



Original Research Article

Knowledge and perception of artificial intelligence among operating room staff in educational hospitals: a cross-sectional survey

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ABSTRACT

Background: Successful implementation of artificial intelligence (AI) in healthcare depends not only on technological performance but also on the readiness of healthcare professionals to understand, trust, and appropriately use AI-enabled systems. Evidence regarding AI knowledge among multidisciplinary operating room (OR) staff remains limited, particularly in low- and middle-income healthcare settings.

Objective: To assess AI-related knowledge and perceptions among OR personnel and examine demographic factors associated with workforce preparedness for AI implementation in clinical practice.

Methods: An analytical cross-sectional survey was conducted among 200 OR healthcare professionals, including nurses, OR technicians, and anesthesiology personnel, working in four educational hospitals affiliated with Isfahan University of Medical Sciences, Iran. Data were collected using a researcher-developed questionnaire, validated for content and construct validity, consisting of demographic characteristics, seven knowledge items, and twenty-five perception items. Because the data were not normally distributed, Mann-Whitney U, Kruskal-Wallis, and Spearman correlation tests were used for statistical analysis.

Results: Participants demonstrated limited AI knowledge (mean score: 2.11 ± 0.76 out of 7; 30.1% of the maximum possible score), whereas perceptions toward AI were generally positive (mean score: 76.8 ± 14.5 out of 125). Knowledge scores differed significantly according to educational level ($P < 0.001$), employment status ($P < 0.001$), professional discipline ($P = 0.026$), work experience ($P = 0.015$), and gender ($P = 0.036$). Perception scores were significantly associated only with educational level ($P = 0.010$). Knowledge and perception showed a moderate positive correlation (Spearman's $r = 0.421$, $P < 0.001$), while age was weakly negatively correlated with knowledge ($r = -0.156$, $P = 0.027$).

Conclusions: Despite favorable attitudes toward AI, OR staff demonstrated substantial deficiencies in AI knowledge. Further research and targeted educational initiatives may be warranted to improve AI knowledge among perioperative healthcare professionals and support the safe integration of clinical informatics.

1. Introduction

The integration of Artificial Intelligence (AI) into healthcare systems has transitioned from theoretical research to clinical reality, presenting both transformative opportunities and complex challenges for workforce preparedness [1]. AI technologies, capable of analyzing complex clinical data and predicting errors, hold significant potential to enhance

diagnostic accuracy, optimize workflow, and reduce adverse events in high-stakes environments such as the operating room (OR) [2]. However, the success of AI implementation depends not merely on algorithmic precision but critically on the cognitive and attitudinal preparedness of end-users [3].

The OR is a complex socio-technical system characterized by high cognitive load, time pressure, and intricate interdisciplinary

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1386-5056/© 2026 Elsevier B.V. All rights are reserved, including those for text and data mining, AI training, and similar technologies.

coordination [4]. In this environment, the misinterpretation of AI-driven recommendations by untrained personnel introduces potential risks to workflow efficiency and patient safety [5]. Applications of AI in the OR range from automated surgical phase recognition and instrument tracking to real-time hemodynamic stability alerts [6]. While these tools can mitigate cognitive load, they also redefine traditional role hierarchies, requiring a deep understanding of system capabilities and limitations [7]. Informatics literature suggests that inadequate understanding of AI probabilistic outputs may lead to delayed clinical interventions or over-reliance on automated suggestions, representing a potential barrier to safe adoption [8].

Conceptually, it is crucial to distinguish between knowledge and perception in the context of Human-AI interaction, grounded in established technology acceptance frameworks. Drawing upon the Technology Acceptance Model (TAM) [9,10], knowledge refers to the cognitive understanding of AI principles, limitations, and ethical boundaries, which directly influences the “perceived ease of use” of a system. Perception, conversely, encompasses attitudinal constructs such as “perceived usefulness,” trust, and behavioral intention to use the technology [11]. Literature suggests that a disconnect between these two constructs can lead to scenarios where staff hold unrealistic expectations of AI capabilities while simultaneously fearing professional displacement [12].

Despite growing research on AI in healthcare, significant gaps remain. Most studies focus either on technical aspects or on single-profession groups, such as surgeons, radiologists, or medical students [13,14], neglecting the multidisciplinary nature of OR teams. The multidisciplinary OR team (comprising nurses, technicians, and anesthesia providers) represents a unique population due to the dynamic, high-stakes nature of their collaborative work. Evaluating this specific group provides additional value compared to surgeon-focused studies, as it captures the collective workflow integration required for systemic AI adoption. Furthermore, the influence of demographic and structural factors on AI knowledge in developing countries like Iran remains underexplored [15].

This study aims to bridge these gaps by simultaneously assessing the knowledge and perception of AI among a multidisciplinary group of OR staff in Isfahan, Iran, explicitly stating its novelty by providing empirical data on team-level informatics preparedness in a resource-constrained setting.

Based on the Technology Acceptance Model (TAM) and previous literature, we formulated the following hypotheses: (H1) operating room personnel would demonstrate limited AI knowledge despite generally positive perceptions toward AI; (H2) AI knowledge would be positively associated with AI perceptions; and (H3) demographic characteristics (educational level, professional discipline, work experience, gender, and employment status) would be associated with AI knowledge and/or AI perceptions.

2. Methods

2.1. Study design and setting

This analytical cross-sectional survey was conducted between March and June 2025 in four major educational hospitals affiliated with Isfahan University of Medical Sciences: Al-Zahra, Amin, Ayatollah Kashani, and Isa ibn Maryam Hospitals. These centers were selected to represent a diverse range of OR environments in the region.

2.2. Participants and sampling

The study population included all clinical staff working in the operating rooms, comprising registered nurses, OR technicians, and anesthesiologists. A census sampling method was employed. Out of 235 eligible staff members invited to participate, 200 completed the questionnaire, yielding a response rate of 85.1%. Non-responders ($n = 35$)

were primarily on annual or sick leave during the data collection period, and no significant demographic differences were observed between the initial invitee list and the final sample. Inclusion criteria were:

(1) full-time or part-time employment in the OR for at least six months, (2) willingness to participate, and (3) availability during the data collection period.

The six-month threshold was selected to ensure participants had sufficient familiarization with standard OR workflows and baseline technologies. Interns, medical students, and temporary trainees were excluded to focus on credentialed clinical staff. Exclusion criteria included staff on long-term leave.

2.3. Data collection instrument

Data were collected using a structured, researcher-developed questionnaire comprising three sections:

Demographics: Age, gender, educational level, field of study, years of work experience, and employment status.

Knowledge: A 7-item section consisting of yes/no questions assessing fundamental understanding of AI concepts, applications, and limitations in healthcare. Items were generated based on the Technology Acceptance Model (TAM) and adapted from previously published instruments [9,10]. A predefined threshold for adequate knowledge was set at $> 60\%$ (scoring 5 or more out of 7).

Perception: A 25-item section using a 5-point Likert scale (1= Strongly Disagree to 5= Strongly Agree) to assess attitudes toward AI, including perceived usefulness, trust, anxiety, and intention to use. One item (Item 15: “AI may reduce job security”) was reverse-scored.

Validity and Reliability: Content validity was established through expert review by a panel of five faculty members in nursing, medical education, and health informatics. The Content Validity Index (CVI) was calculated at 0.86, indicating excellent content validity. Construct validity was confirmed via exploratory factor analysis, which extracted the expected theoretical domains (perceived usefulness, trust, anxiety). Face validity was confirmed via pilot testing with 20 staff members not included in the main study. Reliability was assessed using Cronbach’s alpha, yielding coefficients of 0.76 for the knowledge section and 0.89 for the perception section. The full questionnaire is available as Supplementary File 1.

2.4. Ethical considerations

The study protocol was approved by the Ethics Committee of Isfahan University of Medical Sciences (Code: IR.MUI.MED.REC.1404.206). Written informed consent was obtained from all participants. Confidentiality was maintained, and data were anonymized prior to analysis.

2.5. Statistical analysis

Data were analyzed using SPSS software (version 26). The Kolmogorov-Smirnov test indicated that the data did not follow a normal distribution ($P < 0.05$). Consequently, non-parametric tests were employed. Descriptive statistics summarized demographic and outcome variables. Group comparisons were performed using the Mann-Whitney U test for two independent groups and the Kruskal-Wallis test for more than two groups, followed by post-hoc Bonferroni correction. Spearman’s rank correlation coefficient examined associations between knowledge, perception, and age. Statistical significance was set at $P < 0.05$. Effect sizes were calculated using r for Mann-Whitney and epsilon-squared (ϵ^2) for Kruskal-Wallis.

The predefined study hypotheses were evaluated using non-parametric statistical analyses. Specifically, H1 was examined using descriptive statistics, H2 using Spearman’s rank correlation, and H3 using Mann-Whitney U and Kruskal-Wallis tests.

3. Results

3.1. Demographic characteristics and descriptive statistics

A total of 200 participants completed the survey. Consistent with H1, participants demonstrated limited AI knowledge (mean score: 2.11 ± 0.76 out of 7), whereas perceptions toward AI were generally positive (mean score: 76.8 ± 14.5 out of 125). The majority were female (57%), and most held a Bachelor's degree (79.5%). Regarding employment status, 44% were formal employees, while the remainder were contract, company-based, or outsourced staff. Participants demonstrated limited AI knowledge (mean score: 2.11 ± 0.76 out of 7; 30.1% of the maximum possible score), indicating a low level of AI knowledge. Only 17.5% of participants achieved the predefined adequate knowledge threshold (≥ 5 out of 7). In contrast, the mean perception score was 76.8 ± 14.5 out of 125 (61.4%), which is above the theoretical midpoint (75), indicating a generally positive attitude toward AI adoption. (See Table 1)

3.2. Influence of demographic variables on knowledge and perception

Analysis of demographic influences revealed significant variations in AI knowledge. Gender played a minor role; female participants had slightly higher knowledge scores than males (Mean Rank: 107.83 vs. 90.78, $P = 0.036$), though the effect size was small ($r = 0.15$). No significant gender difference was found in perception scores. Educational level was significantly associated with AI knowledge. Staff with postgraduate degrees demonstrated significantly higher knowledge scores (Mean Rank: 140.91) compared to those with Bachelor's (97.99) or Associate degrees (74.71) ($H = 15.254$, $P < 0.001$). Similarly, postgraduate staff exhibited more positive perceptions ($P = 0.010$). Field of study also influenced knowledge; OR technicians had significantly higher knowledge scores than nursing staff ($P = 0.026$). We hypothesize this may reflect their closer proximity to technical equipment and intraoperative monitoring systems, though this was not directly measured. No significant differences in perception were found across

different professional fields ($P = 0.548$). Work experience showed a complex relationship with knowledge. While age was weakly negatively correlated with knowledge ($r = -0.156$, $P = 0.027$), staff with 15–20 years of experience demonstrated the highest knowledge levels among all experience groups ($P = 0.015$). Employment status emerged as a critical structural factor. Formal employees had significantly higher knowledge scores compared to contract and company-based staff ($H = 18.848$, $P < 0.001$). Regarding H3, AI knowledge differed significantly according to educational level, employment status, professional discipline, work experience, and gender, whereas AI perception differed significantly only according to educational level.

3.3. Correlation analysis

In support of H2, Spearman's correlation analysis revealed a significant positive correlation between knowledge and perception ($r = 0.421$, $P < 0.001$), indicating that higher knowledge levels were associated with more positive perceptions toward AI. (See Table 2)

4. Discussion

This survey provides novel insights into the AI knowledge landscape

Table 2
Spearman correlation matrix of main study variables (N = 200).

Variable	1. Knowledge	2. Perception	3. Age
1. Knowledge	1.000	0.421**	-0.156*
2. Perception	0.421**	1.000	-0.024
3. Age	-0.156*	-0.024	1.000

Abbreviations.

Spearman's rank correlation coefficients (ρ) are reported.

* Significant at the 0.05 level (two-tailed).

** Significant at the 0.01 level (two-tailed).

Note: Knowledge scores range from 0 to 7; Perception scores range from 25 to 125; Age is measured in years.

Table 1
Comparison of knowledge and perception scores by demographic variables (N = 200).

Variable	Group	n (%)	Mean Rank Knowledge	Test Statistic	P-value	Effect Size	Mean Rank Perception	Test Statistic	P-value	Effect Size
Gender	Female	114 (57)	107.83	U = 4066.00	0.036*	$r = 0.15$	100.19	U = 4867.00	0.931	$r = 0.006$
	Male	86 (43)	90.78				100.91			
Education	Associate	19 (9.5)	74.71	H = 15.254	<0.001*	$\epsilon^2 = 0.067$	78.95	H = 9.305	0.010*	$\epsilon^2 = 0.037$
	Bachelor	159 (79.5)	97.99				98.72			
Field	Master	22 (11)	140.91	H = 7.277	0.026*	$\epsilon^2 = 0.027$	131.95	H = 1.205	0.548	$\epsilon^2 = 0.001$
	OR technician	114 (57)	109.55				104.35			
Experience	Nursing	40 (20)	83.44	H = 12.275	0.015*	$\epsilon^2 = 0.042$	94.23	H = 4.082	0.395	$\epsilon^2 = 0.001$
	Anesthesia	46 (23)	92.90				96.42			
	0–5 years	88 (44)	103.89				98.83			
	5–10 years	48 (24)	80.79				90.80			
	10–15 years	32 (16)	97.28				108.31			
Employment status	15–20 years	24 (12)	128.83	H = 18.848	<0.001*	$\epsilon^2 = 0.080$	117.25	H = 3.256	0.354	$\epsilon^2 = 0.001$
	>20 years	8 (4)	109.38				95.56			
	Formal	88 (44)	118.00				104.74			
	Contract	46 (23)	84.57				101.52			
	Company-based	33 (16.5)	102.17				104.11			
	Outsourced	33 (16.5)	74.38				84.15			

Abbreviations.

OR, Operating Room; U, Mann–Whitney U test statistic; H, Kruskal–Wallis test statistic; r , effect size for Mann–Whitney test; ϵ^2 , epsilon-squared effect size for Kruskal–Wallis test.

* Statistical significance at $P < 0.05$.

Note: Knowledge scores range from 0 to 7; Perception scores range from 25 to 125.

among multidisciplinary operating room staff in Iran. Overall, the study findings supported the predefined hypotheses. As hypothesized, operating room personnel demonstrated limited AI knowledge despite generally positive perceptions, knowledge was positively correlated with perceptions, and several demographic characteristics were significantly associated with AI knowledge. The primary finding is a distinct gap between cognitive understanding and attitudinal acceptance: while staff exhibit a positive perception of AI, their actual knowledge remains low. This discrepancy highlights a critical area for implementation science, as positive attitudes without adequate understanding may lead to over-reliance on or misinterpretation of AI systems [16].

The mean knowledge score of 2.11/7 is notably low, with nearly 83% of participants falling below the proficiency threshold. This aligns with findings by Riffat et al. in Pakistan, who reported that healthcare providers often recognize AI terms but lack understanding of underlying mechanisms [13]. In the high-stakes environment of the OR, such knowledge deficits may represent a potential barrier to the safe and effective adoption of AI systems [8]. Conversely, the positive perception score suggests that staff are open to technological integration, a finding consistent with studies in Jordan and Turkey [17,18]. This optimism likely stems from the perceived benefits of AI in reducing workload, as noted in the Technology Acceptance Model [9].

From a medical informatics and implementation science perspective, these findings underscore the complexities of integrating AI into peri-operative workflows. Successful implementation requires more than just technological deployment; it demands organizational readiness and the establishment of safe human-AI collaboration protocols [19]. When multidisciplinary teams lack foundational knowledge, the integration of AI can disrupt established workflow patterns and alter role hierarchies. Therefore, informatics strategies must focus on aligning AI capabilities with the cognitive workflows of the OR team, ensuring that AI acts as a supportive tool rather than a disruptive force [20]. Recent evidence emphasizes that nurturing digital competence among clinicians is essential for translating informatics innovations into routine practice [21].

The positive correlation between knowledge and perception ($r = 0.421$) supports the hypothesis that education can transform blind optimism into informed acceptance [22]. Educational level was significantly associated with AI knowledge, likely due to greater exposure to research literature and digital health concepts during advanced training [15]. Interestingly, work experience showed a non-linear relationship. While older age was weakly associated with lower knowledge, staff with 15–20 years of experience scored highest. This paradox may be explained by the fact that mid-career professionals are often in leadership roles and more actively engaged in continuing education compared to junior staff or those nearing retirement [12].

Employment status also played a crucial role. Formal employees had significantly higher knowledge levels, likely due to better access to institutional training and professional development opportunities. This highlights a structural inequity in digital competence that could compromise workflow efficiency if not addressed [23]. Furthermore, while the associations between demographic variables and AI knowledge are statistically significant, the effect sizes are generally modest. This indicates that demographic factors should be viewed as contributing elements rather than sole predictors, emphasizing the need for universal, baseline training programs rather than highly fragmented targeted interventions.

It is also important to acknowledge measurement limitations. A low knowledge score in this survey could partly reflect unfamiliarity with specific technical terminology, limitations of the self-report questionnaire, or a lack of formal exposure, rather than an inherent lack of clinical competence. Future studies should incorporate objective skills assessments alongside self-reported knowledge.

4.1. Limitations

This study has several limitations. First, its cross-sectional design precludes causal inference. Second, the sample was drawn from educational hospitals, which typically possess greater access to academic resources and technological innovations compared to community or private hospitals; therefore, AI knowledge in non-academic settings may differ. Third, self-reported data may be subject to social desirability bias. Fourth, unmeasured confounding variables, such as previous exposure to AI tools, participation in digital health courses, and personal interest in emerging technologies, may also influence knowledge and perceptions. Finally, the exclusion of surgeons limits the perspective of key decision-makers in the OR. Future studies should employ longitudinal designs, include a broader range of healthcare professionals, and measure objective AI skills.

5. Conclusion

Operating room staff in Isfahan exhibit positive attitudes toward AI but lack sufficient knowledge to ensure its seamless integration. This knowledge-perception gap, influenced by educational, professional, and employment factors, may represent an important consideration for future AI implementation strategies. To mitigate potential workflow disruptions and support safe human-AI collaboration, healthcare administrators must prioritize equitable digital competence programs that address the specific needs of diverse multidisciplinary staff groups.

CRedit authorship contribution statement

Farzaneh Nekuei manesh: Writing – review & editing, Supervision, Project administration, Methodology, Investigation, Conceptualization. **Zahra Eydizadeh:** Writing – review & editing, Writing – original draft, Resources, Methodology, Investigation, Data curation, Conceptualization. **Mohammad Reza Sohrabi:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Conceptualization. **Leila Akbari:** Writing – review & editing, Visualization, Supervision, Conceptualization. **Mina Jouzi:** Writing – review & editing, Supervision. **Farkhondeh Sameipour:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Informed consent: Written informed consent was obtained from all participants. Author contributions: All authors contributed substantially to this work, approved the final version of the manuscript, and agreed to be accountable for all aspects of the study.

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