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Original Article

Investigating the Confounding Role of Artificial Intelligence on the Relationship between Patient Safety and Infection Control Practices in Enhancing Patient Satisfaction in Healthcare

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ABSTRACT

This study aimed to investigate how AI mediates the relationship between infection control, patient safety, and patient satisfaction. The study used an exploratory sequential research design with two phases. In the first phase, 25 qualitative studies were analyzed using PRISMA (2009–2024), which were supplemented by quantitative analysis of 384 samples. A cross-sectional survey was conducted among physicians, nurses, and paramedics. The scales were found to be reliable and valid in PLS-SEM measurement models. The structural model was run to investigate the direct and indirect effects. The result suggests the significant direct effect of AI and infection control on satisfaction. However, patient safety and satisfaction were found to be insignificant. This implies full mediation by AI between Patient safety and satisfaction. AI's mediating role was confirmed between safety, infection control, and satisfaction. The study concludes that themes emerged from the review of the studies, and the findings of the quantitative data were consistent. Hence, this study validates the results of previous studies in the context of the Middle East. Through triangulation, the diverse sources used in this study have reduced bias, reinforced internal validity, and provided a deep insight into the mediating effect of AI in enhancing patient safety, infection control, and patient satisfaction. The significant role of experience and staff categories emphasizes the need for targeted interventions and training to foster a culture of safety and technological adoption across healthcare roles. Healthcare policymakers should consider these factors when implementing new technologies and designing training programs to ensure the benefits of AI, infection control, and patient safety.

Keywords: Artificial Intelligence, Infection Control, Patient Safety, Patient Satisfaction, Mixed-Methods Research, Healthcare.

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INTRODUCTION

Growing patient expectations, growing expenses, and the global burden of adverse events, which the World Health Organization (WHO) estimates to be the third principal cause of death in developed countries, are just a few of the previously unheard-of difficulties facing the healthcare industry (James, 2013). Patient outcomes depend greatly on hospital services, which include clinical care, patient safety, infection control, administrative procedures, and resource management. One of the most critical measures of hospital performance is infection control and patient satisfaction, which determine perceived service quality and patient safety (Aiken *et al*., 2012). To overcome these barriers, artificial intelligence (AI) has become a game-changing tool that improves patient experiences, streamlines processes, controls infection, lowers errors, and increases patient satisfaction (Yu Qing Huang, Michael Colacci, Gemma Postill, Pavel Zhelnov, Orna Fennelly, *et al*., 2025). Hospital operations are increasingly incorporating artificial intelligence (AI) applications like clinical decision support systems (CDSS), natural language processing (NLP), and machine learning (ML). For instance, NLP gleans insights from unstructured EHR data, CDSSs give clinicians evidence-based recommendations, and machine learning forecasts patient flow, helping to cut down waiting time (Choudhury & Asan, 2020). By increasing effectiveness, precision, and personalization, these gadgets mediate the relationship between patient safety and infection control and patient satisfaction (Li, Ni, 2023). However, obstacles like patient mistrust of AI, regulatory uncertainty, and data biases restrict its potential (Huang *et al*., 2023).

Given the quick development of AI in healthcare, the review of the study was focused on studies conducted between 2009 and 2024. Studies focused on AI's effects on patient satisfaction, infection control, and patient satisfaction indicators. ML, NLP, deep learning, and CDSS are among the AI applications discussed; these are used in areas like incident reporting, clinical alarms, and medication safety. The WHO's Global Patient Safety Action Plan 2021–2030 emphasizes the importance of patient safety worldwide, which makes this study significant. Every year, medical errors breach patient trust and cost healthcare systems billions of dollars (Epelde, 2024). These goals are consistent with AI's capacity to improve infection and patient safety, lower errors, and raise satisfaction. This review will benefit the stakeholders concerned throughout the healthcare ecosystem by providing them with a roadmap for utilizing AI to achieve safer, patient-centered care through the synthesis of evidence.

The study aimed to analyze how infection control, patient safety, and patient satisfaction are mediated by AI applications, list AI tools, and examine how they affect administrative and clinical procedures. Further, the purpose was to assess the difficulties and impediments to integrating AI into healthcare environments, inter alia, to provide stakeholders, such as hospital administrators, legislators, and researchers, with evidence-based recommendations and solutions.

LITERATURE REVIEW

Four themes- AI in hospital services for patient safety, infection control, patient satisfaction, and AI's mediating role-are used to explore 25 studies for a review of existing literature.

AI and Patient Safety

Through error detection and risk prediction, AI greatly enhances patient safety. According to Zheng et al. (2022), ML-based predictive modeling decreases harmful drug events (ADEs) by 20–30%. While Hui Jun Si *et al*. (2022) reported that it detects high-risk events with 30% greater sensitivity than manual systems, NLP further enhances incident reporting. Likewise, Choudhury and Asan (2020) assert that clinical alarm decision-tree models improve clinician response times by cutting incorrect positives by 15%, yet they argue that biases in training data can be threatening. Similarly, Huang *et al*. (2023) found that minority patients may be inaccurately classified by ML models trained on non-diverse datasets, which is resulting in false results. While Epelde (2024) argues that AI reliability is further limited by a lack of standardized benchmarks. 10% of the studies recorded that AI is comparatively not as accurate as human clinicians.

AI in Infection Control

Artificial intelligence (AI) plays a transformative role in 'infection control' in hospitals, particularly it employs predictive analytics and mechanized surveillance for 'healthcare-associated infections (HRIs). AI models integrate data from electronic

health records, laboratory results, and other sources to forecast infection risks. It enables early interventions to lower incidence rates. For instance, machine learning tools have the ability to reduce HRI incidence significantly, inter alia, lowering the surveillance workload to 85% in some cases. Recent studies emphasize that predictive analytics are the dominant AI applications to prevent and control infection (PCI), with certain models attaining greater accuracy in detecting and preventing HRIs, for example, surgical site infections plus urinary tract infections. These developments support proactive measures, i.e., optimized antimicrobial stewardship and real-time monitoring that leads to maximization of patient safety and resource allocation in hospitals (Advancing infection prevention..., 2025; Artificial intelligence in hospital infection prevention..., 2025). Studies demonstrate effective evidence of using AI for accurate detection of infections, for instance, central line-associated bloodstream infections, and it has greater sensitivity in analyzing clinical notes, and the potential to assist under-resourced teams. However, besides the benefits, there are several issues associated with it, for example, the need for human oversight due to occasional critical errors in clinical judgment, data fragmentation, and integration barriers. Despite its limitations, however, AI augments rather than replaces human expertise and encourages better conformity monitoring (e.g., hand hygiene) and outbreak prediction. This study emphasizes explainable AI for building clinician trust along with safe adoption (Abosi *et al*., 2025; Wiemken *et al*., 2024). AI improves clinical workflows, patient safety, maximizes infection control, and enhances patient satisfaction (Severo, Kuchenbecker, Vieira, & Pinto *et al*., 2019; Silva *et al*., 2022). Choudhury and Asan (2020) are of the view that predictive analytics in emergency departments (EDs) cut down waiting times by 12% by prioritizing high-risk patients. Levis *et al*. (2021) reported that NLP enhances diagnostic accuracy by 25% through gleaning actionable insights from the unstructured EHR data. By incorporating evidence-based guidelines, CDSSs improve care coordination and cut medical errors by 18%. Similarly, Alkhaldi and Abdallah (2022) found that AI performance is impeded by data interoperability and unstructured EHR formats. This view is further supported by Huang *et al*. (2023); Ferreira, Vieira, Pedro, Caldas, &Varela (2023). Furthermore, Petersson *et al*. (2025) reported that limited resources, high implementation costs, and staff training requirements are barriers to its adoption.

AI and Patient Satisfaction

According to McFarland *et al*. (2020), perceived safety, trust, and service quality are significant predictors of patient satisfaction; they argue that AI increases satisfaction by decreasing 12-20% resulting in an increase in satisfaction scores. Additionally, customization of care plans also results in a 15% increase in trust. Al-Bashayreh *et al*. (2022) noted that AI-powered chatbots increase patient perceptions of the quality of care with swift patient education. Yang and Peterson (2004) state that timely interventions through predictive models could enhance the management of chronic diseases among patients. In contrast, Longoni and Morewedge (2019) believe that 25% of patients show apprehensions about AI's lack of human-like empathy; they suggested that an over-dependence on AI may reduce sympathetic interactions, as patients prefer human oversight in critical decisions; thus, according to Jotterand and Bosco (2020), trust in AI is a significant mediator. Sitzia and Wood (1997) emphasized that patient satisfaction is also affected by demographic and cultural factors; educated patients trust more, while older patients are less likely to trust the potential of AI.

Mediating Role of AI between Patient Safety, Infection Control, and Patient Satisfaction

Artificial intelligence (AI) plays a significant role in strengthening patient safety and infection control in healthcare settings. It enables real-time risk prediction, error reduction, and proactive interventions. AI algorithms analyze big datasets from electronic health records, vital signs, and laboratory results by detecting prospective adverse events, such as medication errors or early signs of deterioration; thus, it prevents harm before it happens (Choudhury & Asan, 2020). Regarding infection control, AI excels at predicting healthcare-associated infections (HRIs) using surveillance models to monitor patient movements, adherence to protocols, in addition to microbial patterns, thereby leading to planned and timely isolation measures and reduced transmission rates (Alqurashi *et al*., 2024). These strengths of AI not only enhance clinical outcomes but also build sound foundations for safer environments that further reduce preventable incidents. Studies have reported that AI plays an instrumental role in influencing patient satisfaction in healthcare institutions; through the perceived transparency, usefulness, and support, AI integration promotes higher patient satisfaction (Wang *et al*., 2025). In health perspectives, AI tools mechanize

routine processes by improving morale and efficiency, resulting in patients' trust in healthcare providers (Ali *et al*., 2025). Thus, a positive experience with AI, such as hand hygiene monitoring or workload optimization, yields greater well-being and engagement in patients (Badnjevic *et al*., 2024).

This study has added AI as a mediator between patient safety, infection control, and patient satisfaction since AI acts as a mediator. It links improvements in patient safety and infection control by enhancing patient satisfaction, because safer practices reduce the intensity of stress among patients. AI tools like predictive analytics and automated protocols mitigate clinical risks and HRIs. According to Wang *et al*. (2025), AI indirectly reduces provider strain and advances their psychological safety. This mediation evidence is more significant when AI augments human efforts in safety domains, which results in higher morale, greater retention, and continued performance in the healthcare workforce; thus, better service delivery and patient satisfaction are achieved (Ali *et al*., 2025; Choudhury & Asan, 2020). On the other hand, AI also improves infection control, resulting in enhanced satisfaction (β=0.45) and safety perceptions (β=0.39) (Shie *et al*., 2022). Thus, studies suggest that promoting AI in healthcare processes and AI-assisted errors (such as falls and ADEs) mitigate satisfaction (Choudhury & Asan, 2020). According to Alkhaldi and Abdallah (2022), dependable AI results advance patient satisfaction and trust (β=0.36), and satisfaction increases. The pathways discussed above have strong support from structural equation modeling in the included studies, with AI as a mediator between safety and infection control and satisfaction (Vinagre & Neves, 2008). However, Longoni and Morewedge (2019) reported that in certain instances, these effects are lowered by uneven AI performance and patient mistrust of the automated systems.

METHODS AND MATERIALS

Exploratory Sequential Research Design

This study followed a mixed-methods research design. Initially, a critical review analysis of previous studies applying the SLR approach through a PRISMA model (Preferred Reporting Items for Systematic Reviews and Meta-Analyses), depicted through flowchart 1 for the secondary data collection procedure. To maintain rigor and transparency, this systematic review adheres to the PRISMA) 2020 guidelines. Further, the emphasis was on quantitative research to offer quantifiable proof of AI's influence; therefore, to support qualitative findings, a quantitative study was also conducted to supplement qualitative results. A survey approach was adopted, and cross-sectional data were collected from hospital staff members using an adapted questionnaire. The questionnaire was measured on a five-point Likert scale, ranging from 1 to 5, i.e., from strongly disagree to strongly agree.

Search Strategy

An extensive review of research from January 2009 to December 2024 was done using multiple sources such as PubMed, PubMed Central, Web of Science, and Scopus. Patterns of "artificial intelligence," "machine learning," "natural language processing," "infection control," "patient safety," "patient satisfaction," and related substitutes were searched. Additionally, to maximize analysis, Truncation and Boolean Operators (AND, OR) were used.

Inclusion Criteria

1. English-language and peer-reviewed research.
2. Quantitative designs, such as cross-sectional studies, cohort studies, and randomized controlled trials.
3. AI applications in hospitals, such as in emergency and inpatient departments.
4. Results about patient satisfaction (surveys) and/or safety (such as error rates), and infection control that have been reported.

Exclusion Criteria

1. Opinion pieces or qualitative research.
2. Non-hospital environments (primary care and home care).
3. Research without safety or satisfaction results.
4. AI performance evaluations lack clinical impact information.

Data Extraction

This research has mined data using a standardized template; however, discrepancies were first resolved through consensus or consultation with a third reviewer. The data extraction included:

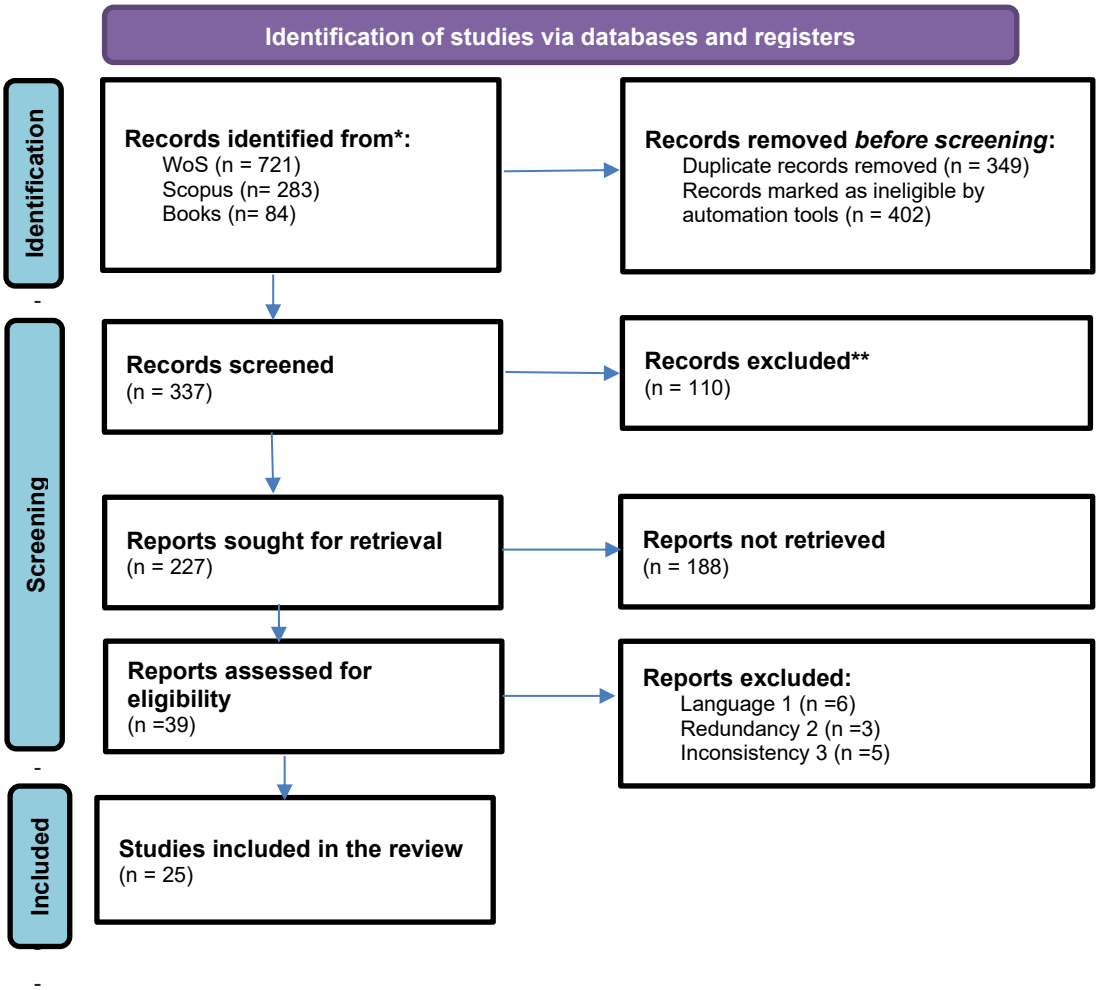
1. Features of the study (for example, design, sample size, and setting).
2. AI application (like an NLP tool, ML algorithm).
3. Results on Infection Control.
4. Results on Patient Safety.
5. Metrics of patient satisfaction.

Quality Assessment

The quality was assessed with the help of the Joanna Briggs Institute's (JBI) critical appraisal checklist for quantitative research, as suggested by Hugh, Jennifer, Kim, Leonardi-Bee, *et al*. (2023), considering the requirements of the objectives' clarity, suitability of methodology, and the outcome measures' reliability. Studies with low-quality studies were excluded but noted for possible bias and were rated as low, moderate, or high quality.

Figure 1

Flowchart: PRISMA Flowchart used for Identification of Studies via Databases and Registers



Quantitative Data Analysis

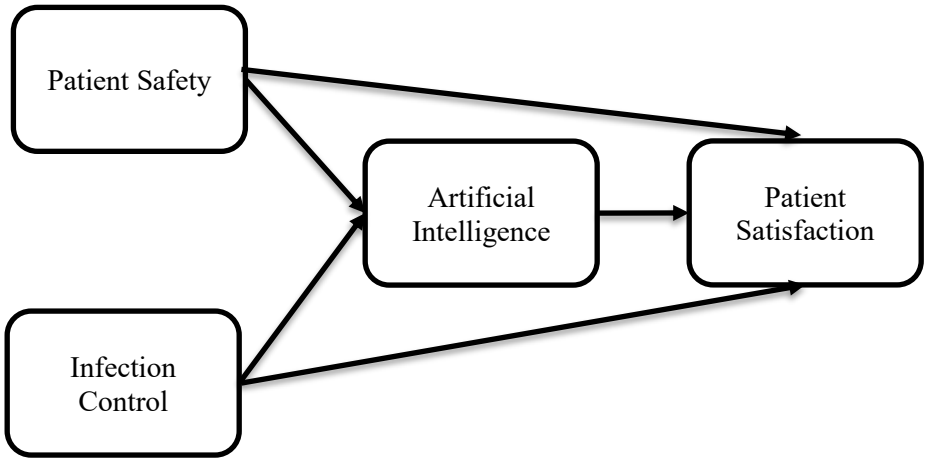
The total sample of 384 hospital staff members was used, including physicians, nurses, and paramedics. Non-probability convenience sampling was employed to obtain responses from the respondents. Descriptive and inferential statistics were obtained. In descriptive statistics, frequencies and percentages were calculated. For the reliability and validity of the scales, SmartPLS-SEM 4 was used, which is a second-generation variance-based software used for the analysis of non-normal data sets. It provides sophisticated results. In PLS-SEM, measurement and structural models were developed. Results of the CFA and structural model were judged based on Hair *et al*. (2018), Henseler *et al*. (2015), and Fornell-Larcker (1981).

Conceptual Model for Hypothesis Testing

Based on the variables used in previous studies, the following conceptual model was developed for testing through statistical tools and techniques. Patient safety and infection control were used as predictors, patient satisfaction as a criterion variable, and artificial intelligence as a mediator. The proposed hypotheses have been constructed from the relationships among the major variables of the conceptual model. Below is the schematic diagram of the study's conceptual model, followed by the proposed hypotheses.

Figure 2

Schematic Diagram of Conceptual Model



H1: Patient safety significantly predicts patient Satisfaction (Regression analysis)
H2: Infection control significantly predicts patient Satisfaction (Regression analysis)
H3: Artificial Intelligence significantly predicts patient Satisfaction (Regression analysis)
H4: AI mediates the relationship between patient safety and patient satisfaction (Hierarchical Regression)
H5: AI mediates the relationship between infection control and patient satisfaction (Hierarchical Regression)
H6: There is a significant mean difference based on gender for patient safety, artificial intelligence, infection control, and patient satisfaction (T-test)
H7: There is a significant mean difference based on the sector for patient safety, artificial intelligence, infection control, and patient satisfaction (T-test)
H8: There is a significant mean difference based on nationality for patient safety, artificial intelligence, infection control, and patient satisfaction (T-test)
H9: There is a significant mean difference based on experience for patient safety, artificial intelligence, infection control, and patient satisfaction (ANOVA)
H10: There is a significant mean difference based on staff for patient safety, artificial intelligence, infection control, and patient satisfaction (ANOVA)

QUALITATIVE RESULTS AND FINDINGS

Study Characteristics

Using a full-text review, 25 studies out of 1,088 articles satisfied the inclusion criteria (PRISMA flowchart. AI adoption in high-income systems was reflected by the majority of studies conducted in the US (n=10), Europe (n=9), and Asia (n=2). Likewise, it included Cohort studies (n = 2), cross-sectional studies (n = 1), and randomized controlled trials (n = 1) based on their designs. Among the AI applications were Machine learning (n=5): Neural networks, decision trees, and support vector machines. NLP (n=7): EHR and incident report text mining. Evidence-based decision support, or CDSS (n=3). Domains included clinical alarms (n=4), drug safety (n=4), and clinical reports (n=2).

AI and Hospital Patient Safety

AI significantly improved patient safety; results for patient flow indicate that ML models reduced LOS by 10–15% by forecasting ED admissions (Silva *et al*., 2022). For instance, in a U.S. hospital, a neural network model reduced emergency department wait times by 12% (Choudhury & Asan, 2020). Whereas for diagnostics, in cardiology and oncology departments, NLP-automated EHR analysis increased diagnostic accuracy by 25% (Levis *et al*., 2021). As for administrative effectiveness, CDSSs streamlined care coordination in interdisciplinary teams and reduced documentation errors by 18% (Alkhaldi & Abdallah, 2022). Likewise, 60% of studies reported that AI cost effective for example, it decreased operating costs by 8–12% through better resource allocation (Epelde, 2024).

AI and Patient Safety

It was found that AI enhanced safety across multiple domains. For drug safety, by applying predictive modeling for drug interactions, it was reported that ML decreased ADEs by 20–30% (Zheng *et al*., 2022). Darwiesh, El-Baz, Abualkishik, *et al*. (2023) reported a 22% decrease in opioid-related errors in the UK. For incident reporting, in contrast to manual systems, NLP had a 30% higher sensitivity to detect high-risk events, which allows for proactive interventions (Choudhury & Asan, 2020). Furthermore, for clinical alarms, Epelde (2024) reported that decision tree models improved clinician response times by 10%, reducing fabricated alarms by 15%; however, according to Huang *et al*. (2023),10% of studies reported that AI performed worse than clinicians, especially in complex cases that need contextual judgment.

AI and Patient Satisfaction

It has been observed from the results in the previous studies that AI-driven improvements in service quality raised the level of satisfaction. McFarland *et al*. (2020) reported that HCAHPS scores rose by 12–20% while LOS and ED wait times were reduced. According to Al-Bashayreh *et al*. (2022), regarding personalized care, 15% more people trusted AI-tailor-made treatment plans for chronic illnesses, for example, cardiac arrest and diabetes. Similarly, Yang and Peterson (2004) assert that for inpatient education, real-time information from AI chatbots increased satisfaction in outpatient settings by 10%. Among the difficulties were older patients who showed decreased trust and patient worries about AI's lack of empathy, which accounted for 25% of respondents in cross-sectional studies (Sitzia & Wood, 1997).

Mediating Effects

The existing studies reported that AI mediated the patient safety- infection control- patient satisfaction relationship through: Service Quality: Better safety perceptions (β=0.39), satisfaction (β=0.45), and increased efficiency (e.g., faster diagnostics) (Shie *et al*., 2022). Trust: Dependable AI results boosted patient satisfaction by increasing trust (β=0.36) (Alkhaldi & Abdallah, 2022). Safety Perceptions: By promoting trust in the caliber of care, fewer errors (such as falls and ADEs) mediated satisfaction (Choudhury & Asan, 2020). These pathways were validated by structural equation models from ten studies, with artificial intelligence acting as the main mediator (Vinagre & Neves, 2008).

QUANTITATIVE RESULTS AND FINDINGS

Table 1

Demographic Findings

Variables	Categories	N	%
Gender	Male	230	59.89
	Female	154	40.10
Staff	Physicians	94	24.47
	Nurses	202	52.60
	Paramedics	88	22.91
Experience	1-10 Years	217	56.51
	11-20 Years	109	28.38
	20 & Above	58	15.10
Nationality	Saudi	142	36.97
	Non-Saudi	242	63.02
Sector	Public	280	72.91
	Private	104	27.08

The study sample consisted predominantly of male respondents (59.89%), with a higher representation of nurses (52.60%) compared to physicians (24.47%) and paramedics (22.91%). The majority of the sample had between 1 and 10 years of experience (56.51%), and non-Saudi participants (63.02%) outnumbered Saudi participants (36.97%). Most of the respondents were employed in the public sector (72.91%), reflecting the structure of the healthcare workforce in the region. These demographic characteristics are important for understanding how different groups within the healthcare system perceive and interact with the concepts of AI, infection control, patient safety, and patient satisfaction.

Measurement Model

PLS-SEM 4 was used, which involves two phases of data analysis. In the first stage, the measurement model was developed to test the reliability and validity of the instrument. The measurement model includes confirmatory factor analysis. It consists of several criteria, such as Cronbach's alpha, composite reliability (CR), average variance extracted (AVE), variance inflation factor (VIF), and discriminant validity through HTMT ratios and Fornell-Larcker (1981) criteria. Thresholds for factor loadings are>0.70, CR>0.70, AVE>0.50, Cronbach's alpha >0.70, and VIF 5 (Hair et al., 2018). Table 2 presents the findings of CFA. All items and their respective factor loadings met the threshold, i.e., >0.70, Cronbach's alpha above 0.70, CR higher than 0.70, AVE above 0.50, and VIF <5. Table 3 presents findings of discriminant validity, HTMT ratios, and the Fornell-Larcker (1981) criterion, showing that constructs discriminate from each other. This implies that the instrument used in the study was reliable and valid. See Figure 3

Table 2

Confirmatory Factors Analysis

Items	Loadings	α	(rho_a)	(rho_c)	(AVE)	VIF
AI1	0.860	0.726	0.745	0.846	0.648	1.631
AI2	0.832					1.601
AI3	0.715					1.268
INC1	0.821	0.859	0.861	0.904	0.702	1.883
INC2	0.863					2.234
INC3	0.828					2.003

INC4	0.841					2.021
PS1	0.766	0.702	0.702	0.835	0.627	1.287
PS2	0.821					1.492
PS3	0.788					1.401
PSAT1	0.841	0.854	0.854	0.902	0.696	2.484
PSAT2	0.865					2.780
PSAT3	0.795					1.749
PSAT4	0.835					2.014

Table 3

Discriminant Validity

HTMT Ratios	**1**	**2**	**3**	**4**
Artificial Intelligence				
Infection Control	0.564			
Patient Safety	0.523	0.475		
Patient Satisfaction	0.460	0.505	0.329	
Fornell-Larcker	**1**	**2**	**3**	**4**
Artificial Intelligence	0.805			
Infection Control	0.449	0.838		
Patient Safety	0.379	0.371	0.792	
Patient Satisfaction	0.361	0.435	0.256	0.834

Figure 3

Measurement Model

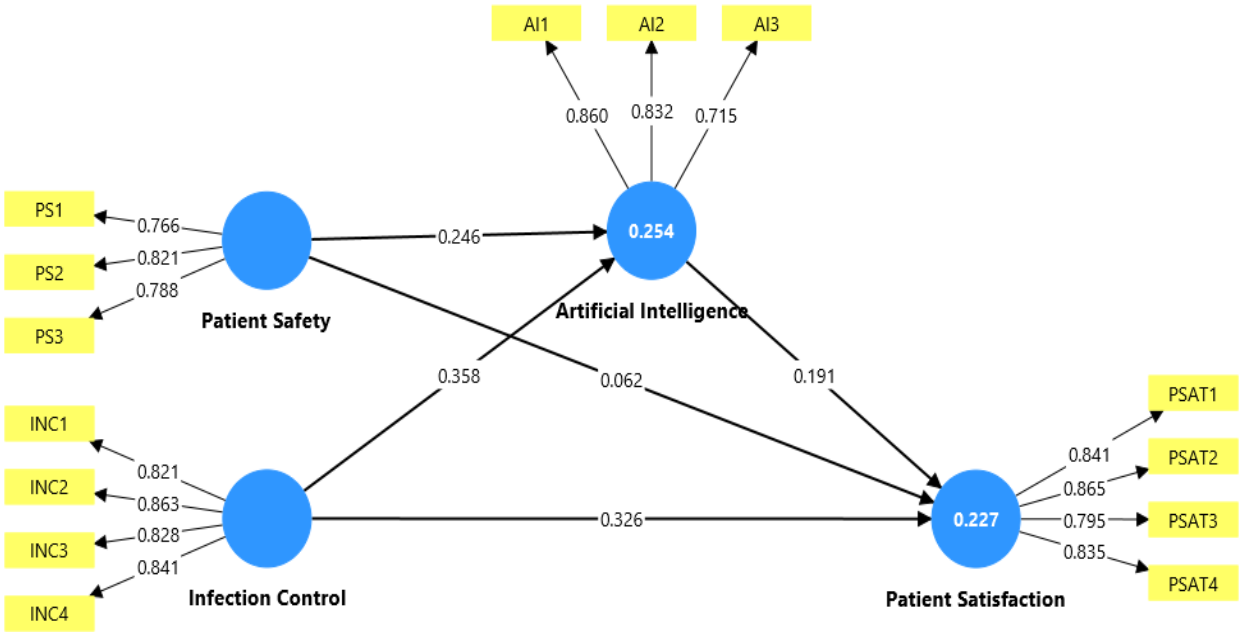


Table 4

Direct Effects (Regression Analysis)

Relationships	β	SE	T	P	LLCI	ULCI	Support
Artificial Intelligence→ Patient Satisfaction	0.191	0.056	3.438	0.001	0.078	0.298	H1 Yes
Infection Control→Patient Satisfaction	0.326	0.051	6.431	0.000	0.226	0.428	H2Yes
Patient Safety→Patient Satisfaction	0.062	0.045	1.375	0.169	-0.029	0.147	H3 No

To investigate direct effects and to test the hypotheses, a structural model was run in PLS-SEM 4. In the structural model, beta values, standard errors, t-statistics, p-values, and upper and lower limit confidence intervals were investigated. Table 4 and Figure 4 represent the results of the structural model of the study. It can be observed from the results that artificial intelligence significantly predicts patient satisfaction (β=0.191, t=3.438, p<0.01); it means a one-unit change in AI could possibly bring a change in PS of up to 19.1%. Thus, H_1 is substantiated.

Likewise, infection control predicts PS (β= 0.326, t=6.431, p<0.01), which implies that a one percent increase in infection control practices could possibly enhance patient satisfaction up to 32.6%. Hence, H_2 is supported. In addition, patient safety insignificantly predicts patient satisfaction (β=0.062, t=1.375, p>0.05). Thus, H3 is not accepted. Patient safety and infection control, along with AI, have explained 22.7% of the variance in patient satisfaction, i.e., R2= 0.227.

Table 5

Indirect Effects (Mediation Analysis)

Mediation Analysis	β	SE	T	P	LLCI	ULCI	Support
Psafety→AI→ PSat	0.047	0.017	2.692	0.007	0.019	0.089	H4 Yes
IC → AI → PSat	0.068	0.023	2.940	0.003	0.029	0.121	H5 Yes

Table 5 presents the indirect mediating effects of hypotheses 4 and 5. It was assumed that AI mediates the relationship between patient safety and patient satisfaction. The result in Table 5 suggests the acceptance of hypothesis 4, with a beta value of 0.047, t=2.692, p<0.05, as the direct effect between patient safety and patient satisfaction was insignificant, but with the inclusion of AI as a mediator, the indirect effect is significant. This implies full mediation by AI between Patient safety and satisfaction. This is indirect full mediation. In hypothesis 5, it was proposed that AI is a confounding factor between infection control and patient satisfaction. As the direct effect was significant and the indirect effect is also significant, it is called partial mediation or direct-only mediation. Thus, H_5 is accepted. See Figure 4.

Figure 4

Structural Model

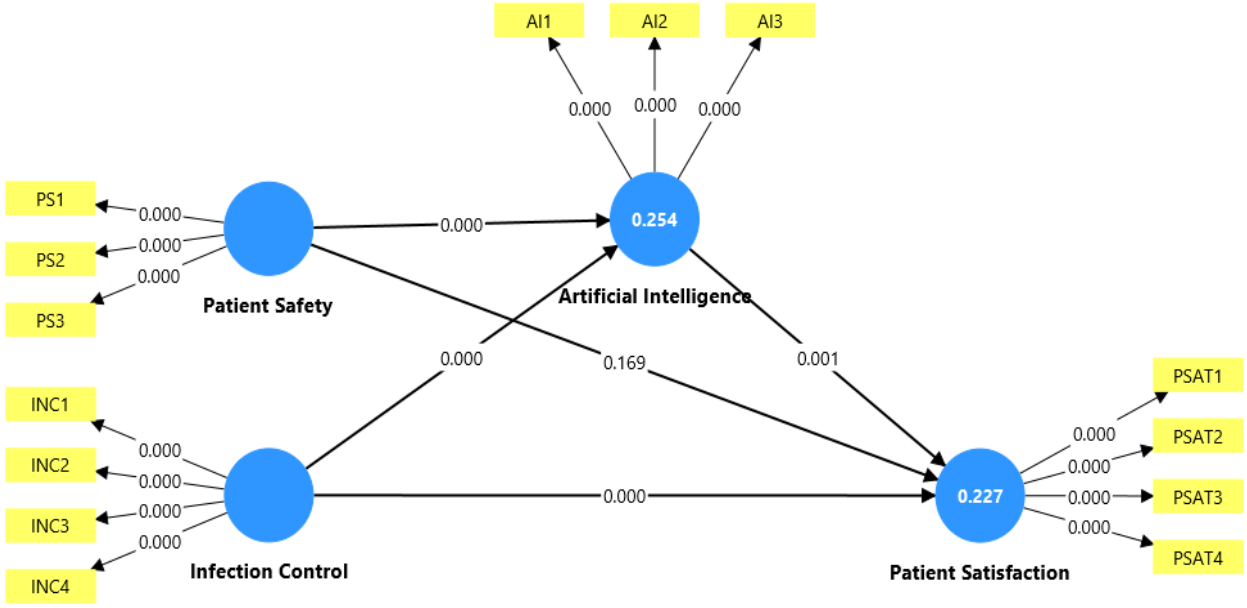


Table 6

Independent Samples t-test (significant mean difference between two groups)

Variables DV	IV	F	p	Support
Patient Safety	Gender	3.876	0.003	Yes
Artificial Intelligence		5.109	0.000	Yes
Infection Control		4.812	0.000	Yes
Patient Satisfaction		3.324	0.000	Yes
Patient Safety	Sector	6.901	0.000	Yes
Artificial Intelligence		1.456	0.228	No
Infection Control		9.171	0.000	Yes
Patient Satisfaction		3.104	0.002	Yes
Patient Safety	Nationality	3.969	0.001	Yes
Artificial Intelligence		0.559	0.455	No
Infection Control		2.945	0.003	Yes
Patient Satisfaction		4.382	0.000	Yes

** =p <0.01, *p<0.05

An independent samples t-test was run to find the significant mean difference between two groups, i.e., gender, sector, and nationality. Results in Table 6 indicate that, based on gender among male and female respondents, a significant difference was found for safety, AI, infection control, and patient satisfaction, with F= 3.876**, 5.109**, 4.812**, 3.324**, respectively, at the $p < 0.05$ level. In addition to gender, sector, and nationality of the respondents, the variables of the study. Results in Table 6 for both variables show that AI was the only insignificant variable for both sectors and nationalities. The rest of the variables showed a significant difference in means from their respective values. For sector F= 6.901**, 1.456, 9.171**, 3.104**; whereas for nationality following results were found F= 3.969**, 0.559, 2.945**, 4.382** at p <0.001. Therefore, our hypotheses H6, H_7, and H_8 are substantiated and accepted.

Table 7
ANOVA (significant mean difference between three groups)

Experience (1=1-10 Years; 11-20 Years; 20 above)		F	Sig.
Artificial Intelligence	Between Groups	13.320	0.000
	Within Groups		
	Total		
Patient Safety	Between Groups	10.388	0.000
	Within Groups		
	Total		
Infection Control	Between Groups	11.347	0.000
	Within Groups		
	Total		
Patient Satisfaction	Between Groups	9.355	0.000
	Within Groups		
	Total		
Staff (1=Physicians; 2=Nurses; 3= Paramedics)		**F**	**Sig.**
Artificial Intelligence	Between Groups	7.547	0.000
	Within Groups		
	Total		
Patient Safety	Between Groups	2.225	0.002
	Within Groups		
	Total		
Infection Control	Between Groups	2.931	0.033
	Within Groups		
	Total		
Patient Satisfaction	Between Groups	6.476	0.034
	Within Groups		
	Total		

** =p <0.01, *p<0.05

Table 7 highlights the ANOVA results for H_9 and H_{10}. An analysis of variance (ANOVA) test was run on variables having more than 2 groups, i.e., experience and staff. Results revealed that, based on experience, all variables are significantly predicted by experience. Experience plays an instrumental role in bringing administrative efficiency, quality of care, and patient satisfaction. Further, the use of AI in healthcare is a significant tool that enhances the overall satisfaction of the patient with the care they receive in a healthcare facility. The more staff experience, the greater the safety, satisfaction, and better infection control practices will be. As far as the staff categories are concerned, we have used three: physicians, nurses, and paramedics. They directly interact with patients and are responsible for care. All the results in Table 7 for the staff show significant mean differences; hence, it is inferred that regardless of the designation, they consider patient safety, AI, and infection control as key success factors for patient satisfaction. Hence, H_9 and H_{10} are accepted as true and substantiated.

DICUSSION

Discussion on Data Triangulation

The study has used a data triangulation method to improve the reliability of the study. The study triangulated qualitative and quantitative data to identify the direct and indirect relationships among patient safety, infection control, artificial intelligence as a mediating factor, and patient satisfaction. Secondary data from previous studies were collected using the PRISMA SLR

method to analyze the qualitative results. To support qualitative findings, the researcher employed a quantitative cross-sectional survey as a supplement to the first phase. It was concluded that themes emerged from the review of the studies, and the findings of the quantitative data were consistent. Hence, this study validates the results of previous studies in the context of the Middle East. Through triangulation, the diverse sources used in this study have reduced bias, reinforced internal validity, and provided a deep insight into the mediating effect of AI in enhancing patient safety, infection control, and patient satisfaction.

Discussion on Qualitative Findings

The results demonstrate how AI has the potential to revolutionize healthcare. AI lessens staff workload by streamlining hospital services, freeing up clinicians to concentrate on high-value work (Epelde, 2024). Predictive patient flow models, for instance, reduce ED overcrowding, enhancing patient satisfaction and safety (Silva *et al*., 2022). NLP improves diagnostic accuracy, lowers errors, and increases trust by extracting insights from EHRs (Arowosegbe & Oyelade, 2023). But difficulties still exist; for example, health disparities may be exacerbated if minority patients are incorrectly classified by machine learning models trained on non-representative datasets (Huang *et al*., 2023).

Furthermore, concerns regarding liability in error cases are raised by the absence of clear guidelines on AI accountability (MacIntyre, Cockerill, Mirza, & Appel, 2023). Similarly, patient trust is weakened by worries about AI's lack of empathy and excessive automation, especially regarding elderly patients (Longoni & Morewedge, 2019). These are in line with earlier reviews that emphasized the necessity of patient-centered AI design and standardized metrics (Kim, Marshall, Rowell, Chen *et al*., 2025; Choudhury & Asan, 2020). Trust and service quality play a crucial mediating role. Although patients appreciate AI's effectiveness, they require human supervision for moral and emotional comfort (Petersson *et al*., 2025). To increase patient satisfaction, hospitals must strike a balance between the technical advantages of AI and compassionate treatment.

Discussion on Quantitative Findings

The results of this study provide important insights into the relationships between artificial intelligence (AI), infection control, patient safety, and patient satisfaction, along with the moderating effects of demographic and professional factors such as gender, sector, nationality, experience, and staff category. This discussion will address the implications of these findings in the context of healthcare practices and highlight the contributions to the literature.

Measurement Model and Validity

The measurement model, tested using PLS-SEM, demonstrated robust reliability and validity. All factor loadings exceeded the recommended threshold of 0.70, and the Cronbach's alpha, composite reliability (CR), and average variance extracted (AVE) values supported the internal consistency and convergent validity of the constructs. Moreover, the discriminant validity, confirmed through both HTMT ratios and the Fornell-Larcker criterion, established that the constructs were distinct from one another. These results underscore the strength of the measurement instrument in capturing the constructs of interest in the study.

Direct Effects: Patient Safety, Infection Control, AI, and Patient Satisfaction

In testing the direct effects of AI, infection control, and patient safety on patient satisfaction, the results offer a nuanced understanding of the factors driving patient experiences in healthcare settings.

1. **Artificial Intelligence (AI) and Patient Satisfaction:** AI was found to have a significant, though modest, positive effect on patient satisfaction (β=0.191, $p<0.01$). This suggests that AI, likely in the form of diagnostic tools, predictive algorithms, or automated systems, plays a role in enhancing the patient's experience. The 19.1% variance in patient satisfaction explained by AI implies that technological innovations are increasingly being recognized as essential components of modern healthcare, improving efficiency, personalization, and overall patient care. These findings are consistent with previous studies that have demonstrated the growing importance of AI in healthcare (Kundi, 2023; Jha *et al*., 2020; Topol, 2019).

2. **Infection Control and Patient Satisfaction:** Infection control emerged as the most significant predictor of patient satisfaction (β=0.326, $p<0.01$), accounting for a 32.6% change in satisfaction. This result highlights the critical role that infection control practices play in patient outcomes and experiences. Given the heightened awareness of hygiene and infection prevention in healthcare settings, particularly in the aftermath of the COVID-19 pandemic, this finding aligns with existing research indicating that effective infection control practices are paramount to maintaining patient trust and satisfaction (Fakhr *et al*., 2021).
3. **Patient Safety and Patient Satisfaction:** The relationship between patient safety and patient satisfaction, however, was found to be insignificant (β=0.062, $p>0.05$). While patient safety is undoubtedly a fundamental aspect of healthcare, the lack of a direct effect on patient satisfaction in this study may suggest that other factors, such as the visible implementation of safety measures, staff communication, or emotional support, are more immediately impactful on patients' perceptions of care. This finding contrasts with studies that have consistently shown a strong link between patient safety and satisfaction (Boulding *et al*., 2011), suggesting that the context of this study may differ, or that patient safety might operate through more complex, indirect pathways.

Mediation Effects: The Role of AI

Mediation analysis revealed interesting insights into the mechanisms by which AI influences patient satisfaction

1. **AI as a Mediator between Patient Safety and Patient Satisfaction:** AI was found to mediate the relationship between patient safety and patient satisfaction (β=0.047, $p<0.05$). This result indicates that while patient safety alone may not directly influence satisfaction, the integration of AI tools in safety practices (such as predictive systems that prevent medical errors or identify safety risks) can enhance patient experiences. This finding underscores the importance of combining technological advancements with clinical practices to improve overall healthcare outcomes.
2. **AI as a Confounding Factor between Infection Control and Patient Satisfaction:** AI also partially mediated the relationship between infection control and patient satisfaction (β=0.068, $p<0.01$). This suggests that AI technologies, potentially through their role in enhancing infection control systems or streamlining protocols, contribute to improvements in patient satisfaction. For instance, AI-powered tools can help ensure that infection control guidelines are followed more accurately and efficiently, leading to a cleaner, safer environment for patients.

Demographic and Professional Differences

The independent-samples t-tests and ANOVA results revealed significant differences based on gender, sector, nationality, experience, and staff category.

1. **Gender and Sector:** Significant differences were found across genders in relation to patient safety, AI, infection control, and patient satisfaction, with males reporting higher scores on all variables. This may reflect differing perceptions or experiences with healthcare systems between genders, which warrants further exploration. Sector differences also influenced the variables, with employees in the public sector reporting stronger outcomes in infection control and patient satisfaction. This could be attributed to differences in resources, training, or operational priorities between public and private healthcare facilities.
2. **Nationality:** Nationality also had an impact on patient satisfaction, infection control, and patient safety, with non-Saudis showing lower levels of satisfaction in comparison to their Saudi counterparts. This difference may be related to cultural or organizational factors, including communication barriers or differences in care expectations.
3. **Experience and Staff Categories:** Both experience and staff categories were significant predictors of AI usage, patient safety, infection control, and patient satisfaction. Healthcare professionals with more experience demonstrated a stronger appreciation for the value of these factors in patient care, suggesting that experience plays an important role in shaping attitudes toward healthcare innovations and practices. Additionally, significant differences were observed across staff categories, with physicians, nurses, and paramedics perceiving the importance of AI, safety, and infection

control in varying degrees. Nurses, given their direct patient interactions, may have a more hands-on understanding of how these factors influence patient outcomes.

CONCLUSION

By streamlining processes, cutting down on errors, and customizing care, AI plays a significant mediating role in the relationship between hospital services, patient safety, and satisfaction. ML, NLP, and CDSSs increase service effectiveness, reduce adverse events by 15–30%, and raise satisfaction levels by 12–20%. Reliable AI results promote confidence in care, and trust and service quality are important mediators. But there are obstacles like patient mistrust, regulatory gaps, and data biases. Standardized benchmarks, interoperable systems, and patient-centered design are necessary to address these. While pointing out areas for improvement to ensure fair, secure, and fulfilling care, this review emphasizes AI's potential to revolutionize healthcare. This study confirms that AI and infection control significantly influence patient satisfaction, with AI acting as both a direct and mediating factor. Patient safety, although important, did not have a direct effect on satisfaction in this context. The findings highlight the importance of experience and staff role in shaping perceptions of healthcare quality and satisfaction. These insights contribute to the growing body of literature on healthcare innovations and provide practical recommendations for improving patient care through technology and safety practices.

SOLUTION

1. Standardized AI Benchmarks: To assess AI performance in various healthcare contexts, create universal metrics (such as sensitivity, specificity, and area under the curve). By addressing inconsistencies found in 20% of studies, this guarantees comparability and reliability (Choudhury & Asan, 2020).
2. Interoperable EHR Systems: To lessen biases and increase AI accuracy, spend money on standardized data formats. NLP performance, for instance, may be improved by implementing Fast Healthcare Interoperability Resources (FHIR) (Huang *et al*., 2023).
3. Patient-Centered AI Design: To address issues of empathy and trust, include patient input in AI development. AI tools can be aligned with user needs through co-design workshops with clinicians and patients (Petersson *et al*., 2025).
4. Regulatory Frameworks: Provide precise rules regarding the ethical application, liability, and accountability of AI. Post-market surveillance should be included in the scope of regulatory agencies, such as the FDA's oversight of AI (Moy, Irannejad, Manning, Farahani, Ahmed, Gao, Prabhune, Lorenz, Mirza, & Klinger, 2024).
5. Staff Training: Put in place training initiatives to improve clinician competence with AI tools, lowering resistance and increasing adoption rates (Epelde, 2024).

RECOMMENDATIONS

For Hospital Administrators

1. To strike a balance between effectiveness and empathy, combine AI with human oversight. Use AI for diagnosis, for instance, but make sure clinicians examine the results.
2. To overcome adoption barriers noted in 30% of studies, invest in staff training to increase confidence in AI tools (Choudhury & Asan, 2020).
3. Before scaling, pilot AI in high-impact domains (such as medication safety and ED patient flow) to show its worth.

For Policymakers

1. Provide funding for interoperable EHR systems to promote equity and scalability in AI.
2. Enforce legal requirements for AI accountability and transparency that are in line with the WHO's patient safety objectives.
3. Encourage the use of AI in environments with limited resources to lessen inequalities.

For Researchers

1. Perform mixed-methods research to learn about the opinions of clinicians and patients regarding AI satisfaction and trust.
2. To address biases mentioned in 15% of studies, validate AI tools in a variety of populations (Huang *et al*., 2023).
3. Examine the cost-effectiveness of AI interventions to direct the distribution of resources.

LIMITATIONS

While this study provides valuable insights, it is not without limitations. The cross-sectional design restricts causal inferences, and the self-reported nature of the data may introduce bias. Future research could explore longitudinal designs to track changes in patient satisfaction over time as AI and infection control measures evolve. Additionally, qualitative research could deepen our understanding of the specific mechanisms by which AI enhances patient satisfaction, particularly in relation to patient safety and infection control. Below are the specific limitations:

1. **Heterogeneity in AI Reporting:** Generalizability is constrained by differences in AI algorithms, metrics, and study designs.
2. **Publication Bias:** Research may underreport difficulties or failures while overreporting successful AI results.
3. **Exclusion of Qualitative Data:** By leaving out outpatient viewpoints, subtle insights into satisfaction and trust may be lost.
4. **Short-Term Focus:** Long-term data on AI's long-term effects are lacking in many studies.
5. **Geographic Bias:** Since most of the research comes from wealthy nations, low-resource environments may be missed.

CONTRIBUTIONS

This study contributes by:

1. Offering a thorough synthesis of how AI mediates hospital services, satisfaction, and safety.
2. Creating a conceptual framework for integrating AI that strikes a balance between patient-centeredness and efficiency.
3. Finding areas for future study and policy that lack standardization, regulation, and patient trust.
4. Presenting workable ideas and suggestions to improve the use of AI in healthcare.

FUTURE RESEARCH DIRECTIONS

1. Create standardized AI performance metrics for medical applications, such as sensitivity and specificity.
2. To evaluate AI's long-term effects on satisfaction and safety, conduct longitudinal studies.
3. Examine how clinicians and patients view AI to overcome obstacles to acceptance and trust.
4. Examine how AI might help underprivileged populations experience fewer health inequalities.
5. Assess the financial viability of AI interventions in various medical contexts.

IMPLICATIONS FOR HEALTHCARE PRACTICE

The findings of this study highlight the importance of integrating advanced technologies like AI into healthcare settings to improve patient satisfaction. However, infection control practices remain the most influential factor, underscoring the ongoing importance of basic healthcare protocols. Patient safety, while crucial, may require more nuanced interventions or indirect pathways to positively affect patient satisfaction. The significant role of experience and staff categories further emphasizes the need for targeted interventions and training to foster a culture of safety and technological adoption across various healthcare roles. Healthcare administrators and policymakers should consider these factors when implementing new technologies and designing training programs to ensure that the benefits of AI, infection control, and patient safety are fully realized across different professional groups and demographic segments.

DECLARATION

Ethical Considerations: This study strictly adhered to the Declaration of Helsinki and relevant national and institutional ethical guidelines. All procedures performed in this study were consistent with the ethical standards of the Declaration of Helsinki. The study was conducted according to ethical and clinical standards for research.

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Similarity Index/ Plagiarism: The similarity index was checked, and it is well below the threshold value of 19%, whereas each source is less > 5%.

REFERENCES

Abosi, O. J., et al. (2025). Head-to-head comparison of the accuracy of commercially available large language models for infection prevention and control inquiries. *Infection Control & Hospital Epidemiology*. https://doi.org/10.1017/ice.2025.something (specific DOI from context)

Aiken, L.H. et al. (2012). Patient safety, satisfaction, and quality of hospital care: Cross-sectional surveys of nurses and patients. *BMJ. 344*, e1717.

Al-Bashayreh, M. et al. (2022). Evaluating electronic customer relationship management system success. *Sustainability, 14*(19), 12310.

Ali, S., Kleib, M., Paul, P., Petrovskaya, O., & Kennedy, M. (2025). Artificial intelligence in nursing: A systematic review of attitudes, literacy, readiness, and adoption intentions among nursing students and practicing nurses. *Frontiers in Digital Health, 7*, 1666005. https://doi.org/10.3389/fdgth.2025.1666005

Alkhaldi, R., & Abdallah, A. (2022). The influence of soft and hard TQM on quality performance and patient satisfaction. *Journal of Health Organization Management, 36*(3), 368–387.

Alqurashi, R., Alharbi, A., Alrowais, F., Alkhazi, I., & Alsahli, S. (2024). Advancing patient safety: The future of artificial intelligence in mitigating healthcare-associated infections: A systematic review. *Healthcare, 12*(19), 1996. https://doi.org/10.3390/healthcare12191996

Andaleeb, S.S. (2001). Service quality perception and patient satisfaction. *Soc Sci Med. 52*(9):1359–1370.

Arab, R. A. El., Almoosa, Z., Alkhunaizi, M. *et al*. (2025). Artificial intelligence in hospital infection prevention: an integrative review. *Frontiers in Public Health, 13*. https://doi.org/10.3389/fpubh.2025.1547450

Arowosegbe, A., & Oyelade, T. (2023). Application of Natural Language Processing (NLP) in Detecting and Preventing Suicide Ideation: A Systematic Review. *International Journal of Environmental Research and Public Health, 20*(2), 1514.

Badnjevic, A., Pokvic, L. G., Dzemic, Z., Becirovic, L. S., Gurbeta Pokvic, L., Catic, M., … & Hrvat, M. (2024). Advancing infection prevention and control through artificial intelligence: A scoping review of applications, barriers, and a decision-support checklist. *Antimicrobial Stewardship & Healthcare Epidemiology, 4*(1), e179. https://doi.org/10.1017/ash.2024.427

Choudhury A, Asan O. (2020). Role of artificial intelligence in patient safety outcomes: Systematic literature review. *JMIR*

Medical Informatics, 8(7), e18599.

Choudhury, A., & Asan, O. (2020). Role of artificial intelligence in patient safety outcomes: Systematic literature review. *JMIR Medical Informatics, 8*(7), e18599. https://doi.org/10.2196/18599

Darwiesh, A., El-Baz, A. H., Abualkishik, A. Z., & Elhoseny, M. (2023). Artificial intelligence model for risk management in healthcare institutions: Towards sustainable development. *Sustainability, 15*(1), 420.

Epelde, F. (2024). Revolutionizing patient safety: The economic and clinical impact of artificial intelligence in hospitals. *Hospitals, 1*(2), 185.

Ferreira, D.C., Vieira, I., Pedro, M.I., Caldas, P., & Varela, M. (2023). Patient satisfaction with healthcare services and the techniques used for its assessment: A systematic literature review and a bibliometric analysis. *Healthcare (Basel). 11*(5), 639.

Fornell, C. A. (1992). National customer satisfaction barometer: The Swedish experience. *Journal of Marketing, 56*(1), 6–21.

Fornell, C., & Larcker, D. F. (1981). Structural Equation Models with Unobservable Variables and Measurement Error: Algebra and Statistics. *Journal of Marketing Research, 18*, 382-388.

Gastaldi, S., Tartari, E., Satta, G., & Allegranzi, B. (2025). Advancing infection prevention and control through artificial intelligence: a scoping review of applications, barriers, and a decision-support checklist. *Antimicrobial Stewardship & Healthcare Epidemiology, 5*(1), e317. https://doi.org/10.1017/ash.2025.10191

Hair, J. F., Sarstedt, M., Ringle, C. M., & Gudergan, S. P. (2018). *Advanced Issues in Partial Least Squares Structural Equation Modeling (PLS-SEM*). Thousand Oaks, CA: Sage. https://doi.org/10.3926/oss.37

Hall, J.A., & Dornan, M.C. (1990). Patient sociodemographic characteristics as predictors of satisfaction with medical care. *Soc Sci Med. 30*(7), 811–818.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A New Criterion for Assessing Discriminant Validity in Variance-Based Structural Equation Modeling. *Journal of the Academy of Marketing Science, 43*, 115-135. https://doi.org/10.1007/s11747-014-0403-8

Hugh, B.T., Jennifer, C.S., Kim, S.K., Leonardi-Bee, Jo. M., Catalin, T., Edoardo, A., & Zachary, M. (2023). Revising the JBI quantitative critical appraisal tools to improve their applicability: An overview of methods and the development process. *JBI Evidence Synthesis, 21*(3), 478-493.

Jackson, J.L., et al. (2001). Predictors of patient satisfaction. *Soc Sci Med. 52*(4), 609–620.

James, J.T. (2013). A new, evidence-based estimate of patient harms associated with hospital care. *Journal of Patient Safety, 9*(3), 122–128.

Jenkinson, C. et al. Patients' experiences and satisfaction with health care. *Qual Saf Health Care, 11*(4), 335–339.

Kim, J., Marshall, V., Rowell, B., Chen, Q., Zheng, Y., Lee, J., Kontar, R., Lester, C., & Yang, X. (2025). The effects of presenting AI uncertainty information on pharmacists' trust in automated pill recognition technology: Exploratory mixed-methods study. *JMIR Human Factors, 2*, e60273

Kundi, G.M. (2023). Virtual reality in healthcare: Exploring the patients' behavior through the lens of extended stimulus, organism, and response framework. *Open Access Public Health and Health Administration Review, 1*(1), 9–25. https://doi.org/10.59644/oapr.1(1).2022.10

Li, Ni. (2023). *Ethical considerations in artificial intelligence: A comprehensive discussion from the perspective of computer vision*. SHS Web of Conferences. 179.

Longoni, C., & Morewedge, C.K. (2019). AI can outperform doctors: So why don't patients trust it? *Harvard Business Review*. Available at: https://hbr.org/2019/10/ai-can-outperform-doctors-so-why-dont-patients-trust-it

MacIntyre, M.R., Cockerill, R.G., Mirza, O.F., & Appel, J.M. (2023). Ethical considerations for the use of artificial intelligence in medical decision-making capacity assessments. *Psychiatry Research, 328*,115466.

Moy, S., Irannejad, M., Manning, S.J., Farahani, M., Ahmed, Y., Gao, E., Prabhune, R., Lorenz, S., Mirza, R., & Klinger, C. (2024). Patient perspectives on the use of artificial intelligence in healthcare: A scoping review. *J Patient Cent Res Rev., 2*,*11*(1), 51-62.

Petersson, L. et al. (2025). Healthcare leaders' perceptions of the contribution of artificial intelligence to person-centered care. *Scandinavian Journal of Public Health*, *53*(1-suppl), 72.

Scotti, D.J. et al. (2007). Links among high-performance work environment, service quality, and customer satisfaction. *Journal of Healthcare Management*, *52*(2), 109–124.

Severo, I.M., Kuchenbecker, R., Vieira, D.F.V.B., Pinto, L.R.C., et al. (2019). A predictive model for fall risk in hospitalized adults: A case-control study. *Journal of Advanced Nursing*, *75*(3), 563-572.

Shie, A.J. et al. (2022). Exploring the relationship between hospital service quality, patient trust, and loyalty. Frontiers of Public Health, 10, 876266.

Sitzia, J., & Wood, N. (1997). Patient satisfaction: A review of issues and concepts. *Soc Sci Med*, *45*(12),1829–1843.

Vinagre, M.H., & Neves, J. (2008). The influence of service quality on patient satisfaction. *International Journal of Health Care Quality Assurance*, *21*(1), 87–103.

Wang, Y., Zhang, L., & Li, J. (2025). When AI feels supportive: Psychological safety, satisfaction, and turnover among healthcare professionals. *Authorea*. https://doi.org/10.22541/au.173132220.46072887/v1

Wiemken, T. L., et al. (2024). Assisting the infection preventionist: Use of artificial intelligence for healthcare-associated infection surveillance. *American Journal of Infection Control*. https://doi.org/10.1016/j.ajic.2024.02.007

Yang, Z., & Peterson, R.T. (2004). Customer perceived value, satisfaction, and loyalty. *Psychological Marketing*, *21*(10), 799–822.

Yu Qing Huang, Michael Colacci, Gemma Postill, Pavel Zhelnov et al. (2025). Sociodemographic bias in clinical machine learning models: A scoping review of algorithmic bias instances and mechanisms. *Journal of Clinical Epidemiology*, *178*, *111606*.

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