study are as follows.

First, the survey was conducted online for medical staff for about two weeks from 8 May to 19 May 2023. A total of 114 questionnaires were collected and 109 questionnaires were used in the analysis, excluding five that could not be completed.

Secondly, 14 hypotheses were tested to determine whether the four variables of personal innovation, facilitating conditions, functional excellence and price value, as well as perceived usefulness and ease of use, have a significant impact on medical staff's intention to use medical AI. As a result of the test, 11 hypotheses were accepted except for three hypotheses that there is a positive effect between personal innovation and perceived ease of use, price value and intention to use, and perceived usefulness and intention to use.

Third, we tested the moderating effect of experience in the relationship between personal innovation, facilitation needs, functional excellence, and price value on intention to use medical AI. The results showed that intention to use medical AI was constant

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regardless of facilitation conditions, while intention to use medical AI increased as facilitation conditions for receiving organizational and technical help and support in using medical AI increased.

The results of this study show that medical AI is economically feasible with a net benefit greater than 0 and a benefit/cost ratio greater than 1, and is expected to contribute positively to reducing healthcare costs when applied in healthcare institutions. In addition, we found that personal innovation, facilitating conditions, and functional excellence are important factors in medical staff's intention to use medical AI. Based on the results of this study, we make the following recommendations for the expansion and efficient promotion of the medical AI business.

First, consider a rational reimbursement method for medical AI. The Health Insurance Guideline for AI-based Medical Technology in Imaging issued by the HIRA(Health Insurance Review & Assessment service) divides AI into four levels, from level 1 to level 4. Levels 3 and 4 are considered for separate coverage by health insurance. However, the medical AI currently being developed in Korea cannot easily meet this requirement. If there is no separate compensation for medical AI, it will be difficult for AI to be used in the medical field. Therefore, it is necessary to establish a compensation system that fits the domestic medical system based on the examples of the United States, Japan, and Germany, and to consider how to compensate medical activities using medical AI by applying a separate fee or a fee in the form of a surcharge.

Second, it is necessary to expand demonstration projects to verify the safety, clinical effectiveness and cost-effectiveness of medical AI. Currently, various demonstration projects are being supported by the Ministry of Health and Welfare, the Ministry of Science and ICT, which are also promoting the verification of the clinical value and cost-effectiveness of medical AI. However, due to the nature of the task, a large number of medical AI are not supported by the demonstration project, so it is necessary to expand the project period and budget so that many companies can benefit. This will require developing specific cost-effectiveness indicators and demonstrating the clinical value of

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medical AI.

Finally, the implications of both the positive and negative aspects of medical AI need to be closely examined. Although medical AI has positive effects, such as increasing patient satisfaction, improving the work environment of medical staff and increasing treatment efficiency, it can also have negative effects, such as problems caused by technical errors, unclear responsibilities and security issues for personal medical information. Therefore, it is necessary to closely examine the negative factors and prepare improvement measures so that medical AI can be used safely and actively in hospitals.

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Appendix : Questionnaire form

Good morning!

Thank you for taking the time to complete this survey.

This is a questionnaire for the purpose of "Research on Intention to Use Medical AI".

It will take about 10-15 minutes to complete this questionnaire and there is no right or wrong answer to any of the items in the questionnaire, so please answer all of them.

We promise that all responses to this questionnaire will be anonymized in accordance with Articles 33 and 34 of the Statistics Act and will only be used for research purposes and will not be used for any purpose other than research.

Department of Medical Device Engineering and Management,
Yonsei University
PhD Candidate Jun-young Lee
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※ For each of the following items, please place a √ to the extent that it matches your view.

<example>

Not at all. ①------- ②------ ③------ ④------ ⑤------ Very much so.

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Question 1) The following questions are related to personal innovation.

No	Questionnaire content	Not at all				Very much so
1	I am curious about AI medical devices.	①	②	③	④	⑤
2	I am interested in using AI medical devices.	①	②	③	④	⑤
3	I try to use AI medical devices before others.	①	②	③	④	⑤

Question 2) The following questions are related to facilitation conditions.

No	Questionnaire content	Not at all				Very much so
1	I will have access to specialized training on AI medical devices.	①	②	③	④	⑤
2	I will have access to expert help if I have difficulty using the AI medical device.	①	②	③	④	⑤
3	I will receive detailed instructions on how to use the AI medical device..	①	②	③	④	⑤

Question 3) The next question is related to functional excellence.

No	Questionnaire content	Not at all				Very much so
1	AI medical devices will enable faster and more accurate diagnosis.	①	②	③	④	⑤
2	AI medical devices will reduce the time needed to read medical images..	①	②	③	④	⑤
3	AI medical devices will reduce diagnosis and treatment time.	①	②	③	④	⑤
4	AI medical devices will provide comprehensive and sufficient information for diagnosis and treatment.	①	②	③	④	⑤

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Question 4) The next question is related to price Value.

No	Questionnaire content	Not at all				Very much so
1	AI medical devices will be affordable.	①	②	③	④	⑤
2	AI medical devices will be good value for money.	①	②	③	④	⑤
3	AI medical devices will be significantly more competitive than similar products.	①	②	③	④	⑤

Question 5) The following questions are related to perceived usefulness.

No	Questionnaire content	Not at all				Very much so
1	AI medical devices will improve care.	①	②	③	④	⑤
2	AI medical devices will improve work performance.	①	②	③	④	⑤
3	The results or information presented by AI medical devices will be useful.	①	②	③	④	⑤

Question 6) The following questions relate to perceived ease of use.

No	Questionnaire content	Not at all				Very much so
1	AI medical devices will be easy to use.	①	②	③	④	⑤
2	AI medical devices will be clear and easy to use.	①	②	③	④	⑤
3	It will not take long to get used to AI medical devices.	①	②	③	④	⑤

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Question 7) The following questions are related to usage intent.

No	Questionnaire content	Not at all				Very much so
1	I think I need an AI medical device.	①	②	③	④	⑤
2	I intend to continue using AI medical devices.	①	②	③	④	⑤
3	I intend to recommend AI medical devices to other healthcare providers.	①	②	③	④	⑤

□ The following are general questions for statistical purposes.

Gender	① Male ② Female
Age	① Thirties ② Forties ③ Fifties ④ Sixties
Healthcare AI enabled or not	① Yes ② No
Medical speciality	①Internal Medicine ②Surgery ③Radiology ④Paediatrics ⑤Obstetrics and Gynaecology ⑥Ophthalmology ⑦Pathology ⑧Mental Health ⑨Urology ⑩Family Medicine ⑪Emergency Medicine ⑫Rehabilitation ⑬Neurology/Neurosurgery ⑭Nuclear Medicine ⑮Dermatology ⑯Radiation Oncology ⑰Other( )
Years of service	①Less than 5 years ②5-10 years ③10-15 years ④15-20 years ⑤20+ years

Thank you so much for taking the time to complete the survey.

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Abstract (In Korean)

의료 AI의 의료진 사용 의도 요인 및 사회적 비용 편익 분석

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이 준 영

배경 : 의료 AI는 의료비를 절감시키고, 질병을 더욱 정확하고 빠르게 진단하고 있다. 이에 따라 전세계 의료AI 시장도 급속하게 성장 중이며, 개발 및 인허가 수도 우리나라뿐만 아니라 미국, 유럽 등에서도 지속적으로 증가 중이다. 그러나, AI가 의료 분야의 다양한 연구에서 효용성이 입증되고 있음에도 불구하고 의료 현장에서 AI의 활용은 여전히 저조하다. 의료 AI는 타 분야의 AI 제품과는 달리 임상적 근거 확보뿐만 아니라, 경제성 분석을 통해 비용 효과적임을 입증해야 건강보험을 적용 받을 수 있다. 또한, 의료진 사이에서 AI 기술을 받아들이는 것이 의료 AI 활성화의 핵심 요인 임에도 불구하고 이러한 태도에 영향을 미치는 요인에 대한 연구는 부족하다. 따라서, 본 연구는 의료 AI의 사회적 비용편익 분석을 통해 의료 AI의 경제성을 검증하고, 의료진의 의료 AI 사용에 영향을 미치는 요인 분석을 목적으로 하고 있다
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방법 : 경제성 분석은 2018년부터 2020년까지 추진된 Dr. Answer 프로젝트를 대상으로 비용과 편익을 추정하였다. 의료 AI의 경제성 평가를 위해, 프로젝트에 투입된 정부지원금과 의료 AI 사용 예상 가격, 그리고 그 결과 나타나는 9개의 편익(검사 및 진료비 절감, 추가 검사비 절감, 수술 등 치료비 절감, 입원비 및 간병비 절감, 교통비 절감 편익, 환자 및 보호자의 소득보전 편익, 판독료 절감 편익)을 기존 문헌고찰과 2차 자료분석을 통해 화폐단위로 추정하였다.

의료 AI 사용 의도에 미치는 영향은 109명의 의료진을 대상으로 온라인 설문을 통해 개인 혁신성, 촉진 조건, 기능 우수성, 가격 효용성, 인지된 용이성과 인지된 사용용이성이 사용 의도에 미치는 영향을 분석하였다. 또한, 의료 AI 사용 경험에 따른 조절효과를 검증하였다. 응답자의 일반적 특징은 IBM SPSS 29를 사용하여 빈도 분석을 진행하였고, 측정 항목의 신뢰도와 타당성 분석, 가설 검증은 Smart PLS 4.0을 활용하였다. 경로 계수 추정 및 유의성 검정에는 부트스트랩 방법(반복 샘플링 5,000회)을 사용하였다.

결과 : 의료 AI의 경제성 분석결과 순편익은 341,180,251천원이며, 편익/비용비는 4.9배로 산출되어 경제적 타당성이 입증되었다. 대상 환자를 25%와 75%로 조정하여 민감도를 분석한 결과, 대상 환자 수가 25%일 경우 순편익 170,590,125천원, 비용 편익비는 3.66배으로 나타났다. 또한, 대상 환자 수가 75%의 경우 순편익은 511,770,377천원, 비용 편익비는 5.54배로 산출되어 경제성이 있는 것으로 나타났다. 의료비 절감효과가 높은 Patient Journey 단계는 질병의 사전 예측을 통해 불필요한 검사 및 진료 등을 사전에 예방할 수 있는 발병 예측 단계로 나타났다. 유방암 발병예측(편익 62,477,977천원, 편익 비용비 5.58배), 대장암 발병예측(44,528,502천원, 23.62배), 심장질환 발병예측(편익 37,596,545천원, 편익 비용비 3.82배), 뇌전증 발작예측(편익

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28,634,041천원, 편익 비용비 11.74배)으로 나타났다.

의료진의 의료 AI 사용 의도에 영향을 미치는 요인 분석 결과, 개인혁신성과 인지된 사용 용이성, 가격 가치와 사용 의도, 인지된 사용용이성과 사용의도 간에는 긍정적인 영향을 미치지 않는 것으로 분석되었다. 또한, 개인 혁신성, 촉진 조건, 기능 우수성, 가격 효용성이 의료 AI 사용 의도에 미치는 영향 관계에서 사용 경험의 조절효과를 검증하였다. 검증결과, 사용경험이 있는 의료진은 촉진 조건에 관계없이 사용 의도가 일정한 반면, 사용경험이 없는 의료진은 의료 AI 사용시 조직적, 기술적 도움과 지원을 받을 수 있는 촉진 조건이 증가할수록 의료 AI의 사용 의도도 증가함을 알 수 있었다.

결론 : 의료 AI는 순편익이 0보다 크고, 편익/비용비가 1보다 커서 경제성이 있으며, 도입 확산 시 의료비 절감에 긍정적으로 기여할 것으로 예상된다. 또한, 개인 혁신성, 촉진 조건, 기능우수성이 의료 AI 사용 의도에 중요한 요인이며, 병원과 기업의 조직적이고 기술적인 도움과 지원이 의료진의 의료 AI 사용을 촉진시킴을 확인하였다.

전 세계적으로 의료 AI의 개발과 인허가가 증가하는 상황에서 현재 의료체계의 효율성을 향상시키고, 의료 AI 산업 육성을 위해 국가차원의 지속적인 지원과 제도개선이 필요하다. 이를 통해 국민건강증진 및 의료비 절감, 그리고 급속하게 성장 중인 글로벌 의료 AI 시장에서 국내 기업의 선전을 기대해 본다.

핵심되는 말 : 의료 인공지능, 경제성 분석, 비용-편익 분석, 기술수용모델, 구조방정식 모형, PLS 구조방정식