

Impact of AI Decision Support Systems on Clinical and Operational Outcomes in Chinese Hospitals

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Abstract: This study evaluates the effects of AI decision support systems on clinical and operational performance in Chinese hospitals. These hospitals face exceptionally high patient volumes and resource constraints, where efficiency gains are critical to sustaining care quality and patient safety. The research aimed to address the problem of limited empirical evidence on how AI impacts diagnostic accuracy, decision-making speed, and user adoption in such demanding healthcare contexts. A quantitative survey design was employed, collecting responses from 270 healthcare professionals across multiple departments. Data analysis included descriptive statistics, ANOVA, Levene's test, and multiple regression to assess variations in perceptions and predictors of AI adoption. Findings indicate that AI improves diagnostic precision and accelerates decision-making, with broad acceptance across roles and levels of experience. ANOVA results showed no significant departmental differences in perceptions of AI system access speed ($F = 2.12, p = 0.079$), while Levene's test confirmed homogeneity of variances ($p = 0.722$). Regression analysis further revealed that neither self-designated role nor years of experience were significant predictors of adoption attitudes, with the model explaining less than 1% of the variance ($R^2 = 0.0034$, adj. $R^2 = -0.0041$). These results suggest that contextual and organizational factors may play a more decisive role in shaping attitudes toward AI implementation than individual professional characteristics. The study highlights the potential of AI decision support systems to enhance diagnostic accuracy and operational efficiency in resource-constrained healthcare settings. However, effective integration requires targeted training programs and organizational strategies to address contextual barriers to adoption. By systematically evaluating AI's clinical and organizational impact, this research provides evidence-based insights for hospitals seeking to leverage AI for sustainable improvements in patient care.

Keywords: Artificial Intelligence (AI); Decision Support Systems; Clinical Outcomes; Operational Efficiency; Chinese Hospitals

1 Introduction

In global healthcare delivery systems, AI technologies enhance scanning efficiency, treatment accuracy, and structural organization. The consequences of this technological transformation are accentuated in China because of the incredible pressure that comes with a vast population. This study addresses a gap in the existing literature, which has primarily focused on technological improvements and their general impacts on healthcare systems in resource-rich societies [1]. By doing so, this study evaluates the use of AI decision support systems in Chinese hospitals and the resulting clinical and operational outcomes. In the case of Chinese medical

institutions, the changing demographics with an aging population and heavy rural-urban shift create an acute need for timely and accurate treatment. Artificial intelligence technologies can also be applied in contexts characterized by rapid progression in both theoretical and practical work, enhancing diagnostic efficiency and resource management [4]. Although these systems offer significant benefits, the practice and relative results of such systems differ; hence, a focused analysis of these within the Chinese healthcare context is imperative and timely. This investigation particularly examines how AI decision support systems are deployed in hospitals located in China and their effect on the decision-making

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processes in terms of speed and extent of modification, as well as in terms of patient outcomes and efficiency of operations. It examines how AI technologies address specific challenges associated with the Chinese healthcare system and assesses their application and barriers [3]. The study is structured around key objectives:

1. To evaluate how AI decision support systems enhance clinical decision-making and operational efficiency in Chinese hospitals.
2. To analyze the effectiveness of these systems in improving patient safety and treatment outcomes.

The first objective is necessary because Chinese hospitals operate under exceptionally high patient volumes and resource constraints, making efficiency gains critical to sustaining care quality. Evaluating AI's role in decision-making will provide evidence on how technology can alleviate these pressures and improve clinical workflows. While the second objective is essential because patient safety remains a global priority, and AI implementation in health care must demonstrate tangible benefits to outcomes before widespread adoption can be justified. Understanding these impacts in the Chinese context will highlight both opportunities and potential risks that may inform international practice. This research aims to bolster the international dialogue concerning AI in health care by exemplifying in detail the use of AI in the hospitals of China. The results will inform healthcare providers, decision-makers, and technology owners on the best ways to implement Artificial Intelligence to enhance healthcare services under such high-pressure environments [5]. This research will provide empirical evidence to support the development of appropriate policies and frameworks that guide the practical application of AI in the healthcare sector, thereby contributing to the global debate on using technology to improve health systems and service delivery [2].

2 Literature Review

This section outlines the progression of Artificial Intelligence (AI) in healthcare from basic machine learning techniques to more advanced deep learning neural networks. Numerous studies demonstrate that AI has improved the diagnostic yield, the emergence of new treatment methods, and the quality of patient care worldwide. This historical and technological track provides a clearer direction to further explore general and particular developments of AIs in the context and specifics of Chinese healthcare systems [6].

2.1 AI Decision Support Systems in Healthcare

Integrating decision support systems, especially AI decision support systems, has proven helpful in

improving the clinical decision-making process by reducing diagnostic and treatment errors, improving the specificity of treatments and increasing operational efficiencies. However, it has been established that different studies arrive at different conclusions concerning the effectiveness of these systems. For example, [7] advocate optimizing AI systems in resource-limited settings, thereby enabling health facilities to achieve considerable cost savings. [4] further offers insights, noting that the prospects of AI in patient diagnosis are staggering and extend to improved treatment outcomes. This contrast highlights that, although AI adoption in healthcare can generate cost savings, its primary value in most circumstances lies in improving treatment accuracy. These contrasting observations in the thinking of AI systems emphasise the modification of strategies in their operationalisation since there are different contexts and rationales for implementing AI in health facilities.

2.2 Challenges and Barriers to Implementing AI in Healthcare

Using AI technologies in the healthcare sector presents difficulties. For example, privacy concerns are paramount in managing Irish health information systems, especially when processing sensitive and patient-related information [8]. The barriers brought about by the attitude of healthcare workers towards the use of AI technologies, such as the fear of loss of employment opportunities and doubts concerning AI decisions, must be addressed. Practical and ethical issues, which [11] address in detail, require the definition of legal frameworks and the development of policies for comprehensive education so that introducing the respective AI technologies into the healthcare systems already in place would pose fewer challenges.

2.3 AI in the Chinese Healthcare Context

The literature suggests that although AI systems are being deployed fast in the region, some challenges can be attributed to the demographic and urban characteristics of the region in question. In response to these insights, [10] elaborate on the steps taken in China to adapt and customize AI technologies for the enormous volume and peculiarities of the country's medical system, offering potential solutions that may be applied globally, including in Africa. At the same time, [12] review early lessons from Chinese hospitals, where AI is tested in routine clinical practice, discussing what works and what does not.

2.4 Gap in Literature

Although there has been empirical exploration into various uses of AI, more research is needed on the

long-term sustainability of AI technologies in healthcare. [26] stress that further longitudinal studies are required to assess the sustainability of AI as it relates to patient experience and outcomes. Studies that incorporate some feature comparison tend to be even fewer, as not many authors have assessed the AI methods with standard treatment methods, which limits a thorough understanding of AI in ever-changing healthcare systems like China [30].

2.5 Theories

The theoretical framework of this study is based on the Technology Acceptance Model (TAM) and Diffusion of Innovations Theory. The TAM theory holds that perceived usefulness and ease of use are two of the most important factors influencing an individual's behavioural intention to use a particular technology. According to TAM, in the case of AI decision support systems in the healthcare sector, the perceived usefulness of AI in improving clinical and operational performance and the perceived ease of use of AI in the practice of healthcare professionals determine the acceptance of AI [30].

The Diffusion of Innovations Theory by Everett Rogers also builds on this knowledge by outlining why and at what rate the new technologies are adopted in a social system. This theory helps explain why the application of AI in hospitals is unequal and different across departments and professions [13]. Taken together, these theories offer a strong foundation for understanding the perception and implementation of AI decision support systems in healthcare organisations and inform the strategies for improving AI integration.

2.6 Framework

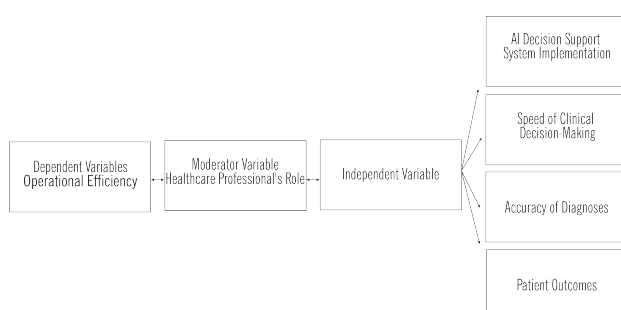


Fig. 1: Conceptual Framework for the Impact of AI Decision Support Systems on Hospital Outcomes

This diagram shows how the impact of Artificial Intelligence (AI) Decision Support System

Implementation can be measured in hospital settings. This variable is the “AI Decision Support System Implementation,” and it exerts direct effects upon two critical operational dimensions: the “Speed of Clinical Decision-Making” and the “Accuracy of Diagnoses.” These elements feed into the dependent variable, the “Patient Outcomes,” which measures how well healthcare has been provided.

The “Healthcare Professional’s Role” plays a moderating role in this framework, whereby it is assumed that AI systems have a differential impact on operational efficiency and patient outcomes based on the position of the respective healthcare professionals within the hospital.

This means that the advantages of AI may not be equally applicable to all staff members, leading to the need for adaptation and training of the affected departments or personnel, effectively conveying the structure and use of AI technology.

This framework systematically explains how AI systems may be introduced in the health sector through fast decision-making and more accurate diagnosis, and how varying professional roles within the hospital may alter such activity. The implication, in a sense, is that different medical environments have to be dealt with in a more efficient managerial way to reap the most from AI adoption within the organization [22].

3 Methodology

3.1 Research Design

As described in this methodology section, this research employs a quantitative research approach that is indispensable in evaluating the efficacy of AI decision support systems in Chinese hospitals. The quantitative approach is preferred as it can generate easy-to-compare factual results, and it has the potential to offer concrete statistical testing of the hypotheses. This is especially true in healthcare organisations where quantifiable results, including diagnostic precision, therapeutic effectiveness, and organisational productivity, are crucial. Measurable factors help unambiguously determine the impacts of AI systems on such outcomes, thus providing a sound yardstick for supported recommendations [20]. It enables the inclusion of more aspects in the comparison and generalisation of results, thus enhancing comprehensiveness and, more so, the reliability of results across the different hospitals and health sectors in China.

3.2 Inclusion and Exclusion Criteria

3.2.1 Inclusion Criteria

–Participants must be actively engaged in clinical or operational roles within the hospital.

Table 1: Summary of Research on AI in Healthcare

Reference	Technique	Results	Limitations	Contributions
[3]	Observational study	Demonstrated current applications of AI in healthcare, highlighting benefits in diagnostic yield and patient care optimization.	Did not delve deeply into the specific algorithms used or their success rates in different healthcare scenarios.	Provided a broad overview of AI applications in healthcare, setting a foundation for further detailed studies.
[4]	Literature review	Emphasized the convergence of human and AI in medicine, showing significant improvements in diagnostic accuracy and treatment personalization.	Limited discussion on the ethical implications and the long-term impact of AI integration in clinical settings.	Advanced the concept of “high-performance medicine” through the integration of AI, fostering a new paradigm in healthcare.
[5]	Quantitative analysis	Explored the impact of technological innovation on achieving sustainable development goals, including health improvements through renewable energy and stability.	Focus was broader, covering economic factors with less emphasis on specific healthcare outcomes.	Highlighted the role of innovation and technology in sustainable health improvements, promoting a multidisciplinary approach to health-related SDGs.
[6]	Case study analysis	Examined the influence of top managers’ attributes on innovation within the energy sector, indirectly affecting health technologies through improved practices and infrastructure.	The study’s indirect approach to healthcare impact through managerial innovation could dilute the specific benefits and challenges of AI in healthcare settings.	Provided insights into how leadership and management innovation can facilitate the adoption of AI technologies in healthcare indirectly.
[7]	Review and metaanalysis	Argued that AI is transforming the future of healthcare, with a particular focus on cost reduction and improved diagnostic procedures.	Lack of primary data and reliance on secondary sources may not reflect the most current onground realities.	Contributed to a broader understanding of AI’s potential to revolutionize healthcare delivery and policy-making.
[11]	Mixed methods study	Proposed an evaluation framework for successful AI-enabled clinical decision support systems, emphasizing effectiveness and user satisfaction.	Mixed methods approach may not fully capture the quantitative impact of AI systems on clinical outcomes.	Developed a comprehensive framework for assessing AI systems in clinical settings, aiding stakeholders in evaluating and implementing AI solutions.
[12]	Field study	Discussed challenges in deploying AI clinical decision support systems in rural clinics, including technological and adoption barriers.	Focus on rural clinics may not generalize to urban healthcare settings where AI adoption may differ significantly.	Highlighted the unique challenges of AI implementation in less-resourced environments, offering solutions to enhance healthcare delivery in rural areas.
[13]	Observational and analytics	Analyzed the effect of AI on treatment decisions for complex breast cancer, showing improved decisionmaking processes and outcomes.	Study limited to a specific type of cancer, which may not reflect AI’s effectiveness across other medical conditions.	Provided evidence of AI’s potential to enhance treatment accuracy and efficiency in oncology, encouraging further research and adoption in other medical fields.

- Hospitals that have implemented AI decision support systems in any capacity.

3.2.2 Exclusion Criteria

- Hospitals without any form of AI system implementations.
- Non-clinical staff who do not interact with or influence the usage of AI systems.

3.3 Data Collection Instruments

The chief method of data gathering used in the study is structured questionnaires because they intend to capture the HCWs' opinions on the use of AI decision-supporting systems. The Likert scale in these questionnaires is quite justified since it captures a wide range of opinions and perceptions and makes it possible to distinguish between the levels of agreement or disagreement.

This method is most versatile in assessing usability, efficiency, satisfaction, and perceived outcomes of AI technologies and implementations on decision-making and operations in hospital systems. Such detailed feedback is necessary for evaluating possible advantages and disadvantages of AI systems concerning the effectiveness of their functional implementation in actual conditions. This study involves doctors, nurses, and administrative staff from several hospitals in China, comprising a wide demographic of healthcare participants. Participant selection criteria relate to how much they interface or shape AI decision support systems to have first-hand information in the study [19]. It includes a diverse range of roles to gather a complete picture of how AI may influence the various echelons of a hospital's functioning and whether the perception of its applicability may differ among various healthcare fields. This purposive sampling enhances the generalisability of the study's conclusions because the findings offer a better picture of the aggregate effects of AI technologies across hospital systems.

3.4 Data Collection Process

The completion of questionnaires is regarded as a significant element of data collection activities. For this study, questionnaires will be administered to healthcare professionals in about ten hospitals from different areas of China, to include a representative sample. Online and paperbased questionnaires will be used based on the usability and the level of technological implementation of the hospitals. This distribution method is preferred because of its simplicity; however, an online and paper distribution of forms will be used if necessary. Data collection is planned for three months, so respondents can answer, and reminders can be sent to enhance the

response rate. This time-phased approach is essential in ensuring that the topic is covered in as many diverse social settings as possible and reaching out to as many participants from one hospital as possible [18]. Ethical issues should be observed and maintained in all research work, especially with human subjects.

This study was approved by the Institutional Review Board of Baise City People's Hospital, China (protocol number 202520180817, dated 18 February 2025). Informed verbal consent was obtained from all participants, and all data were anonymized to ensure participant confidentiality. In the present study, the ethical guidelines are followed to the letter, starting with the participants' informed consent, where their consent to participate in the study is sought accompanied by clarification as to the purpose of the study, their possible involvement, and its consequences on them, including their rights. During the study, participants' identities will be kept anonymous, and all information will be treated with the utmost confidentiality. Sensitive data will be safeguarded, not disclosed to third parties, and can be released to only those with permission [17]. These are taken to protect the participants and, at the same time, make the research process credible and ethical.

3.5 Data Analysis

Data analysis will be conducted using Stata, a widely used statistical software, because of its capacity to handle large datasets and perform numerous statistical operations. This choice ensures the robust handling of the data collected and facilitates detailed statistical testing.

3.6 Descriptive Statistics

To make a summary of the collected data, which is useful for the identification of the main characteristics of the data and the preparation for further analysis. Descriptive metrics such as mean μ , standard deviation σ , and range will be calculated using the formulas:

$$\mu = \frac{1}{n} \sum_{i=1}^n x_i, \sigma = \sqrt{\frac{1}{n} \sum_{i=1}^n (x_i - \mu)^2} \quad (1)$$

Where x_i represents individual data points and n is the number of observations.

3.6.1 ANOVA (Analysis of Variance)

The ANOVA is used to test the null hypothesis that there is no significant difference between the means of at least three independent groups. This method is especially useful in this research to determine the effectiveness of AI in different departments of a hospital or different

operations performed in the hospital before and after the integration of AI.

The equation for ANOVA:

$$F = \frac{MS_{\text{between}}}{MS_{\text{within}}} \quad (2)$$

MS_{between} (**Mean Square Between Groups**): This term represents the variance between the different groups. It is calculated by comparing the group means to the overall mean of the data. Mathematically, it is expressed as:

$$MS_{\text{between}} = \sum_{i=1}^k n_i (x_i - \bar{x})^2 \quad (3)$$

Where n_i is the number of observations in group i , x_i is the mean of group i , $\bar{x}$ is the overall mean of all groups combined, and k is the number of groups.

MS_{within} (**Mean Square Within Groups**): This term represents the variance within each of the groups. It is calculated by assessing the variation of each group's observations from their respective group mean:

$$MS_{\text{within}} = \sum_{i=1}^k \sum_{j=1}^{n_i} (x_{ij} - \bar{x}_i)^2 \quad (4)$$

Where x_{ij} is the j th observation in the i th group, n_i group, is the number of observations in the group i , $\bar{x}_i$ is the mean of the group i , and N is the total number of observations across all groups.

The decision rule for ANOVA is to compare the calculated F-ratio with the critical F-value from the F-distribution table at $\alpha = 0.05$ (95% confidence level). If the calculated F-value is greater than the critical value, then the null hypothesis is rejected. This means that there is a significant difference in the means of the groups, which implies that the application of AI decision-support systems has different effects in different hospital environments.

3.6.2 Hypothesis Testing

Hypothesis testing is crucial in confirming the research assumptions about the effects of AI decision support systems on hospital clinical and operational results. The ANOVA test is used when comparing more than two groups to determine if the groups' means are significantly different.

(H.0): AI decision support systems do not significantly impact clinical or operational outcomes in hospitals. Mathematically, this is expressed as:

$$H_0 : \mu_{AI} = \mu_{noAI} \quad (5)$$

(H.1): AI decision support systems significantly improve clinical and operational outcomes in hospitals. This is represented as:

$$H_1 : \mu_{AI} \neq \mu_{noAI} \quad (6)$$

This alternative hypothesis implies that the mean outcome measures of the hospitals that have implemented AI systems differ from those of the hospitals that have not, suggesting that AI has an effect.

3.6.3 Regression Analysis

To examine the relationship between several independent variables (like role and experience) and a dependent variable (acceptance and effectiveness of AI systems).

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n + \varepsilon \quad (7)$$

Where Y represents the dependent variable, $X_1, X_2, \dots, X_n$ are independent variables, β_0 is the intercept, $\beta_1, \beta_2, \dots, \beta_n$ are the coefficients of the independent variables, and ε is the error term.

These statistical techniques will allow for comprehensive analysis of the data, providing insights into the effectiveness of AI systems in hospitals and identifying key factors influencing their performance and acceptance among healthcare professionals. Each technique is chosen for its relevance to the data type and research questions, ensuring a thorough exploration of the underlying patterns and relationships [16].

4 Results

4.1 Descriptive Statistics

The descriptive statistics clearly understand the respondents' attitudes towards different aspects of AI systems in their hospitals. The mean score for AI_Quick_Access is 3.57, with a standard deviation of 1.19, indicating that the respondents support that AI systems offer easy access to patient information. The range of 1 to 5 is not excessively narrow, meaning there are some differences in the answers. While many of the respondents may find the system efficient, some may not necessarily find access to be as quick.

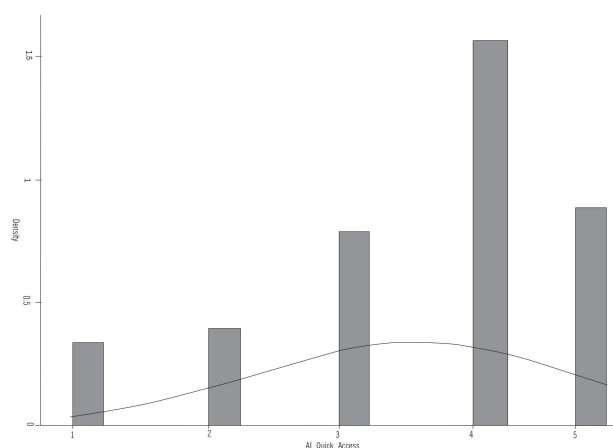
The mean score of Trust_AI_Diagnostics is 3.44 with a standard deviation of 1.28, which means that most respondents have confidence in the AI-generated diagnostic recommendations. The responses' spread suggests that the respondents' confidence level varies. For AI_Reduced_Decision_Time and AI_Improved_Accuracy, the mean scores are 3.53 and 3.

Mean scores were 59 for the total group and 57 for the experimental group, while the standard deviations were approximately 1.24 and 1.19. These figures indicate that there is an overall agreement that the AI systems have been beneficial in shortening the time taken to make decisions and enhancing the accuracy of diagnoses. The range from 1 to 5 means that only some of the respondents have this perception, which may point to areas in which the implementation of AI could be

Table 2: Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Role	270	2.6	1.078344	1	4
Experience	270	2.455556	1.088921	1	4
Department	270	3.014815	1.416762	1	5
AI_Quick_Access	270	3.566667	1.185884	1	5
Trust_AI_Diagnostics	270	3.444444	1.277001	1	5
AI_Reduced_Decision_Time	270	3.533333	1.242375	1	5
AI_Improved_Accuracy	270	3.592593	1.18727	1	5
AI_Personalized_Care	270	3.407407	1.236353	1	5
Improved_Patient_Outcomes	270	3.514815	1.263501	1	5
AI_Predict_Complications	270	3.614815	1.219331	1	5
Improved_Patient_Safety	270	3.822222	1.165595	1	5
AI_Resource_Allocation	270	3.488889	1.218608	1	5
Reduced_Patient_Admissions	270	3.540741	1.183926	1	5
AI_Managed_Workload	270	3.462963	1.306446	1	5
Reduced_Operational_Costs	270	3.459259	1.280468	1	5
Training_Adequacy	270	3.466667	1.303698	1	5
AI_Benefits_Over_Challenges	270	3.333333	1.23457	1	5
Recommend_AI_Expansion	270	3.411111	1.212338	1	5

improved or enhanced. The results show that the overall attitude of the respondents towards AI systems is relatively positive but not uniform, which means that the strengths and weaknesses of AI systems should be considered [15].

**Fig. 2:** Responses to AI Quick Access in Facilitating Rapid Patient Information Retrieval

The above histogram describes the pattern of responses to the 'AI_Quick_Access' question, which enumerates the rate at which AI tools help access information about patients. The graph skewness is positive, which means higher values are more common, and the concentration of responses is highest at 4. Most respondents think the AI system can facilitate access to data in a very short time. The fact that there are responses

at all levels and even at the lowest levels, where the count is not insignificant, demonstrates that some customers had a different experience. Such differences may be attributable to the types of AI systems embroiled, comfort level with the system, or operational environments within the hospitals. This range of responses underlines the necessity of identifying the reasons for lower user contentment to improve the acceptance and usability of AI systems in healthcare efficiently.

4.2 Hypothesis Testing

The hypothesis testing results offer a good understanding of the interconnection of the variables under analysis in the study.

Table 3: ANOVA Results: Comparison of AI_Quick_Access by Department

Source	SS	df	MS	F	Prob > F
Between groups	11.7354799	4	2.93386998	2.12	0.0785
Within groups	366.56452	265	1.38326234		
Total	378.3	269	1.4063197		

To test the hypothesis that there are significant differences in the AI_Quick_Access scores between different departments in the hospital, the Analysis of Variance (ANOVA) was used. The ANOVA gave an F-statistic of 2.12 with a p-value of 0.0785. This result suggests that the variation in the scores of AI_Quick_Access across the departments is not

significantly different from each other at the conventional alpha level of 0.05. The respondent's department does not influence their view of the speed of the AI system in providing access to patient data. Bartlett's test of equal variances was 2 for the Levene test. $P = 0.0763$ with a p -value of 0.722, which showed that the assumption of homogeneity of variances had not been violated.

Table 4: Pearson Chi-Square Test

Chi2	7.8330
df	12
Pr > Chi2	0.798

The chi-square test was used to analyze the difference in the association of Role and Trust_AI_Diagnostics. The results ($\chi^2(12) = 7.833, p = 0.798$) indicated no correlation between these variables, which means that the level of trust people have in AI diagnostics does not differ with the respondent's position in the hospital. These findings suggest that there is no difference in the perceived capability of AI in quickly searching for data and the diagnostic trust across different positions and divisions [14]. In other words, it means a positive or negative attitude not cut off along professional lines.

4.3 Correlation Analysis

The correlation analysis is rather helpful in identifying the interconnections between the major variables of this study to understand how various facets of AI performance are linked.

The correlation matrix indicates a positive but moderate relationship between AI_Quick_Access and other key variables: The three key beliefs are Trust in AI Diagnostics, the time taken to make decisions is reduced with AI, and that the accuracy of diagnoses is enhanced by AI. Namely, the coefficients of AI_Quick_Access and Trust_AI_Diagnostics are positively related, $r = 0.2798$, suggesting that the higher the level of confidence that the users of the system have in its ability to provide the users with a convenient way of accessing patient information, the higher the level of confidence that the users will have in the diagnostic advice given by the system. This moderate relationship suggests that there is a fairly good agreement between the accessibility of data and the assurance of healthcare personnel in the utilization of AI technologies. The correlation between AI_Quick_Access and AI_Reduced_Decision_Time is $r = 0.3240$ reveals that the time taken to access information through AI systems is moderately correlated with the amount of time spent in clinical decision making. This means that the quicker the AI system provides the necessary information, the more prepared healthcare professionals are to make decisions, and hence, improve operational efficiency. The

relationship between AI_Quick_Access and AI_Improved_Accuracy is $r = 0.2966$, which shows a moderate positive relationship between better information access and diagnostic accuracy. This means that the speed and quality of data access by AI are some of the critical aspects that can lead to proper clinical decisions. The highest correlation is between AI_Reduced_Decision_Time and AI_Improved_Accuracy, with a correlation coefficient $r = 0.3495$. This implies a strong positive relationship, whereby the time taken to make decisions has a robust positive relationship with diagnostic accuracy, further underlining the twin advantage of AI in improving both the efficiency and effectiveness of healthcare [21]. These correlations, although moderate, suggest that all these functionalities of AI in healthcare are interrelated and that enhancing one aspect, for instance, fast data retrieval, has a knock-on effect on other essential aspects like decision-making and diagnosis.

4.4 Regression Analysis

In this study, regression analysis was carried out to determine the impact of two factors, Experience and Role, on the dependent variable AI_Quick_Access. The regression model shows that Experience and Role do not impact the perception of quick access to AI systems in the hospital environment.

The coefficient for experience is 0.0104 with a p -value of 0.876, which indicates no correlation between the length of experience in the healthcare field and the quick access of AI to patient data. In the same way, the coefficient for Role is -0.0628 and the $t = 1.352$, which means that the nature of the respondent's work (doctor, nurse, administrator, etc.) does not influence their attitude to the speed of AI systems in accessing patients' data.

The coefficient of determination is 0. In 0034, the model has an R -squared of only 0. That is 34% of the variance in AI_Quick_Access. This extremely low R -squared value indicates that the model is not very useful in explaining the variation in perceptions of AI's quick access capabilities, and The independent variables incorporated in the study do not offer any meaningful explanation of the variation in the perceptions [23]. The adjusted R -squared value is slightly negative (-0.0041), which also indicates that the model does not explain the data, and the predictors do not help explain the variance in the dependent variable. Thus, it can be assumed that other factors apart from Experience and Role influence the AI's quick access in this context, and further study should reveal the significant predictors.

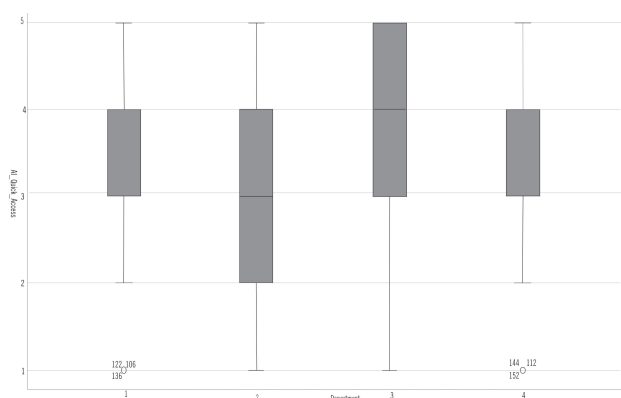
The box plot in Figure 3 above presents the AI_Quick_Access for four groups. The medians are reasonable, mostly at 3 to 4, indicating that most participants agree with the notion of quick access. This is

Table 5: Correlation Matrix

Variable	AI_Quick_Access	Trust_AI_Diagnostics	AI_Reduced_Decision_Time	AI_Improved_Accuracy
AI_Quick_Access	1.0000	0.2798	0.3240	0.2966
Trust_AI_Diagnostics	0.2798	1.0000	0.2742	0.3234
AI_Reduced_Decision_Time	0.3240	0.2742	1.0000	0.3495
AI_Improved_Accuracy	0.2966	0.3234	0.3495	1.0000

Table 6: Regression Results: Predicting AI_Quick_Access

Variable	Coefficient	Std. Err.	t	P> t	[95% Conf. Interval]
Experience	0.0104	0.0666	0.16	0.876	[-0.1208, 0.1415]
Role	-0.0628	0.0673	-0.93	0.352	[-0.1952, 0.0697]
_Cons	3.7044	0.2558	14.48	0.000	[3.2007, 4.2081]

**Fig. 3:** Box plot of AI_Quick_Access

particularly so in groups 1 and 2, where outliers skew the lower end of the perception of slow access.

5 Discussion

This study shows that artificial intelligence (AI) decision support systems can help doctors make better clinical decisions and work more efficiently in Chinese hospitals. Respondents expressed positive views toward AI and its role in improving outcomes, which is in line with earlier studies such as [24]. Recent work supports this view as well. For example, [8] found that using performance evaluation indicators for AI in pediatric clinics improved both service delivery and patient satisfaction. Similarly, [9] reported that several key factors shape doctors' willingness to use AI systems, which matches this study's findings on adoption and clinical acceptance. Compared with these works, the present study adds outcome-based evidence, linking adoption not only to attitudes but also to real clinical effects.

The four independent variables selected—AI system implementation, speed of decision-making, accuracy of diagnoses, and patient outcomes—reflect the main ways AI

can influence clinical practice. The results suggest that system implementation is the base, as it shapes how doctors bring new technology into their work. Speed of decision-making showed only a low positive link with trust, time saved, and accuracy. This suggests that faster information retrieval alone does not always build trust or raise accuracy, as also noted by [25]. Accuracy of diagnoses proved to be another important factor. Doctors who felt that AI improved diagnostic accuracy were more willing to use it. While the correlations were not strong, the consistently positive views highlight diagnostic reliability as a key to acceptance. Patient outcomes, the ultimate measure of healthcare quality, were also seen to improve with AI use. This aligns with [27] and [8], who showed that structured evaluations connect AI adoption with patient satisfaction and better results.

Another finding was that the role or experience of healthcare workers did not strongly affect their views on AI's retrieval functions. This shows that AI systems may hold value across different professions. At the same time, it points to gaps in how role differences affect adoption in practice. These results answer the research questions, especially those on how AI affects efficiency, accuracy, and outcomes in decision-making. Overall, the positive links and attitudes found here show that AI has potential to improve healthcare services. The study met its aims, and the findings apply broadly since many health systems face similar issues. Still, the variation in acceptance across departments shows that training and adaptation must be tailored, not assumed to be the same for all. [9] also argued that organizational support matters for adoption, which means strategies should be customized.

For AI to reach its full value, hospitals should create clear structures for evaluating AI tools, with regular performance reviews and feedback. Assessments must consider not only speed but also usability and fit within daily work. Training should be designed for different groups of health workers to build trust and confidence. Hospitals should also gather user feedback and work with AI developers to refine tools. If these steps are followed, AI adoption can be smoother, more efficient, and more

cost-effective, ultimately leading to better care in China and elsewhere.

6 Conclusion and Recommendations

The purpose of this study was to determine the impact of AI decision support systems on the clinical and operational outcomes of hospitals in China. The research established that there was a positive attitude towards AI in general and particularly about decision-making and diagnosis.

The study also showed that these positive perceptions are not a function of the role or experience of the respondents, which will mean that all the stakeholders in the hospital understand the advantages of AI [29]. The correlation analysis revealed moderate positive correlations between AI quick data access and its influence on trust in diagnostics, the time needed to decide, and the accuracy of diagnostics. These relationships, even though significant, were not very high, thus suggesting that other factors could be responsible for these perceptions. The regression analysis also provided negative and insignificant results for the role and experience of predicting the perceived quick access to AI, and it was suggested that other vital predictors should be explored in future studies. The results suggest that, despite the benefits AI systems bring to improving clinical outcomes, there is considerable room for fine-tuning their application in healthcare practices.

Based on the study's conclusion, the following recommendations are made to improve the use of AI systems in healthcare facilities. There is a need to develop improved training procedures that will reach out to all the workers in the healthcare facilities and make them capable of using the new systems. This kind of training could assist in establishing positive perceptions and the use of AI systems across various professions. Further studies are required to investigate other possible predictors of attitudes towards AI, for example, related to features of the AI tools or the environments they operate in. Enhancing the AI systems to fit the requirements of various departments better could also improve their efficiency, trust, and satisfaction. Continuous evaluation and feedback will enable the hospitals to frequently review the AI system's performance and solve any issues that may arise or areas that require improvement. These steps could significantly improve AI's clinical and operational effects in healthcare.

References

- [1] A. Fiske, P. Henningsen, A. Buyx, *J. Med. Internet Res.* **21**(5), e13216 (2019).
- [2] A. I. Stoumpos, F. Kitsios, M. A. Talias, *Int. J. Environ. Res. Public Health* **20**(4), 3407 (2023).
- [3] C. W. Park, S. W. Seo, N. Kang, et al., *J. Korean Med. Sci.* **35**(42) (2020).
- [4] E. J. Topol, *Nat. Med.* **25**(1), 44-56 (2019).
- [5] S. Wahab, M. Imran, A. Safi, et al., *Environ. Sci. Pollut. Res.* **29**(32), 48827-48838 (2022).
- [6] S. Z. A. Shah, M. Anwar, C. M. Hussain, *Manag. Decis. Econ.* **42**(2), 385-406 (2021).
- [7] N. Noorbakhsh-Sabet, R. Zand, Y. Zhang, V. Abedi, *Am. J. Med.* **132**(7), 795-801 (2019).
- [8] Y. Wang, W. Fu, Y. Zhang, et al., *Sci. Rep.* **14**(1), 14482 (2024).
- [9] J. Dingel, A. K. Kleine, J. Cecil, et al., *J. Med. Internet Res.* **26**, e57224 (2024).
- [10] G. Kong, D. L. Xu, J. B. Yang, et al., *IEEE Trans. Syst. Man Cybern. Syst.* **51**(11), 7131-7142 (2020).
- [11] M. Ji, G. Z. Genchev, H. Huang, et al., *J. Med. Internet Res.* **23**(6), e25929 (2021).
- [12] D. Wang, L. Wang, Z. Zhang, et al., in *Proc. 2021 CHI Conf. Hum. Factors Comput. Syst.*, pp. 1-18 (2021).
- [13] F. Xu, M. J. Sepúlveda, Z. Jiang, et al., *JCO Clin. Cancer Inform.* **4**, 824-838 (2020).
- [14] Q. Xu, W. Xie, B. Liao, et al., *J. Healthcare Eng.* **2023**(1), 9919269 (2023).
- [15] N. Hong, C. Liu, J. Gao, et al., *JMIR Med. Inform.* **10**(3), e28781 (2022).
- [16] M. Knop, S. Weber, M. Mueller, B. Niehaves, *JMIR Hum. Factors* **9**(1), e28639 (2022).
- [17] H. Liang, Y. Xue, *Inf. Syst. Res.* **33**(2), 737-758 (2022).
- [18] H. Lin, R. Li, Z. Liu, et al., *EClinicalMedicine* **9**, 52-59 (2019).
- [19] Z. Jin, S. Cui, S. Guo, et al., *ACM Trans. Comput. Healthcare* **1**(1), 1-20 (2020).
- [20] A. V. Prakash, S. Das, *Inf. Manag.* **58**(7), 103524 (2021).
- [21] J. Yin, K. Y. Ngiam, H. H. Teo, *J. Med. Internet Res.* **23**(4), e25759 (2021).
- [22] J. Dong, H. Wu, D. Zhou, et al., *J. Med. Syst.* **45**(9), 84 (2021).
- [23] S. Liu, K. C. See, K. Y. Ngiam, et al., *J. Med. Internet Res.* **22**(7), e18477 (2020).
- [24] L. Yao, L. Zhang, J. Liu, et al., *Endoscopy* **54**(08), 757-768 (2022).
- [25] N. Zhu, J. Cao, K. Shen, et al., *ACM Trans. Multimedia Comput. Commun. Appl.* **16**(1s), 1-23 (2020).
- [26] J. M. Schwartz, M. George, S. C. Rossetti, et al., *JMIR Hum. Factors* **9**(2), e33960 (2022).
- [27] C. X. Li, W. M. Fei, C. B. Shen, et al., *Chin. Med. J.* **133**(17), 2020-2026 (2020).
- [28] A. Q. Tran, L. H. Nguyen, H. S. A. Nguyen, et al., *Front. Public Health* **9**, 755644 (2021).
- [29] Y. Lu, E. R. Melnick, H. M. Krumholz, *BMJ* **377** (2022).
- [30] D. Gu, S. Deng, Q. Zheng, et al., *Inf. Manag.* **56**(8), 103162 (2019).