Research Square

Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

Caregivers' views towards implementation of artificial intelligence in the Pediatric Intensive Care Units: A Cross-sectional analysis

Evgeni Yakubovski
Safra Children's Hospital, Sheba Medical Center
Sara Steinmetz
Safra Children's Hospital, Sheba Medical Center
Inbar Angel
Safra Children's Hospital, Sheba Medical Center
David Gilad
Safra Children's Hospital, Sheba Medical Center
Ilya Kagan
Ashkelon Academic College
Reut Shoham
Education Authority, Chaim Sheba Medical Center
Gad Segal
gad.segal@sheba.health.gov.il

Education Authority, Chaim Sheba Medical Center
Reut Kassif Lerner
Safra Children's Hospital, Sheba Medical Center

Research Article

Keywords: artificial intelligence, pediatric intensive care, physicians, nurses, attitudes, readiness, implementation intention, cross-sectional survey

Posted Date: November 12th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-11076797/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License.
Read Full License

Additional Declarations: No competing interests reported.

Abstract

Background.

Artificial intelligence (AI) is being increasingly integrated into critical care workflows, yet successful implementation depends on clinical staff acceptance and perceived preparedness, particularly in pediatric intensive care units (PICUs). The objective of the current study was to assess professional caregivers' perceptions, ethical concerns, self-rated readiness, and implementation intentions regarding prospective AI assimilation in PICU departments.

Methods.

In this cross-sectional survey, 119 PICU caregivers (physicians, nurses, and others) completed a validated 34-item questionnaire covering perceived clinical and organizational utility of AI, ethical concerns, readiness, and implementation intention. Differences between groups were examined using t-tests and one-way ANOVA; associations were examined using Pearson correlations; predictors of implementation intention were identified using hierarchical linear regressions.

Results.

Overall, attitudes towards AI were moderately positive with implementation intention of M = 3.95, organizational perceptions M = 3.68 and nursing-care perceptions M = 3.62. Self-rated AI readiness was lower (M = 3.23). A prominent training gap was identified ("the training I received prepared me to use AI at work," M = 1.85), despite high openness to learning (M = 4.13). Prior AI experience at work was reported by 58.5% and differed by profession (physicians 90.5%, nurses 53.1%, other staff 43.8%). In multivariable models, implementation intention was predicted by combined AI perceptions ($\beta = 0.39$, $p<.001$) and AI readiness ($\beta = 0.33$, $p<.001$), with education contributing modestly ($\beta = 0.20$, $p = 0.023$).

Conclusions.

PICU caregivers expressed openness to AI implementation, but perceived readiness lagged substantially behind intention, largely due to insufficient training. Implementation willingness appears potentially modifiable through targeted education and implementation practices that may promote readiness and reinforce perceived clinical and organizational value.

Introduction

Artificial intelligence (AI) refers to methods designed to imitate human intelligence, reasoning, and decision-making processes. Among these is machine learning, which utilizes algorithms and statistical models to improve a computer's capability to make precise decisions. Because AI can process,

understand, and interpret large amounts of data, its application in healthcare has grown significantly (1) and is expected to revolutionize the world of clinical medicine. Therefore, a prudent approach must be adopted regarding patient safety, security and privacy (2).

Creating AI tools explicitly designed for acute medicine can enhance the clinical decision-making process, while the use of generative AI for automating administrative work has the potential to deliver prompt advantages. Nonetheless, issues such as standardized data collection, privacy concerns, bias, and maintaining the integrity of the caregiver-patient relationship remain significant challenges (3). As anticipated, different clinical settings would suit AI at different levels. For example, AI may be especially valuable in the cardiac intensive care unit (CICU), as its ability to process extensive data in real time can help clinicians make better-informed decisions (4).

In recent years, there has been a significant increase in publications on AI models for intensive care, mainly focused on predicting complications, mortality, and on improving prognosis. A recent systematic review showed that machine learning models can accurately predict the onset of sepsis in ICU patients (5). Determining the optimal timing for initiating or discontinuing mechanical ventilation is a key challenge being addressed by AI research. With its advanced computational power, AI enables clinicians to quickly analyze extensive historical ICU data, much as they rely on years of personal experience (and their “intuition”), to predict patient outcomes in the ICU (6). AI analyses are based on the availability of big data; one such dataset would be the data transmitted by a myriad of physiologic sensors in the ICU. Traditionally, sensors gather data which is then interpreted by humans to guide decisions. When AI-based sensors are used, the AI system itself analyzes the sensor data and makes decisions. Increasingly, AI is being integrated into clinical decision-making by continuously monitoring patient data (6).

In pediatric acute care setting, various machine learning models have been developed for diverse pediatric applications. For example, some models predict which children are at risk for clinically significant traumatic brain injury, identify infants with major intra-abdominal injuries, and support decision-making for common emergency department tests such as urinary dipstick, electrocardiogram, abdominal or testicular ultrasound, bilirubin measurement, and forearm radiographs. Additional models have been developed to classify pediatric diagnoses broadly, detect serious bacterial infections in young infants, and assist in managing ventilator support (7). Ganatra et al. demonstrated that machine learning models can predict pediatric intensive care unit (PICU) length of stay with moderate accuracy, just above 70%, and perform better than earlier human-based predictions. These findings indicate that such models could help improve resource allocation and staff planning in PICUs (8). Machine learning methods have also been applied to identify critically ill children who are at elevated risk for deterioration leading to cardiac arrest (9).

In daily clinical routines, the emergence of AI-based technologies offers a promising approach, especially with AI-based voice-to-text (ambient) systems that streamline the documentation process and

reduce administrative workload. Such technologies are now commonly used in hospitals to dictate clinical notes, prepare discharge summaries, and document ward rounds (10).

Aside from technical barriers to AI implementation, the “human barrier” should not be overlooked. While some authors showed that nurses in the PICU were mainly concerned about potential clinical applications of artificial intelligence, worrying about letting AI take over the domains of technical patients’ monitoring (11), others found that the clinical staff's attitude towards artificial intelligence was largely positive, and they believed it could bring about constructive changes; most of the clinical staff said they would support the use of artificial intelligence. At the same time, several concerns were expressed by clinicians, including fear of being replaced by artificial intelligence and apprehensions regarding the possibility of unexpected errors in AI-based systems (11).

Physicians generally expressed positive attitudes toward AI-based clinical decision support systems (CDSS), perceiving them as tools that could reduce human error, alleviate workload, and support clinical care. They did not fear being replaced by AI but rather anticipated a shift toward an “AI-augmented physician” model. At the same time, concerns were raised regarding increased workload, threats to the physician-patient relationship, loss of skills, and over-reliance on AI. Additional concerns included medico-legal liability, risks of defensive medicine, diminished professional autonomy, and the opacity of algorithms. Alongside these concerns, doctors also expressed concern about the lack of transparency regarding the quality of the information, the considerations, and the way the algorithms underlying the systems operate (12).

Overall, healthcare teams perceive AI applications as having significant potential to improve their work, mainly through streamlining workflows, optimal time management, and reducing the routine of administrative tasks. At the same time, concerns have been raised about the development of a technology dependency that could harm clinical professional skills. At the organizational level, AI is seen as a tool that helps deal with staff shortages and improves the quality of clinical decision-making through diagnostic accuracy and connecting different sources of information. For patients, the potential to improve clinical outcomes and patient safety and maintain continuity and uniformity in service quality (13).

Alsaedi et al. found significant concerns among healthcare professionals that led to hesitancy to adopt AI in healthcare. These concerns focused on the loss of clinical skills and the risk of inaccurate decisions resulting from reliance on incorrect data entered or generated by the system. In addition, significant regulatory and ethical issues arose, most notably the fear of legal liability and loss of professional license in cases of errors caused by AI (14).

Despite ethical and practical challenges, AI has the potential to assist pediatric intensive care clinicians in diagnosis, prognosis, and treatment, ultimately contributing to better patient outcomes (15). Since the implementation of AI in clinical practice is directly related to clinicians' motivation, it is important to assess caregivers' attitudes and intentions to participate and to cooperate with these processes. The current study aimed to examine the views of professional caregivers regarding AI in clinical practice,

including their experience, ethical concerns, readiness and intention to implement AI technologies - in two PICUs at a large medical center in Israel. We hope these findings will assist decision-makers more effectively implement AI more effectively in the PICU setting.

Methods

Design, population, and sample

In this cross-sectional study, all clinical staff members with at least one-year experience from the two Pediatric Intensive Care Units at a large medical center were invited to participate. Caregivers, who do not work regularly (e.g., students, interns, volunteers), and those on maternity leave or prolonged sick leave, were excluded from the study. The minimum priori sample size for the study, with a standard α error probability of 5%, and power of 90%, for correlation analysis (bivariate normal model, two-tailed), was estimated by G*Power (v. 3.1.9.7) as n = 90 for a medium effect size of 0.3. The sample size was increased to ensure the ability to perform advanced statistical analyses and to reduce missing data issues.

Tools

Data were collected using a structured, validated questionnaire (16) comprising five sections (34 items): a) views on clinical applications of artificial intelligence, b) ethical aspects of AI use; c) organizational aspects of AI use; d) readiness to use AI; e) caregivers' intention to implement AI technology in clinical practice and f) professional and socio-demographic characteristics of the participants (Table 1).

The original questionnaire was in English. It underwent a process of translation and back-translation to ensure accuracy of the final Hebrew version, which was validated by a panel of experts and reviewed for relevancy to the subject matter. For the original questionnaire, the content validity index for the items ranged from 0.85 to 1.00. Cronbach's alpha coefficients ranged from 0.93 to 0.95 across the subscales, indicating high internal consistency, with the scale showing convergent and divergent validity.

Separate variables included in the study questionnaire related to the following domains (Fig. 1): Intention to implement AI; Organizational perceptions; Ethical concerns; AI Readiness; Previous occupational exposure to artificial intelligence; The use of artificial intelligence tools in daily life; Perceived preparedness for AI and openness to learning AI. Professional and socio-demographic characteristics collected from participants included: age, gender, professional seniority, clinical profession, clinical unit, number of children, and highest academic degree.

Internal consistency for all composite scales was acceptable to excellent. Comparison of the study scales across profession groups is presented in Table 2. Cronbach's α was .86 for Nursing-care perceptions of AI (10 items), .90 for Organizational perceptions of AI (6 items), .81 for Ethical concerns (5 items), .85 for AI Readiness / preparedness (6 items) and .80 for the two-item Implementation

intention scale. Because Nursing-care and Organizational perceptions were highly correlated (r = .83, see Table 3), a combined 16-item AI-perceptions scale was also constructed (α = .92) and used as a single predictor in the multivariable models, in line with the analysis plan implemented in SPSS.

Procedure

After obtaining ethical approval (by the Sheba medical center IRB, according to the Helsinki Declaration, approval # 2672-25), all professional staff members in the department were invited to complete the study questionnaires. The recruitment was conducted through head nurses, the Pediatric Intensive Care Unit director, and co-investigators working in the unit. Two research assistants - registered nurses trained by the authors - personally distributed printed questionnaires to clinicians who agreed to participate. Completion took about 20 minutes. Demographic details were entered in a de-identified manner into the research data collection spreadsheet, which was accessible only to the principal investigator.

Data analysis

The data were analyzed with SPSS version 28 (IBM, USA). For analytic transparency, every reported statistic was independently re-derived in Python 3 directly from the raw data file using the pyreadstat, pandas, scipy.stats, and statsmodels packages, with recomputed values matching the SPSS output to three decimals. Statistical significance was set at $\alpha = 0.05$, two-tailed. Missing data were modest (< 1% per composite scale) and were handled by pairwise deletion in bivariate analyses and by listwise deletion in regression models; no imputation was performed. Internal consistency for each composite scale was assessed with Cronbach's α (threshold of acceptability ≥ 0.70), together with corrected item-total correlations. Continuous variables were represented by means with standard deviations and ranges; categorical variables were summarized as frequencies with valid percentages.

Differences in scale scores across the three profession groups (physicians, nurses, others) were tested with one-way analyses of variance (ANOVA), with the Least Significant Difference (LSD) procedure for pairwise contrasts as specified in the registered analysis plan; Tukey's Honestly Significant Difference (HSD) was added as a sensitivity analysis because of its more conservative control of family-wise type-I error. Eta partial squared (η^2) was reported as the effect-size estimate. Differences across dichotomous variables (gender, country of birth, unit subtype, parental status, prior AI use at work) were tested with independent-samples t-tests; Levene's homogeneity test was inspected for each comparison, and Welch's t-statistic with the Satterthwaite-adjusted degrees of freedom was reported when homogeneity assumption was violated. Cohen's *d* accompanied each two-group comparison. Associations between categorical variables (e.g., profession × prior AI use) were tested with Pearson's chi-square; Fisher's exact test was planned for any 2×2 table with a minimum expected count below 5.

Linear associations among the five composite scales and between each scale and the continuous demographic variables (age, professional tenure, years of formal education) and weekly AI-use

frequency were examined with Pearson correlations, reported two-tailed with the conventional r ≈ 0.20 / 0.30 / 0.50 thresholds for small to moderate effects.

To identify independent predictors of intention to implement AI in clinical practice, hierarchical multiple linear regression analyses (Enter method) were conducted with the two-item Implementation intention composite as the primary outcome and its two constituent items as pre-specified secondary outcomes. Because the 'Other PICU staff' category was small and internally heterogeneous, regression analyses were restricted to physicians and nurses (n = 102 after listwise deletion). Predictors were entered into two blocks: Block 1 — demographic and exposure controls (gender, professional tenure, years of education, prior AI use at work); Block 2 — the three theoretically primary predictors (combined AI perceptions variable, Ethical concerns, and AI Readiness). Unstandardized coefficients (B), standard errors, t-statistics, p-values, and standardized coefficients (β) are reported, together with R^2, adjusted R^2, the change in R^2 (ΔR^2) at Block 2, and the associated F-change. Multi-collinearity was screened with variance inflation factors and condition indices; predictors with $|r| > 0.85$ were consolidated, motivating use of the combined AI perceptions variable in place of separately. As a sensitivity analysis, the Block 2 model was additionally re-fit on the full sample with profession represented by indicator variables (nurse and other vs. physician); coefficient sign and significance status were preserved.

Results

Participants

The sample consisted of 119 healthcare workers from PICU of the largest medical center in Israel – 82 nurses (68.9%), 21 physicians (17.6%), and 16 other health professionals (13.4%). respondents were predominantly female (80.7%), Israeli-born (69.5%), and Jewish (87.4%). The mean age was 37.5 (SD = 9.5); average professional seniority – 8.5 years (SD = 9.1) and mean years of formal education was 17 (SD = 2.3). Two thirds of them (80, 67.2%) worked in the general PICU and one third (39, 32.8%) in the cardiac PICU. Additional demographic characteristics are shown in Table 1.

Table 1
Socio-demographic and clinical characteristics of the study population (N = 119).

Characteristic	Category	n	% (valid)
Profession	Physician	21	17.6%
	Nurse	82	68.9%
	Other	16	13.4%
Gender	Male	23	19.3%
	Female	96	80.7%
PICU subunit	Pediatric General	80	67.2%
	Pediatric Cardiac	39	32.8%
Country of birth	Israel	82	69.5%
	Other	36	30.5%
	Missing	1	—
Religion	Jewish	104	87.4%
	Muslim	9	7.6%
	Christian	2	1.7%
	Other	4	3.4%
Parental status	With children	69	58.0%
	Without children	50	42.0%
Prior AI use at work	Yes	69	58.5%
	No	49	41.5%
	Missing	1	—
Continuous variables	**Unit**	**M (SD)**	**Range**
Age	Years	37.49 (9.46)	20–67
Professional tenure	Years	8.54 (9.13)	0.25–45.00
Formal education	Years	16.99 (2.31)	12–25
AI use at work	1–5 scale	2.74 (1.15)	1–5

“AI use at work” scale − 1 = never to 5 = several times daily; Percentages are of valid (non-missing) responses

Descriptive statistics

Fifty-eight percent of respondents (69/118 valid responses) reported using AI in the course of their clinical work. Prior use differed markedly between professions: physicians 90.5% (19/21), nurses 53.1% (43/81), and other staff 43.8% (7/16), $\chi^2(2, N = 118) = 11.25$, $p = .004$ (Fig. 1). Reported weekly frequency of AI use averaged 2.74 (SD = 1.15) on a 1–5 scale and was also highest among physicians (M = 3.38, SD = 0.92), compared with nurses (M = 2.66, SD = 1.17) and other staff (M = 2.31, SD = 1.01), $F(2, 116) = 4.91$, $p = .009$, $\eta^2 = .078$. Overall, respondents reported moderately positive attitudes toward AI in clinical practice. The highest mean scores were observed for Implementation intention (M = 3.95, SD = 0.94) and Organizational perceptions (M = 3.68, SD = 0.74), followed by Nursing-care perceptions (M = 3.62, SD = 0.65). Ethical concerns (M = 3.38, SD = 0.78) and AI Readiness (M = 3.23, SD = 0.85) were rated lower, although all composites remained above the scale midpoint of 3. The lowest-scoring item was 'the training I received prepared me to use AI at work' (q30, M = 1.85, SD = 0.94), suggesting a substantial training gap despite their overall openness to the technology (q29, 'I am open to learning AI technologies at work,' M = 4.13, SD = 1.06).

Comparative analysis

As presented in Table 2, one-way ANOVAs indicated that perceptions and readiness differed significantly between profession groups for all but one of the study scales. Physicians reported the most favorable views on Nursing-care perceptions (M = 3.99), Organizational perceptions (M = 4.03), combined perceptions (sca12, M = 4.01) and AI Readiness (M = 3.47), whereas the 'Other' profession group scored consistently lowest and reported the strongest ethical concerns (sca3, M = 3.90). Tukey HSD contrasts (familywise $\alpha = .05$), which are conservatively preferable to the LSD pairwise comparisons reported in the SPSS output, confirmed that both physicians and nurses scored higher than the 'Other' on Nursing-care perceptions, combined perceptions, and AI Readiness (all $p < .05$), and that the 'Other' group's stronger ethical concerns differed from nurses ($p = .012$). Implementation intention (sca5) did not differ significantly across professions when the small 'Other' group (n = 16) was included, $F(2, 116) = 2.58$, $p = .080$. These profession patterns are displayed in Fig. 2.

Table 2
Differences by profession: One-way ANOVA with Tukey HSD post-hoc (n = 119)

Variables	Items (α)	All M (SD)	MDs M (SD)	RNs M (SD)	Others M (SD)	*F* (2.12)	*p*	*η²*	Tukey HSD
Nursing-care perceptions	10 (.86)	3.62 (0.65)	3.99 (0.69)	3.62 (0.57)	3.15 (0.74)	8.43	< .001	0.13	MD > RN>O (all p<.05)
Organizational perceptions	6 (.90)	3.68 (0.74)	4.03 (0.70)	3.67 (0.63)	3.26 (1.04)	5.37	.006	0.09	MD > O (p<.01)
Combined	16 (.92)	3.64 (0.66)	4.01 (0.68)	3.64 (0.56)	3.19 (0.84)	7.81	< .001	0.12	MD > RN>O (all p<.05)
Ethical concerns	5 (.81)	3.38 (0.78)	3.34 (0.80)	3.29 (0.71)	3.90 (0.95)	4.26	.016	0.07	O > RN (p<.05)
AI Readiness / preparedness	6 (.85)	3.23 (0.85)	3.47 (0.76)	3.30 (0.81)	2.57 (0.91)	6.42	.002	0.10	MD > O, RN > O (p<.01)
Implementation intention	2 (.80)	3.95 (0.94)	4.26 (0.65)	3.95 (0.88)	3.56 (1.40)	2.58	.080	0.04	n.s.
Frequency of AI use	1 item	2.74 (1.15)	3.38 (0.92)	2.66 (1.17)	2.31 (1.01)	4.91	.009	0.08	MD > RN (p<.05)

α = Cronbach's α for internal consistency; MD = Medical Doctor, RN = Registered Nurse, O = Other health professions; Scales were scored 1–5 (higher = stronger agreement); Frequency of AI use was coded 1 = never to 5 = several times daily; η² = partial eta-squared; Tukey HSD contrasts (familywise α = .05).

Independent-samples t-tests showed that men reported more favorable Nursing-care perceptions (M = 3.91 vs 3.55, t(117) = 2.42, p = .017), combined AI perceptions (sca12: 3.92 vs 3.58, t(117) = 2.28, p = .025), higher AI Readiness (sca4: 3.65 vs 3.13, t(117) = 2.73, p = .007), and higher reported frequency of AI use (AI2: 3.22 vs 2.63, t(117) = 2.27, p = .025) than women; group variances were homogeneous. No significant gender differences emerged for Organizational perceptions, Ethical concerns, or Implementation intention (all p > .07). Subgroup analyses by PICU unit (general vs cardiac), parental status and country of birth did not reveal statistically significant differences on any scale (all p > .07), although Israeli-born respondents tended to report somewhat lower ethical concerns than those born elsewhere (M = 3.30 vs 3.58, t(116) = 1.79, p = .077).

Correlational analysis

As shown in Table 3, the four positively oriented AI scales were strongly and consistently intercorrelated. Nursing-care and Organizational perceptions correlated at r = .83 (p < .001); both correlated moderately to strongly with AI Readiness (r = .53 and r= .54, both p < .001) and with Implementation intention (r = .44 and .46, both p < .001). AI Readiness itself was the single strongest correlate of Implementation intention (r = .55, p < .001). As expected, Ethical concerns were modestly but significantly negatively correlated with Nursing-care perceptions (r = − .31, p < .001), Organizational perceptions (r = − .30, p < .001), and AI Readiness (r = − .22, p = .016), but not with Implementation intention (r = − .14, p = .119). Years of formal education correlated positively with all four positive AI scales (r ranging from .28 to .37, all p < .01) and with weekly AI use (r = .21, p = .020). Age and professional tenure showed weak negative correlations with Organizational perceptions, AI Readiness, and AI use (|r|= .18–.27, all p < .05), and no association with Ethical concerns or Implementation intention.

Table 3
Pearson correlations among the study scales and mean (SD) values (N = 119).

Variable	1	2	3	4	5	6	M	SD
1. Nursing-care perceptions	—						3.62	0.65
2. Organizational perceptions	0.827***	—					3.68	0.74
3. Ethical concerns	-0.307***	-0.304***	—				3.38	0.78
4. AI Readiness	0.526***	0.541***	-0.221*	—			3.23	0.85
5. Implementation intention	0.435***	0.459***	-0.144	0.550***	—		3.95	0.94
6. AI-use frequency	0.359***	0.356***	-0.115	0.510***	0.342***	—	2.74	1.15

Notes. ** p < .05, ** p < .01, *** p < .001 (two-tailed). The original Nursing-care and Organizational scales were also analyzed as a combined 16-item scale (sca12; α = .92, M = 3.64, SD = 0.66) because of their high shared variance (r = .83).*

Regression analyses

In multivariable analyses including only physicians and nurses (n = 102), demographic variables and prior AI use together (Step1) explained 12.5% of the variance in Implementation intention ($F(4, 97) = 3.47$, $p = .011$), with education as the only significant predictor. Adding composite scales for AI perceptions and readiness (Step 2) markedly improved predictive power (total explained variance = 45.6%, $\Delta R^2 = .33$, $p < .001$), with AI perceptions ($\beta = .39$, $p < .001$) and AI Readiness ($\beta = .33$, $p < .001$) as dominant predictors; education remained significant ($\beta = .20$, $p = .023$) (Fig. 3). These patterns were consistent for both individual Implementation intention items (q33, q34). Notably, the frequency of AI use did not add explanatory value.

Three dependent variables were modeled: the two-item Implementation intention composite and each of its constituent items: "team involvement in developing and deploying AI would increase my willingness to use the technology" and "I would invest effort to help implement AI in my clinical work". For Implementation intention, Step 1 (gender, tenure, education, prior AI use) explained 12.5% of the variance, $F(4, 97) = 3.47$, $p = .011$, with education as the only significant predictor ($\beta = .30$, $p = .006$). Adding the three scale composites in Step 2 increased explained variance to 45.6% ($\Delta R^2 = .33$, F-change $(3, 94) = 19.01$, $p < .001$). In the final model, the combined perception scale ($\beta = .39$, $p < .001$) and AI Readiness ($\beta = .33$, $p < .001$) were the dominant predictors; education remained a weaker but significant contributor ($\beta = .20$, $p = .023$). Gender, tenure, prior AI use, and ethical concerns were not independent predictors. For team involvement, the step 2 model explained 31.0% of the variance ($\Delta R^2 = .23$, $p < .001$); with the same predictors remaining significant. For commitment of effort to implementation, the step 2 model explained 44.4% of the variance ($\Delta R^2 = .30$, $p < .001$).

Discussion

This cross-sectional survey examined PICU caregivers' perceptions of artificial intelligence (AI), their ethical concerns, perceived readiness, and willingness to participate in implementation. The findings depict a workforce that is broadly receptive to AI yet reports a pronounced preparedness deficit. This "willing-but-not-ready" pattern is clinically relevant because PICU workflows are high-stakes and time-pressured, and perceived competence with new digital tools can influence both uptake and safe use. Across domains, Implementation intention and Organizational perceptions were rated most favorably, whereas readiness was comparatively lower. At the item level, respondents rated prior training for AI use very low, while simultaneously reporting high openness to learning. Together, these results highlight a modifiable barrier that can be addressed through structured education and the supervised introduction of AI-enabled workflows. For PICU leaders, this suggests that implementation strategies should explicitly allocate resources to profession-tailored training, protected learning time, and competency-based onboarding rather than assuming that availability of the technology alone will lead to adoption.

Our findings regarding the "willing-but-not-ready" paradigm strongly align with recent global assessments of critical care staff. For instance, a 2026 study of ICU nurses found that while nurses hold moderately positive attitudes toward AI, they often lack the technical knowledge required for confident application, raising concerns about job security and the erosion of independent clinical skills (17). Similarly, recent reviews of AI applications in intensive-care nursing underscore that despite the technology's promise to detect subtle patient deterioration and augment decision-making, the risk of overreliance demands that staff fully comprehend an AI system's reasoning before integrating it into practice (18). This further supports our recommendation that AI adoption must be coupled with comprehensive, profession-specific educational initiatives rather than merely deploying the technology at the bedside.

In multivariable models, the strongest independent predictors of implementation intention were positive perceptions of AI (combined nursing-care and organizational perceptions) and self-rated readiness.

Importantly, prior AI use did not remain an independent predictor once these factors were included, implying that hands-on exposure alone is insufficient unless accompanied by perceived usefulness and preparedness. This pattern supports implementation approaches that build confidence and shared understanding (e.g., demonstrations, simulation-based learning, and unit-level champions) and that involve frontline teams in development and deployment decisions, consistent with the notion that participation may increase willingness to adopt.

Physicians reported the most favorable perceptions of AI and the highest readiness and frequency of use, while the “other staff” group consistently reported less favorable perceptions and greater ethical concerns. Nurses were generally intermediate between these groups. These profession-based gradients suggest that AI assimilation may reproduce or widen existing differences in access to training, digital literacy, and decision-making influence within the unit. Therefore, training and implementation planning should be stratified by profession, with particular attention to the nursing workforce, which constitutes the largest professional group and is central to continuous bedside care in PICUs.

Ethical concerns were moderately endorsed and negatively associated with positive perceptions and readiness, yet they were not independently associated with implementation intention. This suggests that, in this context, staff may view ethical risks (e.g., privacy, accountability, transparency) as important but manageable rather than prohibitive. Practically, this supports embedding governance and communication into implementation: clarifying accountability pathways, documenting appropriate oversight, communicating data-security protections, and setting expectations about the role of AI as decision support rather than a replacement for professional judgment.

Furthermore, while our cohort viewed ethical concerns as manageable, the broader literature indicates that skepticism remains a substantial obstacle in pediatric critical care. A recent survey of healthcare staff in a Saudi Arabian PICU setting highlighted that, beyond basic data privacy, practical issues such as cost-effectiveness, algorithm transparency, and potential biases are prominent sources of apprehension (19). These clinicians emphasized that unrepresentative training data could inadvertently perpetuate healthcare disparities or yield unsafe recommendations (18, 19). Therefore, embedding effective regulatory frameworks, clarifying accountability pathways, and ensuring algorithmic transparency are not merely theoretical ethical necessities but practical prerequisites for securing clinical trust and achieving successful AI implementation in the PICU.

Future studies should evaluate whether targeted, profession-adapted training improves readiness and whether readiness gains translate into sustained adoption and measurable workflow or patient-safety benefits. In addition, qualitative work (e.g., focus groups) could further unpack which aspects of “readiness” are most salient in PICUs (technical skills, trust, perceived usefulness, perceived organizational support) and inform the design of implementation bundles.

Limitations

This study has several limitations. First, the cross-sectional design precludes causal inference; associations between perceptions, readiness, and Implementation intention cannot establish directionality. Second, the data are based on self-reports and may be influenced by social desirability bias, differential interpretation of “AI,” or limited familiarity with specific AI-enabled clinical tools. Third, the study was conducted in two PICU settings within a single children’s hospital, which may limit generalizability to other institutions, health systems, or cultural contexts. Fourth, the “other staff” subgroup was relatively small, limiting power for between-group comparisons and increasing uncertainty in profession-based contrasts. Finally, implementation intention is a proximal outcome and may not fully predict actual adoption once AI tools are introduced, underscoring the need for longitudinal follow-up studies that assess whether intention translates into adoption and its impacts.. Despite these limitations, the study provides actionable information for PICU leaders by training as a specific, addressable implementation lever, and by characterizing how perceptions and readiness relate to willingness to implement AI among frontline staff.

Conclusions

This study demonstrates that healthcare professional in PICUs have moderately positive attitudes toward the integration of AI in clinical practice, with a clear willingness to learn and adopt these technologies. Despite this openness, a significant gap exists between caregivers’ intention to implement AI and their sense of preparedness, largely attributable to inadequate training. Staff attitudes and readiness, rather than prior hands-on exposure to AI, were found to be the primary drivers of Implementation intention. Physicians reported the most favorable perceptions and readiness, whereas nurses and other staff reported lower scores and higher ethical concerns. Importantly, ethical concerns did not independently inhibit willingness to implement AI, suggesting that such concerns coexist with positive attitudes toward adoption.

These findings highlight the essential role of targeted, structured training programs in bridging the gap between willingness and preparedness, particularly among staff groups with lower baseline readiness. Investing in such educational initiatives is likely to foster successful and sustainable AI implementation in PICU settings by enhancing staff confidence and competence.

Overall, the results support the view that inclusive implementation strategies that focus on attitudes and readiness can promote effective adoption even among staff with limited prior AI experience. Addressing the training deficit remains the key actionable lever for organizational leaders aiming to integrate AI into pediatric critical care.

Declarations

Conflict of Interest:

The authors declared no potential conflicts of interest (either financial and non-financial) with respect to the research, authorship, and/or publication of this article

Ethical approval information:

The study protocols were approved by the Ethical Committee of the Sheba Medical Center, Israel, the Approval #2672-25-SMC (31th Dec. 2025). All methods were performed in accordance with the ethical standards as laid down in the Declaration of Helsinki and its later amendments or comparable ethical standards.

Patient consent statement

The need to obtain participants' written informed consent was waived by the IRB. Answering the on-line questionnaire was considered consent to participate. The researchers received a data file with no personal details of the participants.

Declaration of generative AI in scientific writing

No AI and AI-assisted technologies were used.

Reporting guidelines

STROBE reporting guidelines were used.

Funding statement:

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Author Contribution

E.Y., S.S., I.A., D.G., I.K., R.S., G.S. AND R.K.L all contributed to the design, data curation, intitial and final writing of this manuscript.

Acknowledgement

NA

Data Availability

The datasets used and/or analyzed during the current study are available from the corresponding author under the terms and conditions of the IRB approval.

Permissions and credits

Not applicable

References

1. Suresh V, Singh KK, Vaish E, Gurjar M, Nambi AA, Khulbe Y et al. Artificial Intelligence in the Intensive Care Unit: Current Evidence on an Inevitable Future Tool. Cureus [Internet]. 2024 May 7 [cited 2025 Sep 15];16(5):e59797.
2. Dailah HG, Koriri M, Sabei A, Kriry T, Zakri M. Artificial Intelligence in Nursing: Technological Benefits to Nurse's Mental Health and Patient Care Quality. Healthcare [Internet]. 2024 Dec 1 [cited 2025 Sep 15];12(24):2555.
3. Artificial Intelligence. its Future and Impact on Acute Medicine - PubMed [Internet]. [cited 2025 Sep 15].
4. Huerta N, Rao SJ, Isath A, Wang Z, Glicksberg BS, Krittanawong C. The premise, promise, and perils of artificial intelligence in critical care cardiology. Prog Cardiovasc Dis [Internet]. 2024 Sep;1:2–12. [cited 2025 Sep 15];.
5. van de Sande D, van Genderen ME, Huiskens J, Gommers D, van Bommel J. Moving from bytes to bedside: a systematic review on the use of artificial intelligence in the intensive care unit. Intensive Care Med [Internet]. 2021 Jul 1 [cited 2025 Sep 15];47(7):750–60.
6. Nguyen D, Ngo B, vanSonnenberg E. AI in the Intensive Care Unit: Up-to-Date Review. J Intensive Care Med [Internet]. 2021 Oct 1 [cited 2025 Sep 15];36(10):1115–23.
7. Ramgopal S, Sanchez-Pinto LN, Horvat CM, Carroll MS, Luo Y, Florin TA. Artificial intelligence-based clinical decision support in pediatrics. Pediatr Res [Internet]. 2022 Jan 1 [cited 2025 Sep 15];93(2):334.
8. Ganatra HA, Latifi SQ, Baloglu O. Pediatric Intensive Care Unit Length of Stay Prediction by Machine Learning. Bioengineering [Internet]. 2024 Oct 1 [cited 2025 Sep 15];11(10):962.
9. Lonsdale H, Jalali A, Ahumada L, Matava C. Machine Learning and Artificial Intelligence in Pediatric Research: Current State, Future Prospects, and Examples in Perioperative and Critical Care. J Pediatr. 2020;221:S3–10.
10. Alboksmaty A, Aldakhil R, Hayhoe BWJ, Ashrafian H, Darzi A, Neves AL. The impact of using AI-powered voice-to-text technology for clinical documentation on quality of care in primary care and outpatient settings: a systematic review. EBioMedicine [Internet]. 2025 Aug 1 [cited 2025 Sep 15];118:105861.
11. Hamedani Z, Moradi M, Kalroozi F, Manafi Anari A, Jalalifar E, Ansari A et al. Evaluation of acceptance, attitude, and knowledge towards artificial intelligence and its application from the point of view of physicians and nurses: A provincial survey study in Iran: A cross-sectional descriptive-analytical study. Health Sci Rep [Internet]. 2023 Sep 1 [cited 2025 Sep 15];6(9):e1543.

12. https://brookdale.jdc.org.il/publication/attitudes-and-perceptions-of-physicians-in-israel-towards-clinical-decision-support-systems-with-emphasis-on-systems-based-on-artificial-intelligence/
13. Henzler D, Schmidt S, Koçar A, Herdegen S, Lindinger GL, Maris MT, et al. Healthcare professionals' perspectives on artificial intelligence in patient care: a systematic review of hindering and facilitating factors on different levels. BMC Health Serv Res [Internet]. 2025;25(1):1–17. Dec 1 [cited 2025 Sep 15];.
14. Alsaedi AR, Alneami N, Almajnoni F, Alamri O, Aljohni K, Alrwaily MK, et al. Perceived Worries in the Adoption of Artificial Intelligence Among Healthcare Professionals in Saudi Arabia: A Cross-Sectional Survey Study. Nurs Rep. 2024;14(4):3706–21. [Internet]. 2024 Nov 28 [cited 2025 Sep 15];.
15. Abdallah ABAA, Sadaka SIH, Ali EI, Bilal SAM, Abdelrahman MO, Mohammed FBF et al. The Role of Artificial Intelligence in Pediatric Intensive Care: A Systematic Review. Cureus [Internet]. 2025 Mar 6 [cited 2025 Sep 15];17(3):e80142.
16. Yıldırım TÖ, Karaman M. Development and psychometric evaluation of the artificial intelligence attitude scale for nurses. BMC Nurs. 2025;24:441.
17. Sayed ZA, Alnjadat R, Khwaldeh A, Alqudah LMM. ICU Nurses' Perspectives on Artificial Intelligence in Adult Intensive Care Units: Knowledge, Attitudes and Job-Security Concerns. Nurs Crit Care. 2026;31(3):e70477. 10.1111/nicc.70477. PMID: 41960613.
18. Bi A, Li T, Cheng G, Hu J. Artificial intelligence applications in intensive care unit nursing: A narrative review (2020–2025). Digit Health. 2025;11:20552076251406302. PMID: 41393841; PMCID: PMC12701216.
19. Al-Sofyani KA. Role of artificial intelligence in pediatric intensive care: a survey of healthcare staff perspectives in Saudi Arabia. Front Pediatr. 2025;13:1533877. 10.3389/fped.2025.1533877. . PMID: 40066464; PMCID: PMC11891184.

Figures

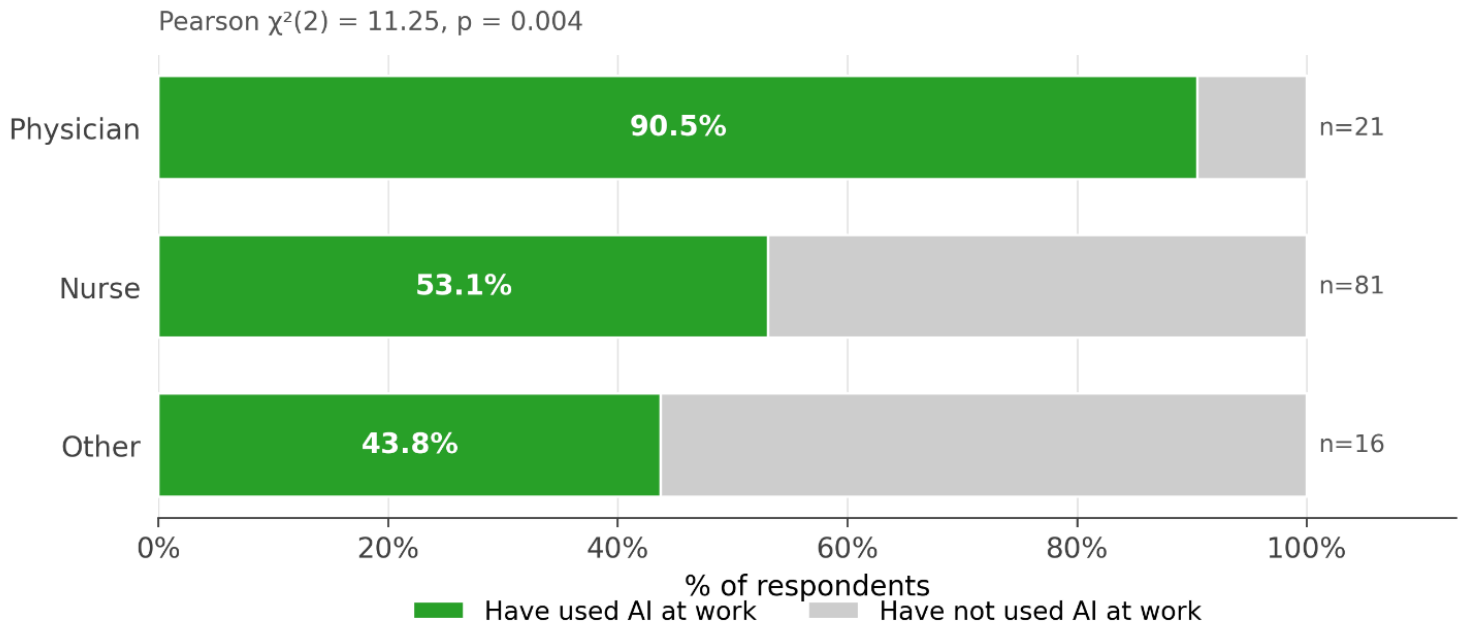


Figure 1

Prior AI used at work, by PICU role

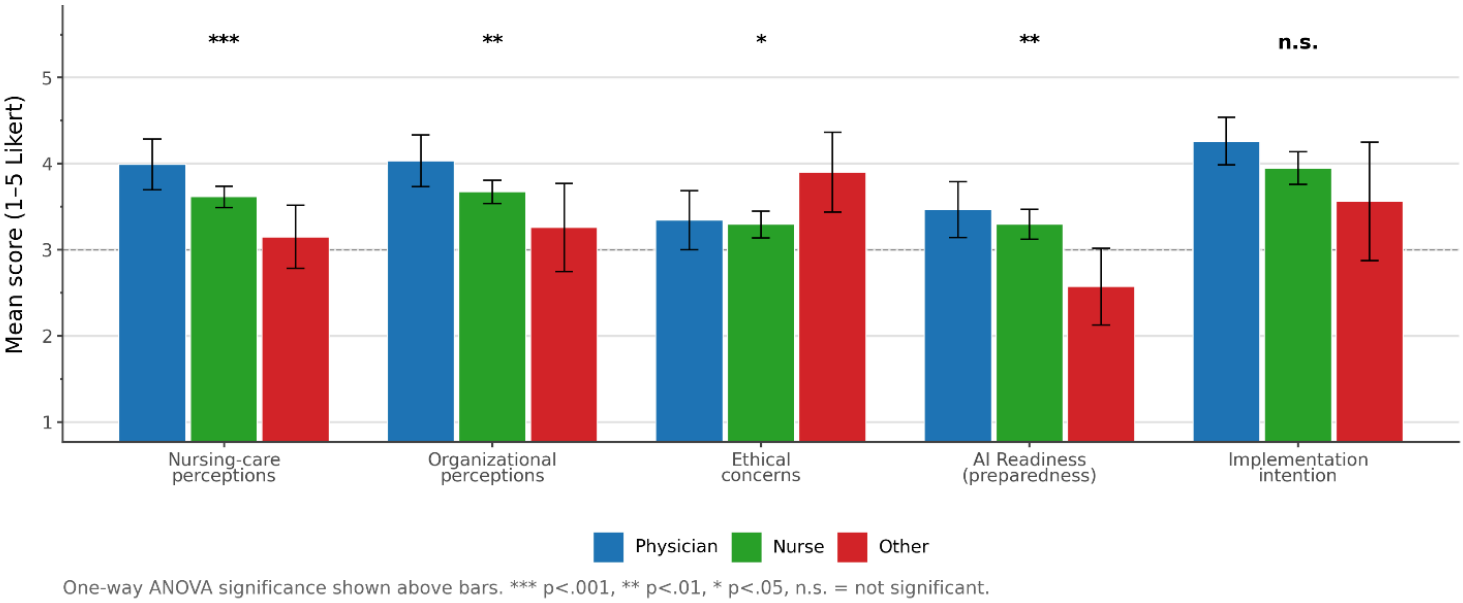


Figure 2

Perceptions and readiness towards AI in PICU staff, by role

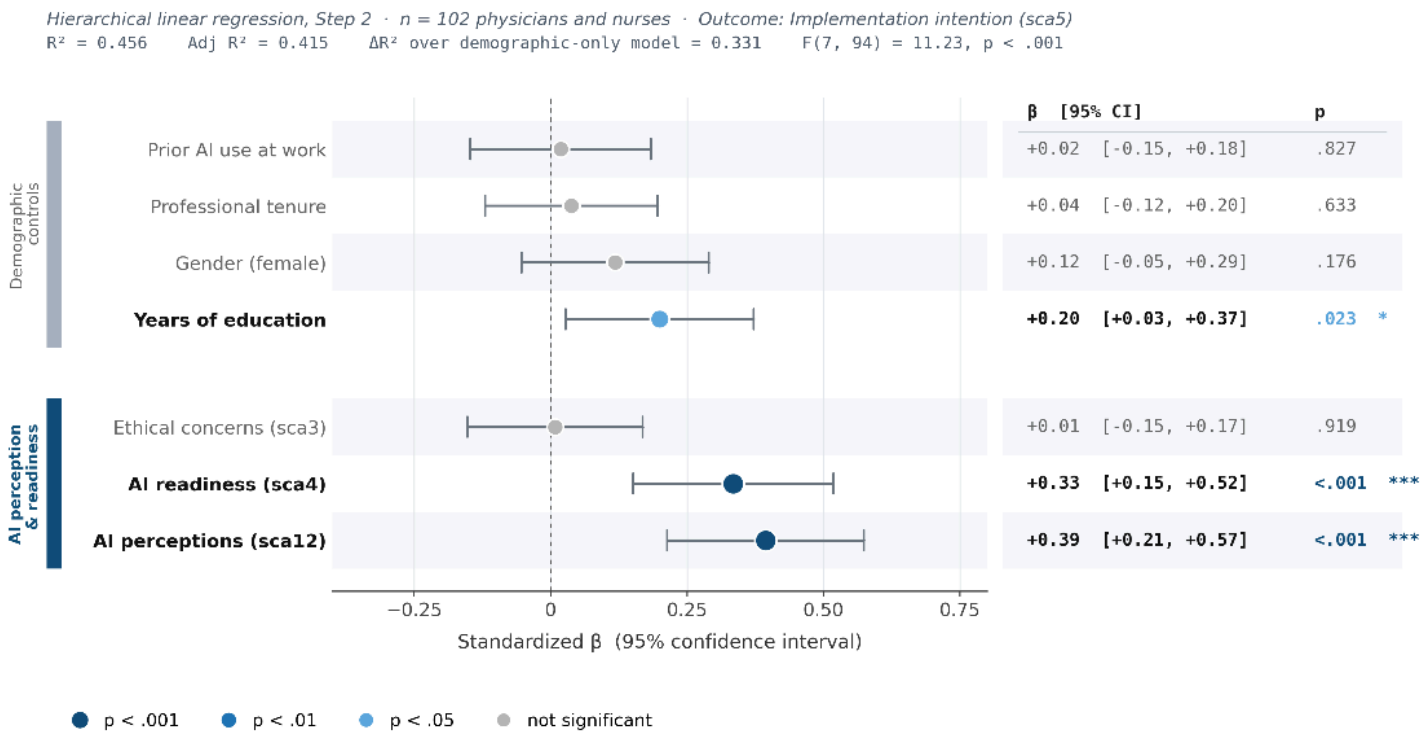


Figure 3

Predictors of PICU staff's intention to implement AI in clinical care