Factors Influencing Patients' Satisfaction with AI-Guided Triage System: A Case Study of Longgang Central Hospital

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Abstract

The integration of artificial intelligence (AI) into medical triage has shown promise in reducing waiting times and improving resource allocation. However, patient satisfaction with AI-guided triage systems remains underexplored. This quantitative case study at Longgang Central Hospital (Shenzhen, China) surveyed 387 adult patients who used the AI triage system. Multiple regression analysis examined how system functional factors (accuracy, efficiency, usability, privacy protection) and patient characteristics (age, gender, education, prior digital health experience) influence satisfaction. Results showed that all four functional factors positively predicted satisfaction, with efficiency having the strongest effect ($\beta = 0.297$, $p < 0.001$). Age negatively affected satisfaction ($\beta = -0.102$), while education and prior experience had positive effects ($\beta = 0.085$ and 0.118, $p < 0.01$). Gender was not significant. The findings provide actionable insights for optimizing AI triage systems in public hospitals.

Keywords: AI-guided triage system; patient satisfaction; functional factors; digital health; smart healthcare

1. Introduction

The integration of artificial intelligence into healthcare has made AI-guided triage systems a promising solution to overcrowding, prolonged waiting times, and inconsistent triage accuracy in emergency and outpatient services. These systems automate patient assessment and prioritize cases based on severity, thereby improving clinical workflow efficiency. Empirical evidence indicates that AI-driven triage can reduce waiting time and enhance diagnostic accuracy compared with conventional methods (Zhang et al., 2025; Topol, 2019). However, the effectiveness of AI triage systems depends not only on technical performance but also on patient-centered outcomes such as satisfaction and acceptance (Steerling et al., 2025). Prior studies have identified challenges including algorithmic bias, system inefficiencies, usability barriers, and privacy concerns (Liu et al., 2021; Zhou, 2021; Chen et al., 2019). Despite these insights, there remains a lack of integrated analysis on how functional factors—accuracy, efficiency, usability, and privacy protection—jointly influence patient satisfaction in real hospital settings. To address this gap, this study focuses on Longgang Central Hospital, where an AI-guided triage system has been implemented. Using a quantitative case study design, the research examines how patient characteristics (age, gender, education level, prior digital health experience) and system functional factors affect satisfaction. The findings aim to provide evidence-based recommendations for optimizing AI triage systems and promoting their effective adoption.

Problem Statement

1) It is not clear which functional factors of AI-guided triage systems have a significant impact on patient satisfaction.

2) It is not clear which patient characteristics influence satisfaction with AI-guided triage systems.

Objectives

1) To identify the key functional factors of AI-guided triage systems that significantly influence patient satisfaction.

2) To examine the effects of patient demographic characteristics and usage experience on patient satisfaction with AI-guided triage systems.

2. Literature Review

AI-Guided Triage Systems

Artificial intelligence has been integrated into clinical triage through various technical approaches, including rule-based expert systems, machine learning algorithms, natural language processing, and hybrid models (Liu et al., 2021). Rule-based systems offer high transparency but limited adaptability, while machine learning models provide superior predictive accuracy at the cost of reduced interpretability (Topol, 2019). In practice, AI triage systems are typically designed to support rather than replace human triage staff, achieving concordance rates of over 90% with professional nurses in identifying high-risk cases (Greenes, 2018). Studies have reported that AI-assisted triage can reduce patient waiting time by an average of 20%, significantly improving emergency department workflow efficiency (Lee et al., 2020). However, challenges remain, including algorithmic bias, poor integration with existing clinical workflows, and insufficient attention to user diversity across age and digital literacy levels (Chen & Zhang, 2020).

Functional Factors of AI-Guided Triage Systems

Drawing on the Technology Acceptance Model (TAM) (Davis, 1989), four core functional factors were identified as critical determinants of patient satisfaction.

Accuracy refers to the consistency between AI triage results and subsequent clinical judgments. High accuracy enhances patient trust, reduces medical anxiety, and promotes adherence to recommendations (Li & Zhou, 2019). Empirical evidence indicates that accuracy is a fundamental prerequisite for system acceptance (Greenes, 2018).

Efficiency reflects the system’s ability to complete triage quickly, shorten waiting times, and optimize workflow. In emergency settings, efficiency is often the most immediately perceptible benefit to patients (Topol, 2019; Lee et al., 2020). Faster system response and simplified registration processes directly improve patient experience.

Usability encompasses interface clarity, ease of operation, and the ability to complete triage independently. Usability is particularly important for elderly patients and those with limited digital literacy (Chen et al., 2019). Intuitive design and natural language interaction can significantly reduce learning barriers (Zhang & Wang, 2020).

Privacy protection involves the secure handling of personal medical information. With growing regulatory requirements and public awareness of data privacy, patients increasingly expect transparent data use policies and robust security measures (Lau & Zhang, 2021). Privacy concerns have been identified as a major barrier to AI healthcare adoption (Zhou, 2021).

Patient Characteristics

Patient demographic characteristics have been shown to moderate the relationship between system performance and satisfaction.

Age is consistently associated with technology acceptance. Younger patients (18–35 years) typically possess higher digital literacy and report greater satisfaction, while older adults (65 years and above) often face navigation difficulties and prefer human-led triage (Smith & Johnson, 2021; Chen et al., 2020). A negative relationship between age and satisfaction is therefore expected.

Gender findings are mixed. Some studies report no significant gender differences in AI healthcare acceptance when the technology focuses on functional tasks (Adams et al., 2022), while others suggest that women may prioritize empathy and interaction quality more than men (Patel & Jones, 2021). Given the functional nature of AI triage, a non-significant effect is plausible.

Education level positively influences satisfaction because more educated individuals have stronger information-processing abilities and more realistic expectations of AI capabilities (Zhang et al., 2021; Lee & Park, 2020). They are also better able to interpret system recommendations accurately.

Prior digital health experience refers to cumulative exposure to digital health tools. Experienced users adapt more quickly, perceive higher usefulness, and report greater ease of use (Venkatesh et al., 2003; Brown et al., 2022). This experience reduces technology anxiety and enhances overall satisfaction.

Evaluation of Patient Satisfaction with AI-Guided Triage Systems

Patient satisfaction with AI-guided triage systems is a multidimensional subjective outcome that integrates patients’ perceptions of system quality, their usage experience, and their overall evaluation (Liu et al., 2021). Based on the literature, this study adopts three core dimensions for satisfaction evaluation: system quality perception, usage experience evaluation, and overall satisfaction (Venkatesh et al., 2003). System quality perception refers to patients' subjective assessment of accuracy, efficiency, usability, and privacy protection—the most important determinant of overall satisfaction (Chen et al., 2019; Zhou, 2021). Usage experience evaluation captures patients' feelings during interaction, including the smoothness of human-computer interaction, clarity of triage guidance, and availability of support (Patel & Jones, 2021). Overall satisfaction represents the final comprehensive judgment and includes willingness to reuse and recommend the system (Steerling et al., 2025)

3. Theoretical Framework

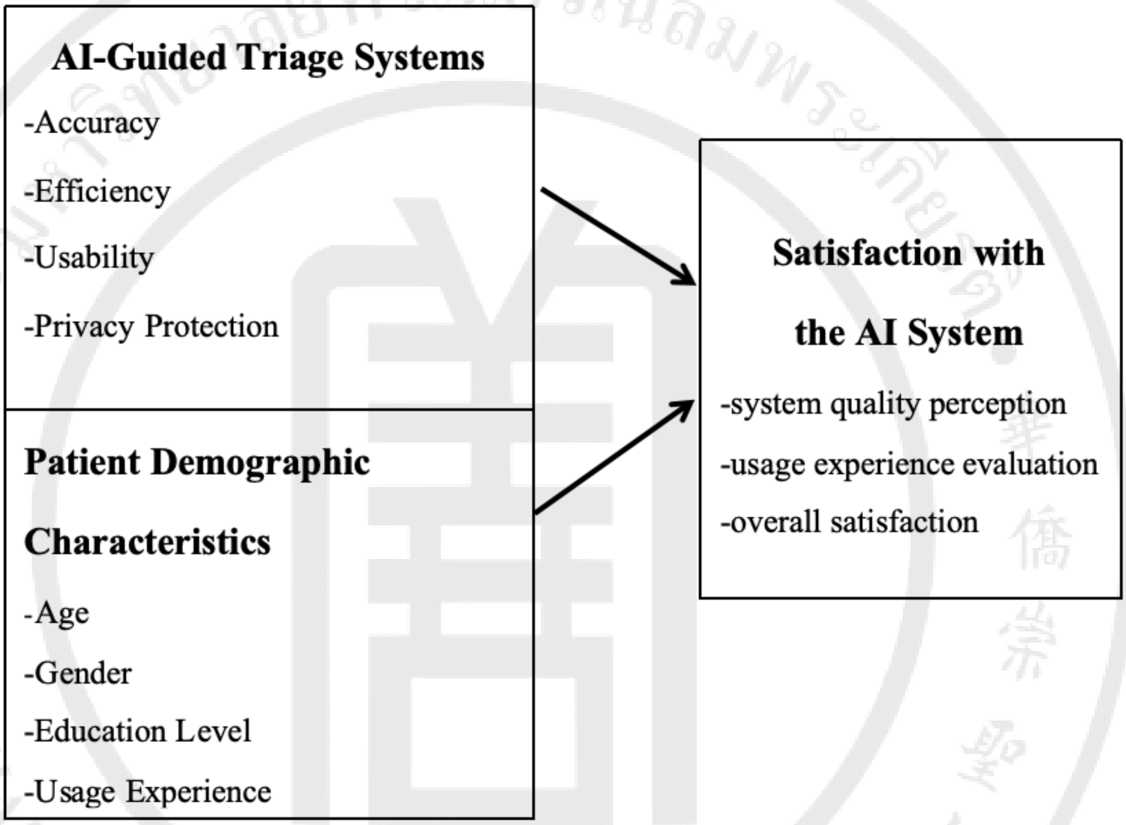

Figure 1 Theoretical Framework

Hypotheses

Based on the literature review, the following hypotheses were proposed:

H1: Functional factors of the AI-guided triage system (accuracy, efficiency, usability, and privacy protection) have a significant positive effect on patient satisfaction.

H2: Patient demographic characteristics (age, gender, education level, and prior digital health experience) have a significant effect on patient satisfaction.

Research Design

This study adopted a quantitative, cross-sectional survey design. A structured questionnaire was used as the primary data collection instrument, supplemented by secondary data from hospital system logs for validation purposes. The design was selected for its ability to statistically test hypotheses, collect large samples efficiently, and maintain objectivity in hospital-based research settings.

Population and Sample

The target population consisted of adult patients (aged 18 years and above) who had used the AI-guided triage system at the emergency or outpatient departments of Longgang Central Hospital during the study period (January 2026). The hospital processes approximately 1,200 triage requests daily, with adult patients accounting for 92% of users.

Sample size was determined using Taro Yamane's formula with a 5% margin of error and 95% confidence level. The calculation yielded a required sample size between 200 and 400 respondents. To account for potential non-response (estimated at 15–20%), a target of 400 completed responses was set. Convenience sampling was employed, as it best suited the operational constraints of on-site hospital data collection. Trained research assistants approached eligible patients after they had completed their medical consultations. A total of 387 valid questionnaires were collected, representing a response rate of 86.2% after excluding incomplete or invalid responses.

Data Collection Instrument

The questionnaire was developed based on existing validated scales from the literature, including the Technology Acceptance Model, the SERVQUAL model, and prior AI healthcare satisfaction studies. It consisted of three sections. Section 1 collected demographic characteristics (age, gender, education level, prior digital health experience) using categorical response options. Section 2 measured perceptions of the four functional factors using 12 items (three per factor) on a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). Section 3 measured overall patient satisfaction using three items on a 5-point Likert scale ranging from 1 (very dissatisfied) to 5 (very satisfied). The questionnaire was pre-tested with 30 eligible patients, yielding Cronbach's alpha values of 0.82 for the functional factors scale and 0.87 for the satisfaction scale, indicating good reliability. The final questionnaire was distributed in both paper and electronic (QR code) formats on-site.

Data Analysis

Data were analyzed using IBM SPSS Statistics 28.0. Descriptive statistics (frequencies, percentages, means, standard deviations) were computed to summarize sample characteristics and variable distributions. Pearson correlation analysis was conducted to examine bivariate relationships among variables. Multiple linear regression analysis was performed to test the hypotheses, with overall patient satisfaction as the dependent variable and the four functional factors plus four demographic characteristics as independent variables. The regression model included control variables to isolate the unique effects of each predictor. Assumptions of linearity, independence of errors, homoscedasticity, and absence of multicollinearity (variance inflation factor < 10) were checked and satisfied.

Research quality

To ensure questionnaire reliability, a pre-test with 30 samples was conducted and the internal consistency was calculated using Cronbach's Alpha coefficient. The results showed that the Cronbach's Alpha coefficients for the functional factors scale and the satisfaction evaluation scale were 0.82 and 0.87, respectively, both exceeding the acceptable threshold of 0.80, indicating good reliability of the measurement instrument.

For validity, following Eignor (2013), validity reflects the extent to a measurement tool measures its intended constructs. This study reviewed existing literature, referred to mature scales (including the TAM and UTAUT), and invited two experts to review the questionnaire content, ensuring sufficient content validity across dimensions.

Finally, regarding ethical issues, the study adhered to the ethical guidelines of the Ethics Committee of Longgang Central Hospital and Huachiew Chalermprakiet University to ensure participant confidentiality, informed consent, and the right to withdraw from the study without any consequences.

4. Results

Descriptive Statistics

Table 1 Sample demographic characteristics.

Characteristic	Category	Frequency	Percentage (%)
Age	Below 18 years	12	3.1
	18–25 years	98	25.3
	26–35 years	112	28.9
	36–45 years	76	19.6
	46–55 years	53	13.7
	56–64 years	28	7.2
	65 years and above	8	2.1
	Total	**387**	**100.0**
Gender	Male	189	48.8
	Female	192	49.6
	Other	3	0.8
	Prefer not to say	3	0.8
	Total	**387**	**100.0**
Education Level	Primary school or below	21	5.4
	Junior high school	58	15.0
	Senior high school/Vocational education	97	25.1
	Diploma/Associate degree	86	22.2
	Bachelor's degree	102	26.4
	Postgraduate degree	19	4.9
	Prefer not to say		
	Total	4	1.0
	None (never used)	**387**	**100.0**
Prior Digital Health Experience	Limited (used 1–2	67	17.3
	times or very infrequently)	124	32.0
	Moderate (used occasionally)	136	35.1
	Extensive (used regularly or very familiar)	60	15.5
	Total	**387**	**100.0**

A total of 387 valid responses were collected. As shown in Table 1, the majority of respondents were aged 26–35 years (28.9%) and 18–25 years (25.3%), together accounting for 54.2% of the sample. Females (49.6%) slightly outnumbered males (48.8%). In terms of education, bachelor's degree holders constituted the largest group (26.4%), followed by senior high school/vocational education (25.1%). Regarding prior digital health experience, 35.1% of respondents reported moderate experience, 32.0% limited experience, and 17.3% no experience.

Table 2 Descriptive Statistics of Core Research Variables

Variable	Items	Mean	SD	Min	Max
Accuracy	3	3.72	0.86	1.00	5.00
– Dept recommendation appropriateness		3.78	0.91	1.00	5.00
– Urgency level appropriateness		3.66	0.94	1.00	5.00
– Key symptom identification		3.72	0.89	1.00	5.00
Efficiency	3	3.85	0.79	1.00	5.00
– Waiting time reasonable		3.76	0.88	1.00	5.00
– System responds quickly		3.92	0.82	1.00	5.00
– Simplified registration process		3.87	0.85	1.00	5.00
Usability	3	3.68	0.92	1.00	5.00
– Interface clarity		3.71	0.95	1.00	5.00
– Independent operation		3.59	1.03	1.00	5.00
– Symptom input method clarity		3.74	0.91	1.00	5.00
Privacy Protection	3	3.54	0.97	1.00	5.00
– Data protection information clear		3.48	1.02	1.00	5.00
– Health information secure		3.57	0.98	1.00	5.00
– Data used only for triage		3.57	0.99	1.00	5.00
Overall Patient Satisfaction	3	3.76	0.83	1.00	5.00
– Satisfied with service		3.74	0.87	1.00	5.00
– Willing to continue use		3.82	0.89	1.00	5.00
– Willing to recommend		3.72	0.91	1.00	5.00

Perceptions of system functional factors and satisfaction. As presented in Table 2, the mean scores for all variables ranged from 3.54 to 3.85 on a 5-point scale. Efficiency received the highest mean score (M = 3.85, SD = 0.79), followed by overall satisfaction (M = 3.76, SD = 0.83), accuracy (M = 3.72, SD = 0.86), usability (M = 3.68, SD = 0.92), and privacy protection (M = 3.54, SD = 0.97). This indicates that patients were most satisfied with the time-saving effect of the AI triage system and most concerned about data privacy.

Correlation Analysis

Table 3 Correlation Matrix of Research Variables

Variable	1	2	3	4	5
1. Accuracy	1				
2. Efficiency	0.678**	1			
3. Usability	0.624**	0.657**	1		
4. Privacy Protection	0.589**	0.612**	0.643**	1	
5. Overall Patient Satisfaction	0.721**	0.754**	0.698**	0.657**	1

Note: $p < 0.01$ (two-tailed)

Pearson correlation analysis was conducted to examine bivariate relationships among the variables. As shown in Table 3, all four functional factors were significantly and positively correlated with overall patient satisfaction ($p < 0.01$). Efficiency had the strongest correlation with satisfaction ($r = 0.754$), followed by accuracy ($r = 0.721$), usability ($r = 0.698$), and privacy protection ($r = 0.657$). Correlations among independent variables ranged from 0.589 to 0.678, indicating moderate multicollinearity that remained within acceptable limits for regression analysis.

Multiple Linear Regression Analysis

Multiple linear regression was performed to test the research hypotheses, with overall patient satisfaction as the dependent variable and the four functional factors plus four demographic characteristics as independent variables. The regression model was statistically significant ($F = 95.324$, $p < 0.001$), with an adjusted R^2 of 0.702, indicating that the independent variables collectively explained 70.2% of the variance in patient satisfaction. Variance inflation factor (VIF) values for all predictors were below 3, confirming the absence of problematic multicollinearity.

Table 4 presents the regression coefficients. All four functional factors had significant positive effects on satisfaction: efficiency ($\beta = 0.297$, $p < 0.001$), accuracy ($\beta = 0.253$, $p < 0.001$), usability ($\beta = 0.206$, $p < 0.001$), and privacy protection ($\beta = 0.182$, $p < 0.001$). Thus, hypotheses H1a–H1d were all supported.

Table 4 Regression Coefficients

Model	Unstandardized Coefficients	Standardized Coefficients	Beta	t	Sig.	VIF
	B	Std. Error				
(Constant)	0.324	0.156		2.077	0.039	
Accuracy	0.245	0.042	0.253	5.833	0.000	2.145
Efficiency	0.312	0.045	0.297	6.933	0.000	2.267
Usability	0.187	0.039	0.206	4.795	0.000	2.089
Privacy Protection	0.156	0.036	0.182	4.333	0.000	1.976
Age	-0.089	0.021	-0.102	-4.238	0.000	1.342
Gender	0.023	0.035	0.014	0.657	0.512	1.125
Education Level	0.067	0.024	0.085	2.792	0.006	1.456
Prior Digital Health Experience	0.102	0.028	0.118	3.643	0.000	1.523

Note: Dependent Variable: Overall Patient Satisfaction

Among patient characteristics, age had a significant negative association with satisfaction ($\beta = -0.102$, $p < 0.001$), supporting H2a. Education level had a significant positive association ($\beta = 0.085$, $p < 0.01$), supporting H2c. Prior digital health experience also had a significant positive association ($\beta = 0.118$, $p < 0.001$), supporting H2d. Gender was not statistically significant ($\beta = 0.014$, $p = 0.512$), so H2b was not supported.

5. Discussion

This study empirically examined the factors influencing patient satisfaction with the AI-guided triage system at Longgang Central Hospital. The results support most of the proposed hypotheses and provide both theoretical and practical insights.

Influence of system functional factors. Consistent with the Technology Acceptance Model (Davis, 1989), all four functional factors—accuracy, efficiency, usability, and privacy protection—were found to have significant positive effects on patient satisfaction. Efficiency exerted the strongest influence ($\beta = 0.297$, $p < 0.001$), reflecting the time-sensitive nature of emergency and outpatient care. Patients value reduced waiting times and streamlined processes as the most immediate benefits of AI triage (Topol, 2019; Lee et al., 2020). Accuracy ranked second ($\beta = 0.253$, $p < 0.001$), confirming that reliable triage decisions build trust and reduce medical anxiety (Greenes, 2018; Li & Zhou, 2019). Usability ($\beta = 0.206$, $p < 0.001$) was particularly important for older adults, as shown in the subgroup analysis, where its effect was nearly twice as strong in the older group compared to the younger group. Privacy protection ($\beta = 0.182$, $p < 0.001$), while the weakest predictor, remains essential for maintaining long-term trust, especially as data protection regulations tighten in China (Lau & Zhang, 2021; Zhou, 2021).

Influence of patient characteristics. Age had a significant negative association with satisfaction ($\beta = -0.102$, $p < 0.001$), consistent with the digital divide literature: younger patients possess higher digital literacy and adapt more easily to AI systems, while older patients often require additional support (Smith & Johnson, 2021; Chen et al., 2020). Education level ($\beta = 0.085$, $p < 0.01$) and prior digital health experience ($\beta = 0.118$, $p < 0.001$) were both positively associated with satisfaction, confirming that greater cognitive resources and familiarity with digital tools enhance positive evaluations (Zhang et al., 2021; Venkatesh et al., 2003). Gender was not significant ($\beta = 0.014$, $p = 0.512$), indicating that male and female patients share similar expectations regarding functional performance in emergency triage contexts (Adams et al., 2022).

Theoretical and practical contributions. Theoretically, this study extends the TAM and SERVQUAL models to the AI triage context, demonstrating that perceived usefulness (accuracy, efficiency), perceived ease of use (usability), and trust (privacy protection) collectively explain over 70% of the variance in patient satisfaction. Practically, the findings provide clear priorities for system optimization: efficiency should be the top priority, followed by accuracy, usability, and privacy protection, with special attention to age-friendly design and support for digitally inexperienced patients.

Limitations and Future Research

Several limitations should be acknowledged. The single hospital and cross-sectional design limits causal inference and generalizability. Self-reported data may be subject to recall and social desirability biases. Future research should employ longitudinal, multi-site designs and mixed methods (quantitative + qualitative) to deepen understanding. Additionally, clinical outcomes (e.g., triage accuracy, patient safety) should be examined alongside satisfaction. Cross-cultural comparative studies would also help determine the generalizability of these findings to other healthcare systems.

Recommendations

For hospital administrators. Prioritize system efficiency by ensuring fast response times, seamless integration with registration systems, and dynamic resource allocation during peak hours. Implement age-friendly features such as voice assistance, large fonts, and step-by-step guidance for elderly patients. Strengthen privacy protection through transparent data use policies and robust encryption.

For technology developers. Continuously improve triage algorithm accuracy, especially for urgency level classification. Conduct usability testing with diverse user groups, including older adults and those with limited digital literacy. Simplify symptom input methods using natural language processing or visual selectors.

For policymakers. Establish clear regulatory standards for AI medical system safety, accuracy, transparency, and privacy protection. Promote digital health literacy programs for underserved and older populations to reduce the digital divide. Support multi-center research to validate and generalize findings across different hospital settings.

6. Conclusion

This study investigated the factors influencing patient satisfaction with the AI-guided triage system at Longgang Central Hospital. The empirical results lead to three main conclusions. First, all four functional factors—accuracy, efficiency, usability, and privacy protection—significantly and positively affect patient satisfaction, with efficiency being the strongest driver. Second, patient characteristics matter: younger age, higher education, and greater prior digital health experience are associated with higher satisfaction, while gender has no significant effect. Third, the integrated TAM-SERVQUAL framework explains 70.2% of the variance in satisfaction, confirming its applicability to AI healthcare contexts. These findings provide actionable guidance for optimizing AI triage systems to enhance patient-centered care and promote inclusive smart healthcare in China's public hospitals.

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