DOI 10.24412/2686-7702-2024-3-92-115

Влияние искусственного интеллекта на ключевые факторы, определяющие успех проектов в секторе здравоохранения Китая

Шах Мехмуд Ваган[1],
Мухаммад Усман Ашар[1],
Сидра Сидра[1]

[1] Сычуаньский университет, Китай

Аннотация. Правительство Китая уделяет особое внимание технологиям искусственного интеллекта (ИИ) во многих отраслях, включая здравоохранение. Успех инициатив в области ИИ зависит от внедрения и привлекательности ИИ для врачей, медсестёр, лиц, принимающих решения, и пациентов. Данное исследование направлено на изучение основных факторов при реализации инициатив в области ИИ в сфере здравоохранения. В исследовании анализируется модель принятия технологии и выявляются наиболее распространённые факторы, а также простота использования, полезность, отношение к применению ИИ и личное намерение использовать. Была проведена систематическая оценка 34 смежных исследований, опубликованных с 2020 по 2023 г., с целью выявления наиболее часто используемых элементов. В ходе исследования авторы также использовали метод структурных уравнений в частных производных с применением метода наименьших квадратов (PLS-SEM). Данные были собраны в ходе опросов 154 сотрудников сектора здравоохранения и IT в Китае. Результаты показали, что на восприятие полезности и простоты использования проектов ИИ определённо влияют управленческие, организационные, операционные факторы, а также факторы IT-инфраструктуры.

***Ключевые слова*:** управленческие факторы, фактор успеха, сектор здравоохранения, искусственный интеллект (ИИ).

***Авторы*:**

Шах Мехмуд Ваган, доктор философии (наука управления и инженерия), студент, бизнес-школа Сычуаньского университета (адрес: 610064 Китай, Чэнду, Дорога Цзюяньцяо Ванцзян, 29). ORCID: 0009-0003-0449-2655. E-mail: shah.mehmood04@outlook.com

Мухаммад Усман Ашар, магистр (деловое администрирование), студент, бизнес-школа Сычуаньского университета (адрес: 610064 Китай, Чэнду, Дорога Цзюяньцяо Ванцзян, 29). ORCID: 0009-0009-8498-4441. E-mail: usmanashar1298@gmail.com

Сидра Сидра, магистр (управление и инженерия), студент, бизнес-школа Сычуаньского университета (адрес: 610064 Китай, Чэнду, Дорога Цзюяньцяо Ванцзян, 29). ORCID: 0009-0003-1689-3296. E-mail: sidra_scu@outlook.com

Конфликт интересов. Авторы заявляют об отсутствии конфликта интересов.

Для цитирования**:** Шах Мехмуд В., Мухаммад Усман А., Сидра С. The influence of artificial intelligence on the key factors that determine the success of projects in China's health sector [Влияние искусственного интеллекта на ключевые факторы, определяющие успех проектов в секторе здравоохранения Китая] // Восточная Азия: факты и аналитика. 2024. № 3. С. 92–115. (На англ.). DOI 10.24412/2686-7702-2024-3-92-115

The influence of artificial intelligence on the key factors that determine the success of projects in China's health sector

Shah Mehmood Wagan[1],
Muhammad Usman Ashar[1],
Sidra Sidra

[1] Sichuan University, China

Abstract. The Chinese government is focusing on Artificial Intelligence (AI) techniques for numerous sectors, such as healthcare. The achievement of AI initiatives depends on the adoption and attractiveness of AI by way of physicians, nurses, decision-makers, and patients. This study aims to explore essential achievement factors for implementing AI initiatives inside the healthcare industry. The research analyzes the Technology Acceptance Model (TAM) and identifies the broadly applied factors, together with the perceived ease of use, perceived usefulness, attitude towards use, and behavioral intention to use. A systematic evaluation of 34 related studies among 2020 and 2023 was carried out to discover the most popular elements. The authors also used Partial Least Squares Structural Equation Modelling (PLS-SEM). The data was collected through surveys from 154 employees within the health and IT sectors in China. The findings demonstrated that perceived usefulness and ease of use of AI projects are definitely influenced by management, organizational, operational and IT infrastructure factors.

Keywords**:** Managerial Factors, Success Factor, health sector, Artificial Intelligence (AI).

Authors**:**

Shah Mehmood Wagan, PhD (Management Science & Engineering), Student, Business School of the Sichuan University, China (address: 29 Jiuyanqiao Wangjiang Road, Chengdu Zip: 610064 China). ORCID: 0009-0003-0449-2655. E-mail: shah.mehmood04@outlook.com

Muhammad Usman Ashar, Master (Business Administration), Student, Business School of the Sichuan University, China (address: 29 Jiuyanqiao Wangjiang Road, Chengdu Zip: 610064 China). ORCID: 0009-0009-8498-4441. E-mail: usmanashar1298@gmail.com

Sidra Sidra, Master (Management Engineering), Student, Business School of the Sichuan University, China (address: 29 Jiuyanqiao Wangjiang Road, Chengdu Zip: 610064 China). ORCID: 0009-0003-1689-3296. E-mail: sidra_scu@outlook.com

Conflict of interests. The authors declare the absence of the conflict of interests.

For citation**:** Shah Mehmood W., Muhammad Usman A., Sidra S. (2024). The influence of artificial intelligence on the key factors that determine the success of projects in China's health sector. *Vostochnaya Aziya: fakty i analitika* [*East Asia: Facts and Analytics*], 3: 92–115. DOI 10.24412/2686-7702-2024-3-92-115

1. Introduction

Artificial intelligence (AI) is revolutionizing medical care by assisting doctors in making informed decisions based on patients' health conditions and history. The Shanghai government in China is implementing AI projects to improve patient monitoring services. This research aims to identify crucial success elements for AI initiatives in the healthcare industry, using the Technology Acceptance Model (TAM) framework. AI can help predict future diseases and combat medication shortages, benefiting developed countries and supporting society. This article aims to analyze importance and success for the implementation of AI projects in China, especially in healthcare. The study uses the technology acceptance model as a theoretical framework to analyze previous studies and experimentally examine the impact of multiple external factors, including managerial, organizational, operational, strategic, and IT infrastructure challenges, that affect the acceptability and implementation of AI initiatives in healthcare. The study shows the crucial success factors of AI initiatives in China and Shanghai and adds to the body of current work in this area. The Chinese government is working towards building a fully smart country, and AI in healthcare is one of the key components of this strategy. The study will help the Chinese government achieve its AI strategies in the health domain, considering the primary determinants that have the most impact on the desired objective.

The implementation and approval of AI initiatives would broaden the scope of the healthcare sector, enabling efficient surveillance of patient situations and aiding in the management of individual health records. The acceptability and implementation of AI initiatives in the healthcare sector rely on their operational functionality and the benefits they provide. The attitudes of nurses towards AI projects have a critical role in the adoption of certain AI initiatives. The five factors (managerial, operational, strategic, IT infrastructure, and organizational) involved in implementing AI projects in the healthcare sector have not been particularly studied yet. This research looks at how AI projects in the healthcare sector are being used in Shanghai, a well-known East Asian city. The objective of the study is to fill the current vacuum in knowledge on these subjects and provide essential elements for the implementation of AI initiatives in Shanghai's healthcare system. The research seeks to examine the correlation between these crucial determinants of success and AI projects, emphasizing the significance of comprehending the factors that impact the performance of AI projects in the healthcare industry.

2. Literature Review

This study uses a technology acceptance model (TAM) to investigate the use of artificial intelligence in the healthcare industry. Most relevant studies typically examine various external factors used in the technology acceptance model (TAM) [Barber et al. 2023]. These factors include system quality, computer games, automaticity, content quality, perspective, accessibility, enjoyment, and information quality. They influence the five main pillars of the TAM for various forms of AI and user categories [Shou et al. 2020].

The data produced is deemed genuine, since it was examined via published papers using TAM's statistical meta-analysis. The TAM is widely recognized as a legitimate and resilient framework that can be used across many areas and contexts [Signorile 2005]. A moderator analysis was performed to evaluate the factors that might lead to different results, taking into account both user and use types [Song et al. 2006]. Health professionals have a crucial role in executing AI initiatives in their respective fields [Vanwelkenhuysen 1998]. The study highlights the complex relationship between AI and human life, as digital disruptions and information technologies can impact service delivery in the healthcare sector [Bongini et al. 2022]. AI projects in healthcare have been gaining popularity due to their benefits, such as improving workflows and enhancing patient care [Wilson et al. 2021]. However, some implementations fail due to stakeholder rejection. Various technological measures have been developed to address this, and the following principles are commonly used in psychology and sociology. The following theories are commonly used to study technology acceptance and use: The Uniform Theory of Acceptance and Use of Technology (UTAUT), Technology Acceptance Model (TAM), Theory of Diffusion of Innovation (DOI), Theory of Rational Action (TRA), Theory of Planned Behavior (TPB), and social psychological theory (SCT) [Selcon et al. 1995].

The main objective of the study is to identify the critical factors contributing to the success of AI systems in healthcare in Shanghai through technology adoption [Chaibdraa 1995]. The AI technologies integration across several sectors is crucial for AI projects in East Asia, particularly those focused on smart cities. The existing corpus of the study mostly focuses on the general acceptability of technology efforts, without specifically investigating the use of artificial intelligence in the healthcare sector [Shokouhyar et al. 2019].

2.1. Projects using artificial intelligence in the field of healthcare

Artificial intelligence is playing an important role in the healthcare industry, improving patient outcomes and reducing costs. The China's Shanghai Health Authority is adopting a strategy combining AI and robotics to automate healthcare processes. AI technologies like IBM Watson are being used to analyze patient data and provide solutions to biomedical problems. The objective of the China AI plan is to establish itself as the global leader in AI investments [Cheng et al. 2010].

AI systems are excelling in predictive analytics in medicine, predicting hospitalization risks and probability of mortality. AI initiatives in healthcare aid in the censorship of data, improving prognosis modeling, and enhancing computer-aided diagnosis systems [Easton & Rosenzweig 2012]. Advanced AI methods improve care quality by identifying non-obvious issues, enhancing clinical relationships, and enabling timely interventions. However, there is a deficiency in the existing body of literature about the integration of AI in the healthcare industry and user acceptance, particularly in the East Asia, where smart cities are requiring AI implementation in all sectors [Fidan et al. 2011].

2.2. The Technology Acceptance Model (TAM)

It is an essential framework for easing the acceptance of technologies in different industries [Guimaraes et al. 1995]. Based on person perceptions of usefulness and usability, system-specific and external variables have impacted it. The TAM assists in assessing customers' preparedness for embracing information systems. This is proven by Figure 1 [Hines 2019].

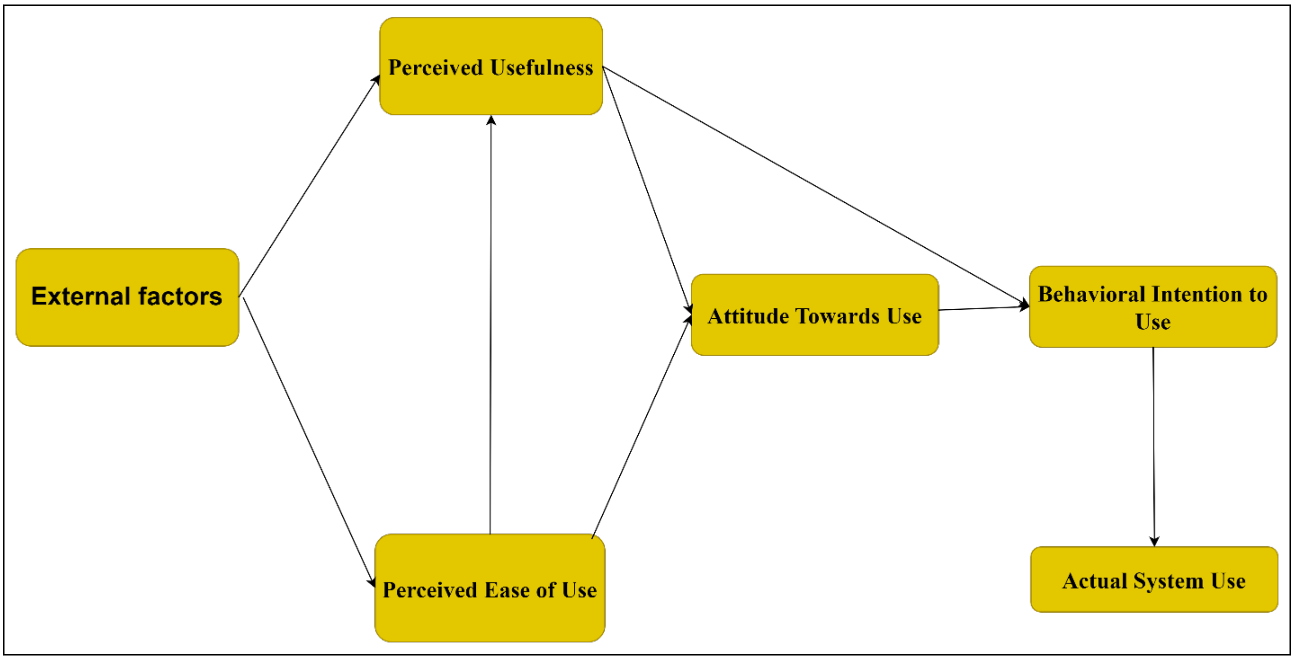

Figure 1. Actual Technology Acceptance Model (TAM).

Source: Developed by the authors.

It is a comprehensive model that examines the multitude of variables that affect the adoption and technology use throughout numerous settings [Hooda & Singla 2021]. It gives a platform for identifying the factors that affect the acceptance of technology amongst numerous user corporations. The goal of the TAM is to study the impact of external factors on attitudes, intentions, and beliefs by means of figuring out variables which have been studied within the past [Kim 2020]. [Jayasena et al. 2023] contend that the technology acceptance system takes into consideration cognitive and emotional factors that influence person corporations.

2.3. AI projects integration with the Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) is a notable prediction model that may help user organizations embrace AI initiatives in the healthcare industry [Klumpp & Zijm 2019]. Although the TAM was first utilized in the United States, it has swiftly spread over the world and has been widely adopted in this industry [Malanchini et al. 2021], [Sandkuhl et al. 2020]. Based on a comprehensive analysis of 34 publications from 2020 to 2023, [Peng & Nunes 2009] discuss that user companies often use five external factors – management, operations, planning, programming, and IT systems – to increase time awareness. One study found that IT-related management, operations, policy and strategy can enhance the field of technology applications in the healthcare sector.

3. Research model and hypothesis

The Technology Acceptance Model (TAM) is widely and effectively used in many industries, including the commercial sector, training, and healthcare. A moderator conducted a survey to identify user groups and AI users. A meta-evaluation approach is used to identify the factors affecting the adoption of AI in the healthcare industry. Typical external factors involve various aspects of IT infrastructure, operations, technology, and strategy. The ultimate goal is to develop a revised version of the TAM that incorporates key concepts and provides connections between the five key TAM variables and common external factors.

3.1. Research framework and hypothesis

The proposed framework of the modified technology acceptance model in this segment elucidated the current research project and operationalized a research model.

3.1.1. Managerial Factors

[Costantino et al. 2015] claim that in addition to the adoption of technology, managerial factors also influence a range of characteristics inside an organization. The acceptance of truth is significant in the scientific domain since it conveys gratitude and agreement with the other character. It has a positive influence on the value and usability of AI initiatives in the healthcare industry. Perceived pressure to avoid certain sports is also influenced by social norms, or the idea that other people rely on one another to behave well. As a consequence, people might also get preoccupied on their own emotional reactions and worldviews. Consequently, the following ideas might be proposed:

H1a: Managerial factor influences perceived usefulness positively.

H1b: The ease of use is positively impacted by managerial factors.

3.1.2. Organizational Factors

Organizational factors play an important role in figuring out whether people will approve or reject a new technology. Factors inclusive of supporting innovative initiatives, presenting training packages, and having neighborhood know-how make contributions to multiplied adoption. Additionally, forming international partnerships and collaborating with different organizations enhance adaptability. These factors have an effect on how people understand the artificial intelligence usefulness and the ease of use of services within the healthcare sector. As a result, subsequent stereotypes were furthered:

H2a: Organizational factors have a positive impact on perceived usefulness.

H2b: Organizational factors have a positive impact on the ease of use.

3.1.3. Operational Factors

When evaluating the efficacy and user-friendliness of artificial intelligence initiatives in the healthcare sector, perceived amusement is an essential consideration. It has a positive effect on both consumer perception of the technology and intrinsic variables. A new era device's consumer-experience entertainment can reduce the person's worries about its use. Thus, the acceptance or adoption of AI tasks is essentially determined through the diploma of perceived usefulness. Two theories may be developed from this finding, which are as follows:

H3a: Perceived usefulness has a positive impact on operational factors.

H3b: The ease of use has a positive impact on operational factors.

3.1.4. Strategic Factors

The importance of strategic factors in a business enterprise's performance with stakeholders is emphasized by [Zare 2017]. In the healthcare enterprise, consumer pride is essential to the deployment of AI tasks that prevail. The ease of use and perceived usefulness of AI initiatives in the healthcare industry are influenced by perceived satisfaction. The relevance of user satisfaction in AI project development is shown by research, which indicates that happy users are more likely to find AI projects pleasant and beneficial. Consequently, this explanation leads to the formulation of the following two hypotheses:

H4a: Perceived usefulness is positively impacted by the strategic aspect.

H4b: The strategic component facilitates the ease of use.

3.1.5. Information Technology (IT) Infrastructure factor

Hardware and IT infrastructure are examples of the physical components of a business that are referred to as system quality. It is essential in deciding how readily available, easily operated, flexible, and dependable technology is. Users of technology in the healthcare industry are affected by artificial intelligence in general. For AI initiatives in the healthcare industry to be accepted, adopted and used, certain system quality requirements must be met. The quality of the material has a big impact on whether AI projects are adopted and used. The ease of use and perceived utility of AI projects are positive outcomes. Information quality is the aspect applied to label the level of data provided by the healthcare industry AI projects. AI frameworks must provide patients and medical professionals with the fast and accurate information. The data quality has a big impact on how valuable AI projects are seen to be in the healthcare sector. These claims allow for the development of two hypotheses of the information quality impact on the ease of use and perceived usefulness of AI initiatives in the medical field.

H5a: Perceived usefulness is positively impacted by the infrastructure component.

H5b: The ease of use is positively impacted by infrastructure.

3.2. Technology Acceptance Model Constructs

The ease of use and perceived usefulness, two perceptions which are main to the TAM model, are among the broad factors of acceptance that explain user behavior.

3.2.1. Perceived ease of use (PEOU)

It contains the degree of technological sophistication and the perceived simplicity of appropriate use. The research indicates that the perception of how easy something is to use greatly affects one's desire to actually utilize it. Perceived ease of use, referring to the level of simplicity with which physicians may use AI initiatives, is a concept often employed in the healthcare industry. The following hypothesis may be framed based on the available facts:

H2a1: Perceived ease of use has a positive effect on the willingness to adopt artificial intelligence in the healthcare industry.

H2a2: Perceived ease of use has a positive effect on the perceived usefulness of using artificial intelligence in the healthcare industry.

H2a3: Perceived ease of use positively influences attitudes towards the use of AI services in the healthcare industry.

3.2.2. Perceived usefulness (PU)

In the healthcare context, perceived usefulness describes how users expect technology to enhance productivity. While physicians' perceptions of how artificial intelligence works will determine their accreditation, it can improve physician performance. Perceived benefits greatly influence attitudes towards the use of AI in healthcare.

H2b1: Perceived usefulness has a positive effect on the intention to use AI services in the healthcare industry.

H2b2: Perceived ease of use has a positive effect on the willingness to use AI in healthcare.

3.2.3. Attitude towards use (ATU)

[Bahrom, Khorma, Mohd, and Bashayreh 2011] argue that an individual's positive or negative attitudes shape their points of view and affect how they accept and use them intelligently applied to healthcare. Thus, the following hypothesis can be made:

H2c: Attitude towards artificial intelligence has a positive effect on behavioral intention to implement AI projects in the healthcare industry.

3.2.4. Behavioral intention (BI)

The study has proved that the intention to utilize AI in a certain context is strongly influenced by the goal to adopt AI project in the healthcare industry. This, in turn, significantly affects the actual use of these projects. As a result, the following hypothesis may be put forward:

H2d: The healthcare industry utilizes a system that effectively applies artificial intelligence creativities.

3.2.5. Actual system use (ASU)

[Teeroovengadum, Heeraman, and Jugurnath 2017] define system implementation as when a technology system has been implemented in its intended format by the subject and adopted by IT and medical staff. However, this theory is dependent on other theories (TAM), in particular the notion of the behavior.

H2e: The adoption of artificial intelligence products in the healthcare industry has a positive effect on the intention to use the system.

The TAM has been up to date, and the studied model and hypothesis offer many theories on its constructs. The approach primarily emphasizes organizational, managerial, strategic, operational, and IT infrastructure as the most often employed external factors. The model explores the relationship between external factors and the 5 key elements of the TAM. As seen in Figure 2, hypothesis become related to each aspect, and the findings of the exploration could be used to decide the validity and efficacy of these hypotheses.

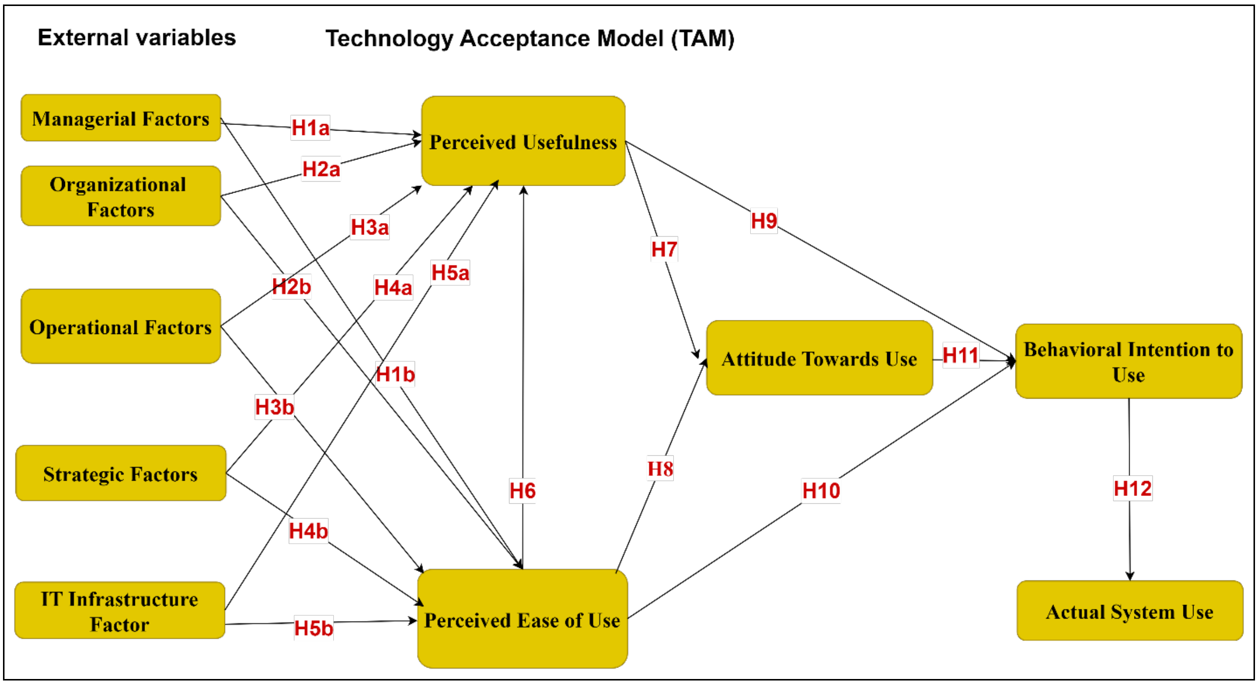

Figure 2. Modified Research Model.

Source: Developed by the authors.

4. Research Methodology

The acceptance and adoption of artificial intelligence health initiatives are investigated in this study applying the Technology Acceptance Model (TAM) paradigm. It recognizes external factors, such as IT infrastructure and managerial, operational, organizational, and strategic components, within the fields of training, IT, healthcare, and business. In order to offer thorough causes on survey shape and design, the studies use the Structure Equation Model for replies to online questionnaires.

4.1. Research design

Two alike kinds of research designs have been used to determine the essential components of success for jobs using AI in the healthcare industry. The survey design is the first kind, while the meta-evaluation design is the second. The following provides full details for both types.

4.2. Survey Design

Quantitative primary data from 154 individuals from different companies were gathered for this research using a survey approach. Understanding employee attitudes regarding artificial intelligence initiatives in the IT and health areas was the major goal of the study. Researchers benefit from the survey research design since it measures respondents' attitudes and reveals important success factors impacting the execution of AI projects.

4.3. Meta-Analysis Design

By increasing the sample size and conforming to the study's scope, the meta-analysis design structure contributes to a fresh synoptic reasoning perspective of the issue. It assists in analyzing discrepancies in research results between 34 studies, increasing precisions, and calculating implications. Inadequate data gathering, however, may jeopardize the validity and applicability of the study's conclusions. More divergent results, according to [Nardi 2018], make it difficult to justify interpretations.

With a specific importance on the project staff and owners' attitudes, the research study attempts to examine the success elements of AI initiatives in the healthcare industry. An online survey questionnaire was used for the research, which was carried out in Shanghai, China. Healthcare workers' attitudes have a big impact on whether or not they are willing to include AI systems into patient treatment regimens.

4.4. Methodology Challenges

Since there had not been any prior reliable studies on the successful execution of AI projects in the healthcare industry, the study encountered difficulties in gathering data and finding sources. Due to their hectic schedules and emergency procedures, the research also had trouble finding interested doctors and project managers at Shanghai hospitals to participate in interviews.

4.5. Sample description

154 surveyors participated in this research, which focused on Shanghai's IT and medical personnel. For the online poll, doctors from Changning Hospital, Pudong Hospital, and Jing'an Hospital were chosen. Individual judgment was employed in the purposeful sampling process to choose participants. The study's objective was to provide precise information for a particular use.

4.6. Methods and Tools for Data Collection

The validity and reliability of measurement model were assessed using Structural Equation Modeling, which replaced the prior path model, utilizing an online questionnaire survey to gather quantitative data for this research.

4.7. Study Instrument

To evaluate research hypotheses on the Technology Acceptance Model constructs, a survey instrument was created to assess the constructions by using a diverse set of questions derived from the five factors seen in Table 1.

Table 1. Study Factors

PART	Factors	Number of questions
3	Operational Factors	2
2	Managerial Factors	3
6	Organizational Factors	4
5	IT Infrastructure Factors	4
4	Strategic Factors	2

Source: Developed by the authors.

4.8. Survey Structure

Crucial success factors for implementing AI initiatives in the healthcare sector were gathered for this research study via a questionnaire survey. The survey was comprised of six sections: demographics, IT infrastructure factors, organizational factors, managerial considerations, operational aspects, and strategic factors. The survey had 28 questions with multiple choice answers on a 5-point Likert scale.

4.9. Ethical consideration

In order to guarantee accurate and legitimate research results, this study focuses on ethical issues and adherence to human standards of ethics. Through the research, the healthcare systems in Shanghai and other parts of China will be improved by identifying key determinants for successfully applying AI projects. The survey results will use the technological acceptance model to examine the factors for applying AI projects in the healthcare industry in Shanghai, therefore addressing the study questions. Furthermore, the findings will investigate the correlation between these characteristics and AI initiatives.

5. Results

5.1. Descriptive Statistics

The study results from an online survey questionnaire show (see Table 2) that within total of 154 participants this study recruited, 74 % are young professionals with a high acceptance of new technologies; 16 % are middle-aged professionals with rich work experience, and 10 % are senior professionals who may be more conservative about new technologies. 39 % of the total number of people are directly involved in medical services and have a deep understanding of the medical applications of AI technology; 26 % are direct executors of medical services and have practical experience in using AI technology;

19 % of the overall count of individuals are accountable for the advancement, maintenance and optimization of AI systems; while 15 % are responsible for formulating medical policies and promoting the applying of AI projects. 7 % of the total number of people are basic medical workers or junior IT personnel. They account for 39 % of the total number of people and are the backbone of the medical and IT fields. 54 % are senior medical and IT professionals, who have a high acceptance of new technologies. 13 % of the total number of employees are full of curiosity and desire to learn new technologies; 39 % have some work experience and are more receptive to new technologies; 19 %, or senior employees, are cautious about new technologies; 29 % are senior professionals, who have a more comprehensive assessment of new technologies. 84 % of the total population believe that AI will greatly improve the efficiency and quality of medical services; 12 % are cautiously optimistic about AI technology and need to further observe its actual effects, while 4 % have complaints about AI technology and are concerned about its potential risks and impacts. Figure 3 shows a pie chart for occupational distribution and views on AI in the medical field.

Table 2. Descriptive statistics.

Statistical indicators	Frequency	Percentage
Total number of participants	154	
Age distribution		
– 25 to 34 years old	114	74
– 35 to 44 years old	25	16
– Over 45 years old	15	10
Occupational Distribution		
– Doctor	60	39
– Nurse	40	26
– IT Professionals	30	19
– Management staff	24	15
Education		
– College degree and below	10	7
– Undergraduate	60	39
– Master degree or above	84	54
Years of working experience		
– 1 to 3 years	20	13
– 4 to 7 years	60	39
– 8 to 10 years	30	19
– 10 years or more	44	29
Views on AI in the medical field		
– Very supportive	130	84
– Support but need to observe	18	12
– Unsure/Disagree	6	4

Source: Developed by the authors.

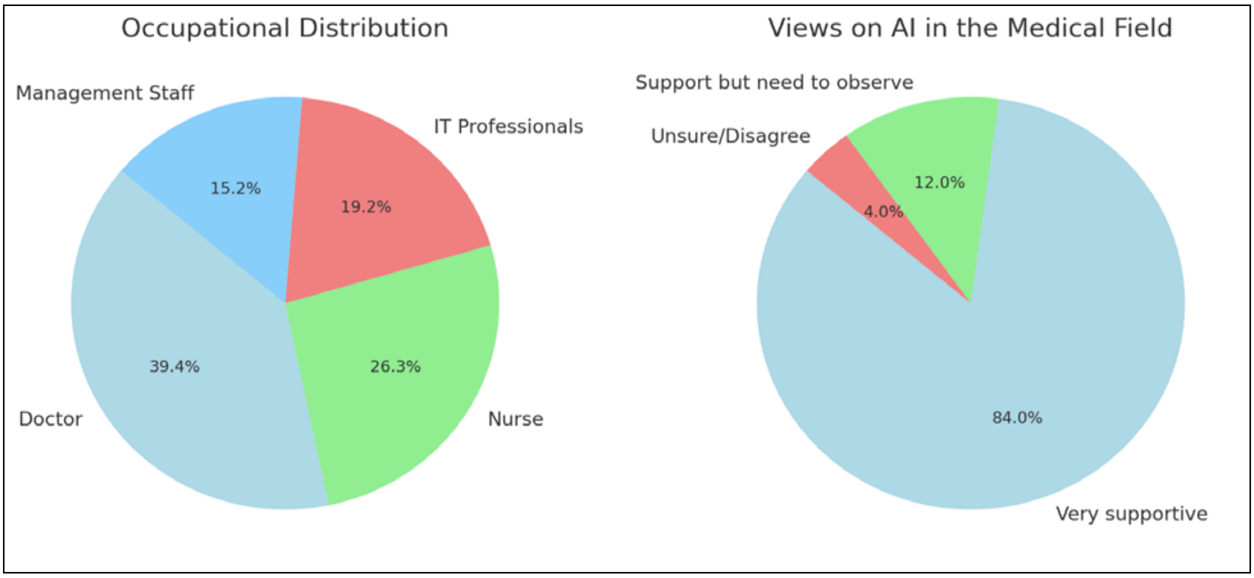

Figure 3. Pie chart for occupational distribution and views on AI in the medical field.

Source: Developed by the authors.

5.2. Questionnaire Pilot Study

The reliability of a questionnaire for medical and IT workers at health facilities in Shanghai was evaluated via a pilot study. By using Cronbach's alpha, the TAM internal reliability constructs were assessed. All constructs exhibited reliability coefficients over 0.70, suggesting their high level of dependability.

5.3. Methodology for Partial Least Squares analysis

5.3.1. Evaluation of the measuring model (Outer model)

This study uses smart PLS software to develop Partial Least Squares Structural Equation Modeling (PLS-SEM) application due to user-friendly interface and advanced reporting features. Relationships among latent constructs are described using a measurement model and indicators between. To assess the efficiency of the model, [Chin 1998] suggests convergent and discriminant validity. Discriminant validity establishes evidence of difference, and convergent validity establishes evidence of theoretical similarity.

5.3.2. Convergent validity

The research included two methods to assess convergent reliability: calculating composite reliabilities and examining the loadings of individual measurements in Table 3. To establish convergent validity, the Smart PLS 4 Partial Least Squares (PLS) technique was used. Crucial information on loadings, t-values, weights, average variance extracted (AVE), and overall reliability for each item were obtained from the first boot trapping PLS method. This operation included 315 samples. With individual scores ranging from 0.777 to 0.922, the findings demonstrated an acceptable internal consistency with a composite reliabilities rating of 0.70.

Table 3. Results of convergent validity (Factor loading, composite reliability, Cronbach's Alpha, >= 0.70 & AVE > 0.5) guarantee satisfactory values.

Constructs	Items	Factor Loading	Cronbach's Alpha	CR	AVE
Managerial factors	MG1	0.896	0.827	0.897	0.869
	MG2	0.983			
	MG3	0.796			
	MG4	0.902			
	MG5	0.823			
Organizational factors	OF1	0.862	0.839	0.856	0.638
	OF2	0.915			
	OF3	0.791			
	OF4	0.935			
	OF5	0.865			
Operational factors	PF1	0.762	0.902	0.786	0.832
	PF2	0.915			
	PF3	0.912			
	PF4	0.878			
	PF5	0.769			

Constructs	Items	Factor Loading	Cronbach's Alpha	CR	AVE
Strategic factors	ST1	0.897	0.762	0.769	0.725
	ST2	0.942			
	ST3	0.713			
	ST4	0.793			
	ST5	0.852			
IT Infrastructure factor	ITF1	0.796	0.789	0.875	0.841
	ITF2	0.846			
	ITF3	0.798			
	ITF4	0.857			
	ITF5	0.926			
Perceived Usefulness	PD1	0.934	0.893	0.845	0.821
	PD2	0.826			
	PD3	0.794			
Perceived Ease of Use	PEU1	0.988	0.793	0.852	0.616
	PEU2	0.904			
	PEU3	0.885			
Attitude towards use	ATU1	0.845	0.812	0.843	0.754
	ATU2	0.912			
	ATU3	0.763			
Behavioral intention to use	BIU1	0.834	0.912	0.764	0.867
	BIU2	0.876			
	BIU3	0.834			
Actual System Use	ASU1	0.907	0.912	0.891	0.792
	ASU2	0.934			

Source: Developed by the authors.

5.3.3. Discriminant validity

Discriminant validity is the process of distinguishing a particular construct from other constructs in a research paradigm. This study used two methods to assess discriminant validity: calculating correlations between measurement items and latent variable measures and examining the retrieved mean differences. The analysis indicated that all measurement items had significant weights based on their latent components, with AVE values ranging from 0.837 to 0.926 because each concept had significant variance among the measurements, this indicates that Table 4 has definite discrimination.

5.3.4. Heterotrait-Monotrait Ratio of Correlations (HTMT)

Recently, a new technique for evaluating discriminant validity in PLS-SEM has been devised, which makes use of the Heterotrait-Monotrait ratio of the correlations (HTMT) in Table 5. It is believed to be more actual than more traditional methods like the Fornell-Larcker method and partial cross-loadings in Table 6. It is correlated with the mean of correlations between monotrait and heteromethod. Significant correlations between model constructs are indicated by values below 1, while values above 1 indicate discriminant validity. Many studies advise a threshold of 0.85 or 0.90. A higher variance between each construct's results indicates discriminatory validity.

Table 4. The Scale of Fornell-Larcker.

	Actual System Use	ATU	BIU	ITF	MG	PF	PEU	PD	ST	OF
Actual System Use	**0.913**									
ATU	0.426	**0.879**								
BIU	0.312	0.397	**0.856**							
ITF	0.167	0.264	0.235	**0.865**						
MG	0.312	0.213	0.313	0.225	**0.884**					
PF	0.122	0.128	0.247	0.524	0.269	**0.849**				
PEU	0.118	0.168	0.115	0.656	0.287	0.423	**0.918**			
PD	0.076	0.248	0.119	0.285	0.326	0.489	0.675	**0.846**		
ST	0.039	0.243	0.314	0.458	0.316	0.652	0.364	0.542	**0.869**	
OF	0.176	0.413	0.475	0.522	0.624	0.675	0.428	0.546	0.537	**0.863**

Source: Developed by the authors.

Table 5: Cross-loading Results.

	Actual System Use	ATU	BIU	ITF	MG	PF	PEU	PD	ST	OF
ASU1	**0.907**	0.473	0.912	0.082	0.021	0.105	0.024	0.073	0.045	0.134
ASU2	**0.934**	0.453	0.686	0.027	0.015	0.144	0.027	0.064	0.047	0.154
ATU1	0.254	**0.845**	0.341	0.067	0.026	0.063	0.148	–0.042	0.073	0.034
ATU2	0.287	**0.912**	0.474	0.031	0.022	0.005	0.16	0.057	0.044	0.017
ATU3	0.579	**0.763**	0.667	0.038	0.024	0.004	0.125	0.053	0.009	0.034
BIU1	0.556	0.726	**0.834**	0.075	0.031	0.05	0.135	0.137	0.087	0.013
BIU2	0.475	0.512	**0.876**	0.116	0.023	0.094	0.045	0.124	0.052	0.104
BIU3	0.495	0.535	**0.834**	0.072	0.012	0.054	0.022	0.057	0.024	0.114
ITF1	0.028	0.082	0.015	**0.796**	0.256	0.453	0.547	0.574	0.448	0.381
ITF2	0.087	0.014	0.082	**0.846**	0.18	0.356	0.623	0.582	0.375	0.423
ITF3	0.085	0.038	0.042	**0.798**	0.135	0.435	0.562	0.474	0.248	0.403
ITF4	0.028	0.082	0.015	**0.857**	0.015	0.144	0.027	0.064	0.047	0.154
ITF5	0.087	0.014	0.082	**0.926**	0.026	0.063	0.148	–0.042	0.073	0.034
MG1	0.023	0.015	0.021	0.213	**0.896**	0.354	0.287	0.276	0.274	0.551
MG2	0.058	0.027	0.043	0.169	**0.983**	0.167	0.224	0.243	0.324	0.524
MG3	0.029	0.029	0.07	0.192	**0.796**	0.283	0.16	0.265	0.372	0.526
MG4	0.023	0.015	0.021	0.213	**0.902**	0.031	0.05	0.135	0.137	0.087
MG5	0.018	0.056	0.023	0.087	**0.823**	0.144	0.027	0.064	0.047	0.154

	Actual System Use	ATU	BIU	ITF	MG	PF	PEU	PD	ST	OF
PF1	0.127	0.012	0.069	0.453	0.201	**0.762**	0.367	0.263	0.363	0.623
PF2	0.132	0.013	0.036	0.495	0.177	**0.915**	0.411	0.356	0.583	0.631
PF3	0.057	0.017	0.02	0.403	0.347	**0.912**	0.252	0.426	0.676	0.432
PF4	0.018	0.056	0.023	0.087	0.014	**0.878**	0.042	0.113	0.009	0.526
PF5	0.035	0.035	0.562	0.085	0.038	**0.769**	0.313	0.485	0.433	0.069
PEU1	0.112	0.014	0.079	0.652	0.287	0.362	**0.988**	0.654	0.368	0.442
PEU2	0.042	0.113	0.009	0.526	0.24	0.37	**0.904**	0.532	0.234	0.264
PEU3	0.313	0.485	0.433	0.069	0.024	0.041	**0.885**	0.064	0.041	0.016
PD1	0.074	0.023	0.054	0.581	0.183	0.427	0.546	**0.934**	0.356	0.431
PD2	0.034	0.034	0.043	0.504	0.315	0.341	0.423	**0.826**	0.423	0.439
PD3	0.107	0.054	0.042	0.556	0.312	0.462	0.52	**0.794**	0.537	0.515
ST1	0.013	0.017	0.025	0.231	0.215	0.452	0.225	0.353	**0.897**	0.394
ST2	0.075	0.025	0.018	0.363	0.305	0.576	0.238	0.412	**0.942**	0.458
ST3	0.007	0.032	0.016	0.418	0.147	0.514	0.374	0.464	**0.713**	0.352
ST4	0.074	0.023	0.054	0.581	0.183	0.427	0.546	0.034	**0.793**	0.032
ST5	0.057	0.017	0.02	0.403	0.347	0.012	0.252	0.025	**0.852**	0.031
OF1	0.104	0.026	0.072	0.274	0.534	0.266	0.268	0.373	0.283	**0.862**
OF2	0.142	0.032	0.054	0.316	0.651	0.402	0.264	0.414	0.326	**0.915**
OF3	0.116	0.014	0.024	0.512	0.206	0.804	0.35	0.421	0.524	**0.791**
OF4	0.058	0.027	0.043	0.169	0.983	0.167	0.224	0.243	0.324	**0.935**
OF5	0.014	0.023	0.071	0.072	0.032	0.256	0.258	0.343	0.073	**0.865**

Source: Developed by the authors.

Table 6: HTMT technique.

	Actual System Use	ATU	BIU	ITF	MG	PF	PEU	PD	ST	OF
Actual System Use										
ATU	0.621									
BIU	0.137	0.564								
ITF	0.075	0.092	0.106							
MG	0.046	0.042	0.046	0.245						
PF	0.167	0.066	0.125	0.644	0.305					
PEU	0.321	0.745	0.417	0.426	0.352	0.584				
PD	0.123	0.075	0.137	0.443	0.385	0.655	0.132			
ST	0.065	0.139	0.124	0.513	0.414	0.235	0.534	0.702		
OF	0.226	0.123	0.124	0.623	0.235	0.289	0.65	0.783	0.466	

Source: Developed by the authors.

5.3.5 The Structural model evaluation

To identify causal relationships between the latent coefficients of the research model, the study looks at the structural model and hypothesis, testing how R-squared and path coefficients are used to assess the power of the model capable of prediction. Figure 4 shows how PLS-Graph (SmartPLS 4) was used to validate the design process.

5.3.6 Coefficient of determination

The coefficient of determination (R2) is widely used to analyze structural models, predict accuracy, and determine the amount of variation between constructs. Data are expressed as squared correlations between actual and expected values for endogenous constructs. According to [Chin 1998], R2 statistics ranging from 0.19 to 0.33 indicate moderate predictive power, values from 0.33 to 0.67 indicate good predictive power, and values from 0.67 to 1 indicate strong power predicting. Table 7 illustrates behavioral intention to use, actual system use, perceived usefulness, attitude towards use and perceived ease of use, as well as R2 values of usefulness.

Table 7. Endogenous latent variables'.

Constructs	R^2	Results
Behavioral intention to use	0.376	Moderate
Actual System Use	0.637	Moderate
Perceived Usefulness	0.489	Moderate
Attitude towards use	0.598	Moderate
Perceived Ease of Use	0.468	Moderate

Source: Developed by the authors.

5.3.7. Hypotheses testing – Path coefficient

The study used Structural Equation Modeling to examine many postulated connections inside a research model. The results showed that structural model successfully conformed to the data for the study model, as all values fell within the specified range. The results confirmed sixteen out of the seventeen hypotheses, and all endogenous variables were validated in Figure 4. The findings indicated that the perceived utility of the system had a noteworthy impact on several aspects, including managerial, organizational, strategic, operational, perceived ease of use, IT infrastructure features. The perceived level of usefulness and ease of use significantly influenced individuals' attitudes and their desire to engage in the practice. No statistically significant correlation was seen between strategic considerations and perceived ease of use. Additionally, Hypotheses H4b were mostly unsupported in Table 8. A statistically significant association was shown between the behavioral intention to utilize and the attitude toward system use. The study proposes recommended values for the research model suitable fit indices.

Table 8. The structural model results are statistically significant at a level of $p^{**} \leq 0.01$ and $p^{*} < 0.05$.

Hyp.	Relationship	Path	t-value	p-value	Supported or Not
H1a	Managerial factor–>Perceived Usefulness	0.324	3.124	0.014	Yes
H1b	Managerial factor–>Perceived Ease of Use	0.154	2.252	0.03	Yes
H2a	Organizational factors–>Perceived Usefulness	0.178	2.385	0.012	Yes
H2b	Organizational factors–>Perceived Ease of Use	0.148	4.416	0.034	Yes
H3a	Operational factors–>Perceived Usefulness	0.159	1.962	0.041	Yes
H3b	Operational factors–>Perceived Ease of Use	0.263	1.512	0.045	Yes
H4a	Strategic factors–>Perceived Usefulness	0.227	3.217	0.001	Yes
H4b	Strategic factors–>Perceived Ease of Use	0.047	0.383	0.695	Not
H5a	IT Infrastructure factor–>Perceived Usefulness	0.518	7.428	0	Yes
H5b	IT Infrastructure factor–>Perceived Ease of Use	0.617	7.256	0	Yes
H6	Perceived Ease of Use–>Perceived Usefulness	0.235	3.179	0.002	Yes
H7	Perceived Usefulness–>Attitude towards use	0.127	4.645	0.003	Yes
H8	Perceived Ease of Use–>Attitude towards use	0.247	6.794	0.007	Yes
H9	Perceived Usefulness–>Behavioral intention to use	0.513	7.147	0.004	Yes
H10	Perceived Ease of Use–>Behavioral intention to use	0.117	7.588	0.004	Yes
H11	Attitude towards use–>Behavioral intention to use	0.678	17.786	0.001	Yes
H12	Behavioral intention to use–>Actual System Use	0.912	77.783	0.001	Yes

Source: Developed by the authors.

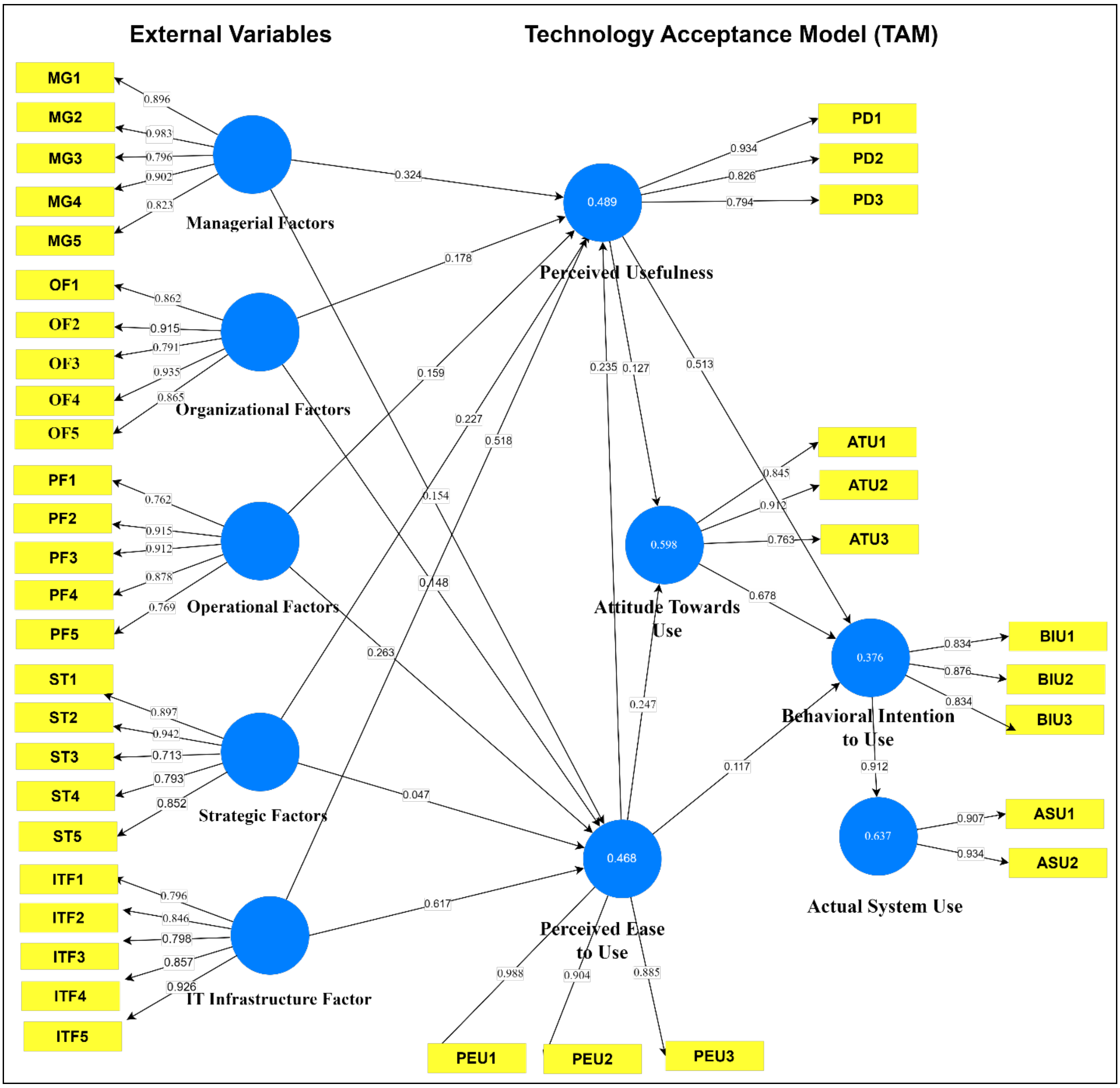

Figure 4. The coefficient values are statistically significant at p** <= 0.01 and p* < 0.05.

Source: Developed by the authors.

6. Discussion

First, management factors are crucial to the success of AI projects. An effective governance structure and sufficient financial resources provide a solid foundation for the advancement of AI projects. Management decisions in project planning, resource allocation, and risk control directly affect the efficiency and results of project execution. Therefore, improving management and strengthening policy support are one of the key measures to ensure the success of AI projects. The efficacy of artificial intelligence initiatives in the healthcare industry is largely dependent on a number of factors, including IT infrastructure, organizational, managerial, operational, and strategic aspects. Examining these critical project success factors in conjunction with the corpus of existing research on AI projects is the aim of this study. Structural equation modeling was used to assess the validity of the study hypotheses (PLS-SEM). The study included 315 samples, and Table 3 shows the results of 17 different hypotheses. The coefficient of determination (R2) values was found to be moderate, with high, moderate, and weak values ranging from 0.33 to 0.67, according to the findings. Observed variables with moderate power included physical variables of actual use, one's attitude towards users, behavioral intention to use, perceived ease of use, and the perception of usefulness with R2 values ranging from 0.636 to 0.464. At the same time, providing systematic training to help employees master new technologies and methods is also an important guarantee for the smooth implementation of AI projects. In addition, cooperation with internationally renowned AI companies can introduce advanced technology and management experience, further improving the probability of project success.

All seventeen hypotheses were validated by the SEM, with the exclusion of one, and the coefficient combination of the variables showed proposed correlations. Perceived usefulness is significantly influenced by managerial, organizational and operational factors, infrastructure, IT infrastructure factors and perceived ease of use. These factors were also significantly influenced by attitudes towards implementation and willingness to engage in it. However, there was no empirical evidence to support the claim that there is a relationship between perceived ease of use and the strategy dimension H4b. Ultimately, project managers and consumers within the health sector should give priority to these factors when developing AI initiatives, as they will raise project success rates and opportunities, which will ultimately help individual health conditions. The role of strategic factors in the success of AI projects cannot be ignored. Clear strategic goals and long-term planning can provide directions and paths for project implementation. At the same time, by regularly evaluating project progress and effects and timely adjusting strategies and resource allocation, we can ensure that the project is always moving towards the established goals. However, this study also found that the impact of strategic factors on perceived ease of use was not significant, which may be related to the complexity in the formulation and execution of strategic goals. Therefore, when formulating and executing strategies, it is necessary to pay more attention to operability and effectiveness.

7. Conclusion and Future work

The authors comprehensively analyzed 34 relevant studies published between 2020 and 2023, and used the extended Technology Acceptance Model (TAM) and Partial Least Squares Structural Equation Model (PLS-SEM) to explore the key factors affecting the success of artificial intelligence (AI) projects in the medical field in China, especially in Shanghai. The study covered five external factors: management, organization, operation, strategy, and IT infrastructure, and collected feedback from 154 employees in the medical and IT fields in China through a questionnaire survey.

Management factors have a significant positive impact on the perceived usefulness and ease of use of AI projects. Effective governance and the availability of financial resources are critical to the success of AI projects. Organizational factors also positively influence the perceived usefulness and ease of use of AI projects. Organizational culture, employee training, local experience, and international partnerships play an important role in improving the success rate of AI projects. Operational factors are significant compared to AI projects perceived usefulness, and also affect perceived ease of use. The accuracy and complexity of AI projects are important to their success. Strategic factors significantly impact AI projects perceived usefulness, but no significant correlation was seen in favor of perceived ease of use. Long-term planning and clear strategic goals are important to project success. IT infrastructure factor may impact AI projects success the most and have a positive impact on ease of use and perceived usefulness. Resource allocation, system quality, and content quality are the key to success.

7.1. Future Work

Based on the results of the present study, future work could expand and deepen the following aspects. Future research could be extended further into the country, and not just Shanghai, to obtain more universal data. At the same time, it is also possible to analyze the success factors of AI projects across industries and sectors. The present-day research mainly focuses on the success factors of AI projects. In the upcoming, an in-depth analysis of the fundamental reasons of failure of AI projects can be carried out to better comprehend the situations that impact the success of the project. By tracking the implementation and efficiency of specific AI applications over time, we can gain a deeper understanding of the dynamic changes in various factors over the lifecycle of the project and the ongoing impact on its success. New AI technologies and solutions are constantly emerging as technology continues to evolve. Future research could focus on the impact of emerging technologies on the success factors of AI projects and how businesses can adapt to these technological changes. There are differences in cultural, legal and economic environments in various countries and regions, which can have different impacts on the success of AI projects in the future. Therefore, cross-cultural comparative studies can be conducted to identify similarities and differences in AI project success factors in different cultures. Through these future research directions, we can strengthen and deepen our understanding of the success factors of AI projects and provide comprehensive and powerful guidance for practices in related industries.

7.2. Implications for Practice

This research project utilizes a modified Technology Acceptance Model (TAM) to comprehend the artificial intelligence initiatives adoption and acceptance in the health sector. To guarantee the implementation of best practices and enhance attitudes towards AI projects in their corporate setting, researchers evaluate significant external factors according to their company's culture and processes.

7.3. Research Limitations

The present research on the Technology Acceptance Model (TAM) and artificial intelligence (AI) engineering project in East Asia, particularly in China, has faced many difficulties. It lacks research for the role of AI accomplishments in the healthcare industry. Conducting extensive research in several nations is crucial to examine the significance of important factors that lead to success. Conducting interviews with physicians and health project managers for government and commercial organizations may be a challenging task that sometimes causes hesitation. The results concentrate on the essential components that contribute to the effective execution of AI projects in Shanghai, China, without discussing the factors that lead to failure.

Appendix A: Questionnaires / Employees Survey
Shanghai Questionnaire: Success Factors for Using Artificial Intelligence (AI) Projects in the Health Sector
Part One: Managerial Factor
1 – Does the implementation of effective governance have an impact on the success of AI projects?
2 – Do you believe that cooperation has an impact on the success of AI projects?
3 – Does the success of AI initiatives depend on the availability of financial resources (government support)?
Part Two: Operational Factor
1 – Does the success of AI projects depend on how complicated the AI system or solution is?
2 – Does the accuracy of health information in AI systems/solutions impact the success of AI projects?
Part Three: Strategic Factor
1 – Do you believe that the presence of well-defined strategic objectives has an impact on the success of an AI project?
2 – Do you believe that the organization's implementation of long-term planning has an impact on the success of an AI project?
Part Four: Information Technology Infrastructure Factor
1 – Do you believe that the allocation of adequate resources has an impact on the success of an AI project?
2 – Do you believe that the simplicity of AI design, namely its user-friendliness, has an impact on the success of an AI project?
3 – Do you believe that the quality of a system, in terms of its ability to fulfill required activities, has an impact on the success of an AI project?
4 – Do you believe that the quality of content/information has an impact on the success of an AI project?
Part Five: Organizational Factor
1 – Do you believe that the organizational culture has a role in the success of AI projects?
2 – Do you believe that providing enough training for the staff contributes to the success of AI projects?
3 – Do you believe that incorporating local experience in AI projects enhances the likelihood of their success?
4 – Do you believe that establishing worldwide partnerships with prominent AI businesses contributes to the success of AI projects?

REFERENCES

Barber, S., Izagirre, U., Serradilla, O., Olaizola, J., Zugasti, E., Aizpurua, J.I., Milani, A.E., Sehnke, F., Sakagami, Y., & Henderson, C. (2023). Best Practice Data Sharing Guidelines for Wind Turbine Fault Detection Model Evaluation. *Energies*, 16 (8), Article 3567. DOI 10.3390/en16083567

Bongini, P., Osborne, F., Pedrazzoli, A., & Rossolini, M. (2022). A topic modelling analysis of white papers in security token offerings: Which topic matters for funding? *Technological Forecasting and Social Change*, 184, Article 122005. DOI 10.1016/j.techfore.2022.122005

Chaibdraa, B. (1995). Industrial applications of distributed AI. *Communications of the Acm*, 38 (11): 49–53. DOI 10.1145/219717.219761

Cheng, M.-Y., Tsai, H.-C., & Sudjono, E. (2010). Conceptual cost estimates using evolutionary fuzzy hybrid neural network for projects in construction industry. *Expert Systems with Applications*, 37 (6): 4224–4231. DOI 10.1016/j.eswa.2009.11.080

Easton, G.S., & Rosenzweig, E.D. (2012). The role of experience in six sigma project success: An empirical analysis of improvement projects. *Journal of Operations Management*, 30 (7–8): 481–493. DOI 10.1016/j.jom.2012.08.002

Fidan, G., Dikmen, I., Tanyer, A.M., & Birgonul, M.T. (2011). Ontology for Relating Risk and Vulnerability to Cost Overrun in International Projects. *Journal of Computing in Civil Engineering*, 25 (4): 302–315. DOI 10.1061/(asce)cp.1943–5487.0000090

Guimaraes, T., Yoon, Y., & Oneal, Q. (1995). Success factors for manufacturing expert-system development. *Computers & Industrial Engineering*, 28 (3): 545–559. DOI 10.1016/0360-8352(94)00208-5

Hines, A. (2019). Getting Ready for a Post-Work Future. *Foresight and Sti Governance*, 13 (1): 19–30. DOI 10.17323/2500-2597.2019.1.19.30

Hooda, A., & Singla, M.L. (2021). Core – competencies – a key to future – oriented and sustainable e-governance implementation: a mixed method research. *Transforming Government – People Process and Policy*, 15 (1): 80–107. DOI 10.1108/tg-12-2019-0122

Jayasena, N.S., Chan, D. W. M., Kumaraswamy, M.M., & Saka, A.B. (2023). Applicability of public-private partnerships in smart infrastructure development: the case of Hong Kong. *International Journal of Construction Management*, 23 (11): 1932–1944. DOI 10.1080/15623599.2022.2027076

Kim, J.-S. (2020). A Legal Policy Study on the Safety of Artificial Intelligence and Human Ethics [인공지능의 안전성과 인간윤리에 대한 법정책적 고찰]. *Law Review*, 20 (1): 1–35. URL: https://www.dbpia.co.kr/journal/articleDetail?nodeId=NODE09323581

Klumpp, M., & Zijm, H. (2019). Logistics Innovation and Social Sustainability: How to Prevent an Artificial Divide in Human-Computer Interaction. *Journal of Business Logistics*, 40 (3): 265–278. DOI 10.1111/jbl.12198

Malanchini, I., Agostini, P., Alam, K., Baumgart, M., Kasparick, M., Liao, Q., Lipp, F., Marchenko, N., Michailow, N., Pries, R., Schotten, H., Stanczak, S., & Strzyz, S. (2021). Leveraging Machine Learning for Industrial Wireless Communications. *KICK White Paper*. DOI 10.48550/arXiv.2105.02051

Peng, G.C., & Nunes, M.B. (2009). Surfacing ERP exploitation risks through a risk ontology. *Industrial Management & Data Systems*, 109 (7): 926–942. DOI 10.1108/02635570910982283

Sandkuhl, K., Shilov, N., & Smirnov, A. (2020). Facilitating digital transformation: success factors and multi-aspect ontologies. *International Journal of Integrated Supply Management*, 13 (4): 376–393. DOI 10.1504/ijism.2020.110739

Selcon, S.J., Smith, F.J., Bunting, A.J., Irving, M.A., Coxell, A.W., & Shorter, N. (1995). An explanatory tool for decision-support on data-fused panoramic cockpit displays. *Proceedings of SPIE*. Conference on Cockpit Displays II, Orlando, Fl.

Shokouhyar, S., Seifhashemi, S., Siadat, H., & Ahmadi, M.M. (2019). Implementing a fuzzy expert system for ensuring information technology supply chain. *Expert Systems*, 36 (1), Article e12339. DOI 10.1111/exsy.12339

Shou, W., Wang, J., Wu, P., & Wang, X. (2020). Value adding and non-value adding activities in turnaround maintenance process: classification, validation, and benefits. *Production Planning & Control*, 31 (1): 60–77. DOI 10.1080/09537287.2019.1629038

Signorile, R. (2005). A decision support system for inventory control using planning and distributed agents. In M. Ali & F. Esposito (Eds.), *Innovations in Applied Artificial Intelligence*, 3533: 192–196. DOI 10.1007/11504894_28

Song, L., Wang, P., & AbouRizk, S. (2006). A virtual shop modeling system for industrial fabrication shops. *Simulation Modelling Practice and Theory*, 14 (5): 649–662. DOI 10.1016/j.simpat.2005.10.012

Vanwelkenhuysen, J. (1998). The tender support system. *Knowledge-Based Systems*, 11 (5–6): 363–372. DOI 10.1016/s0950-7051(98)00065-3

Wilson, A., Saeed, H., Pringle, C., Eleftheriou, I., Bromiley, P.A., & Brass, A. (2021). Artificial intelligence projects in healthcare: 10 practical tips for success in a clinical environment. *Bmj Health & Care Informatics*, 28 (1). DOI 10.1136/bmjhci-2021-100323

Поступила в редакцию: 10.08.2024 Received: Aug 10, 2024
Принята к публикации: 24.08.2024 Accepted: Aug 24, 2024