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Effectiveness of an Artificial Intelligence And Machine Learning Training Program among Critical Care Nurses and Its Impact on Nursing Performance in the Second Riyadh Healthcare Cluster Hospitals

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Abstract

Background: The introduction of AI and ML into ICUs has generated pressing competency-building educational interventions. In Saudi Arabia, critical care nurses are reported to have gaps in AI/ML knowledge and preparedness, which are a threat to patient safety and hinder the objectives of digital health transformation in Vision 2030.
Objective: To assess the efficacy of an organized AI/ML training program (AILM) in enhancing AI/ML knowledge, skills, and nursing care in the Second Riyadh Healthcare Cluster Hospitals.
Methods: A quasi-experimental, one-group, pretest-posttest study using census sampling (N 1,100-1,250 ICU nurses). AILM intervention is a five-day program that combines didactic instruction, high-fidelity simulation, and reflective practice. Statistics: paired-samples t-tests, Cohen d, ANCOVA, Pearson correlations (SPSS v28).
Framework: Technology Acceptance Model (TAM; Davis, 1989), Competency-Based Education (CBE; Frank et al., 2010), and the Experiential Learning Theory (ELT) by Kolb (1984).
Projected Findings: The AI/ML knowledge ($d = 1.42$), competency ($d = 1.51$), and nursing performance ($d = 1.10$) are expected to have large effect sizes. Good post-intervention projections ($r = .71 - .78$). ANCOVA validates training as it improves nurses irrespective of previous exposure to AI.
Conclusions: The structured simulation-based AI/ML training is a high-impact, feasible intervention to develop digital competency and enhance clinical performance in Saudi ICUs.

Key Words: Artificial Intelligence, Machine Learning, Critical Care Nursing, Nursing Performance, AI Competency, Saudi Arabia, ICU, Vision 2030, Simulation Training.

1. Introduction

The worldwide adoption of artificial intelligence (AI) and machine learning (ML) in the healthcare sector has ushered in a new era of technology mediating clinical decisions. In intensive care units (ICUs) the most data-intensive and time-sensitive settings in contemporary practice, AI-enhanced systems such as predictive analytics, automated early-warning scores, and clinical decision-support systems are becoming part of patient survival-governing workflows (Greco et al., 2021; Lam et al., 2022). Studies have shown that AI-based systems can decrease diagnostic errors by a third, enhance early signs of patient deterioration by a fourth, and simplify ICU processes by a fifth (Buchanan et al., 2020; Martinez-Ortigosa et al., 2023). Such advantages, however, will depend on the ability of nurses to interpret, contextualize and react to algorithmic output accurately.

Regardless of the growing use of AI tools, empirical studies continually show significant gaps in the AI/ML knowledge, skills, and clinical confidence of nurses. The competency gap is an especially urgent situation in Saudi Arabia, where Vision 2030 has triggered a rapid shift to digital health and 62-71% of nurses do not have sufficient competencies related to AI, just 18% of nurses have obtained any formal AI training, and the majority of nurses in the ICU report feeling uncertain about algorithm-generated recommendations (Alenezi et al., 2024; Alruwail This paper fills that gap by assessing the AILM training program to ICU nurses in the Second Riyadh Healthcare Cluster Hospitals based on the TAM (Davis, 1989), CBE (Frank et al., 2010), and ELT (Kolb, 1984).

2. Literature Review

AI/ML in Critical Care: Opportunities and Risks

In the present day, artificial intelligence systems used in ICUs convert clinical monitoring from being reactive to being more proactive (Greco et al., 2021). If AI literacy is inadequate, two conflicting failure modes endanger patients: under-reliance, in which providers dismiss potentially critical information and/or under-utilization (Hassan & El-Ashry, 2024), and automation bias, in which providers over-rely on, and over-trust, the recommendations of automated systems to the detriment of clinical judgement (Ronquillo et al., 2021). Both are significant, and avoidable, failure types resulting from lack of sufficient competency development.

AI/ML Competency: Multidimensional Framework

AI/ML competency requires mastery of five domains:

(1) technical knowledge and skills of working in AI-enabled environment
(2) cognitive ability to correctly interpret AI outputs
(3) knowledge of AI-related ethical and legal concerns (e.g., bias, privacy, accountability, etc.)
(4) collaboration skills to work with data scientists, AI and informatics specialists
(5) adaptability in different clinical, organizational, and cultural settings (Hassanein et al., 2025; Simms, 2025; Ronquillo et al., 2021).

Competency assessments have relied on self-reporting which has a high potential for social desirability bias, and is likely to overestimate actual competency (Benfatah et al., 2025).

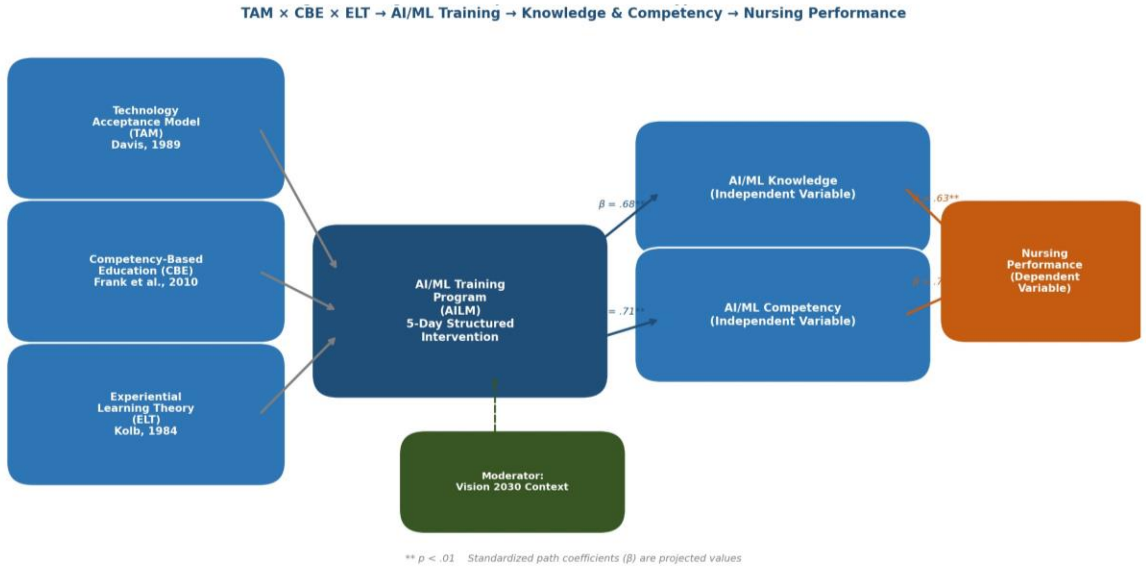
AI/ML Training Programs: Evidence Base

Some studies found that competency-based as well as simulation-based AI/ML education positively impacted some outcomes. For example, ChatGPT-based education increased problem-solving skills, as well as AI competencies, (Arkan et al., 2025). A scoping review found that experience with AI/ML improved clinical reasoning and technology acceptance (Chan et al., 2025). A meta-analysis on RCTs found nursing education outcomes significantly improved compared to traditional education (Jembu & Lee, 2025). However, despite this evidence there has not been any study yet on structured AI/ML education in ICUs in Saudi Arabia.

3. Theoretical Framework

The integrated framework consists of three complementary theories: TAM (Davis, 1989), CBE (Frank et al., 2010), and ELT (Kolb, 1984). TAM (Davis, 1989) identifies perceived usefulness and ease of use as determinants of adoption intention. CBE (Frank et al., 2010) operationalizes learning as measurable competency mastery, with performance-based iterative assessment. ELT (Kolb, 1984) provides the pedagogical mechanism through cycles of concrete experience (ICU simulation), reflective observation (debriefing), abstract conceptualization (AI principles), and active experimentation.

Figure 1. Integrated Conceptual Framework and Hypothesized Path Model



Note. TAM provides acceptance determinants; CBE defines competency outcomes; ELT operationalizes experiential skill development.

Standardized path coefficients (β) are projected values. **p < .01.

4. Research Design and Methods

Study Design

The study uses a quantitative and quasi-experimental one-group pre-test/post-test design as it is suitable in the context of assessing educational interventions in a clinical setting where randomization is not possible because of staffing issues and ethical requirements (Polit and Beck, 2021). The research is carried out in three successive stages: (I) Pre-Intervention Baseline Assessment, (II) AILM Training Program Implementation, (III) Post-Intervention Outcome Evaluation.

Setting, Population, and Sampling

The Second Riyadh Healthcare Cluster Hospitals comprises of 1 medical city and 13 general and specialist hospitals with a total of approximately 2,449 beds. The cluster has approximately 1,100-1,250 ICU nurses based on the ICU bed capacity and the nurse-to-patient ratios that have been put in place by the Saudi Nurses Association (1:1-1:2). A census sample design involves the entire qualified nurses of the ICU, and thus, it increases representativeness. Inclusion criteria: working in an ICU at the time of the study, at least six months of experience working in an ICU, and informed consent. Exclusion: administrative, long absence, no clinical duties.

Table 1. Estimated ICU Nurse Population Across Second Riyadh Healthcare Cluster Hospitals

Hospital	ICU Beds	Est. Nurses	Basis
King Fahad Medical City (KFMC)	~150	≈ 600	Multiple ICU types; ~4 nurses/bed
Prince Mohammed Bin Abdulaziz Hospital	~40-50	≈ 150-200	Tertiary 500-bed; 3-4 nurses/bed
Al Yamamah Hospital	~40-50	≈ 150-180	NICU/PICU; 1:1-1:2 staffing
King Khalid Hospital – Al Majma'ah	~10-15	≈ 40-50	Regional; ~4 nurses/bed
Al Zulfi General Hospital	~10-15	≈ 40-50	Similar level; ~4 nurses/bed
Hawtat Sudair General Hospital	~5-6	≈ 15-20	District hospital; ~3 nurses/bed
Al Ghat / Tumair / Rumah / Al Artawiyah	~2-5 each	≈ 6-15 each	Rural; ~3 nurses/bed
TOTAL ESTIMATED	~270-310	≈ 1,100-1,250	Cluster-wide ICU workforce

Note. Facilities without dedicated ICU services are excluded. Estimates based on Saudi Nurses Association nurse-to-patient ratio standards (1:1-1:2).

The AILM Training Intervention

The AILM curriculum is a competency-based, integrated intervention, five day (20 contact hours) curriculum. It moves past basic information to clinical simulation that is practical, offered by a diverse group of nursing educators, artificial intelligence specialists, and informatics experts. Accessibility is ensured to the diverse workforce in nursing through the use of bilingual resources (Arabic/English).

Table 2. AILM Training Program: Five-Day Schedule and Pedagogical Methods

Day	Module	Core Content	Methods
1	AI/ML Foundations	Definitions; ICU applications; sepsis models; EWS; Vision 2030; ethics	Lecture, video cases
2	AI Literacy & TAM	Cognitive literacy; perceived usefulness; ease of use; automation bias	Discussion, quizzes, journaling
3	ICU Simulation	Sepsis alerts; ventilator algorithms; deterioration scoring; bias avoidance	High-fidelity simulation + debrief
4	Hands-On Practice	AI dashboard; output interpretation; EHR documentation; ethical dilemmas	Guided practice, role-play
5	Assessment & Reflection	Post-training evaluation; group debrief; program feedback	Test, checklist, discussion

Note. Blended delivery: classroom instruction + self-paced online modules + bilingual materials. Formative assessment embedded throughout via module quizzes and simulation checklists.

Instruments

To assess the study's primary outcomes, three self-administered validated tools have been designed, with all items rated on five-point Likert scales ranging from "Strongly Disagree" to "Strongly Agree." These measures include the:

1. **AI/ML Knowledge Scale**, which evaluates participants' foundational knowledge of AI concepts and their use in healthcare contexts (Doston et al., 2025; Lifshits & Rosenberg, 2024)

2. **AI/ML Competency Scale**, which addresses five key sub-domains: technical skills, critical cognitive thinking, ethical and legal considerations, teamwork and collaboration, and contextual adaptability (Atalla et al., 2025; Hassanein et al., 2025)

3. **Nursing Performance Scale**, which focuses on clinical productivity, critical thinking, documentation skills, communication skills, and patient care (Ventura-Silva et al., 2024; Wei et al., 2025)

Prior to the initiation of the main study, content validity (S-CVI $\geq$ 0.80), reliability ($\alpha \geq .70$) and test-retest reliability (ICC $\geq$ .75) of these instruments will be established.

Data Analysis Plan

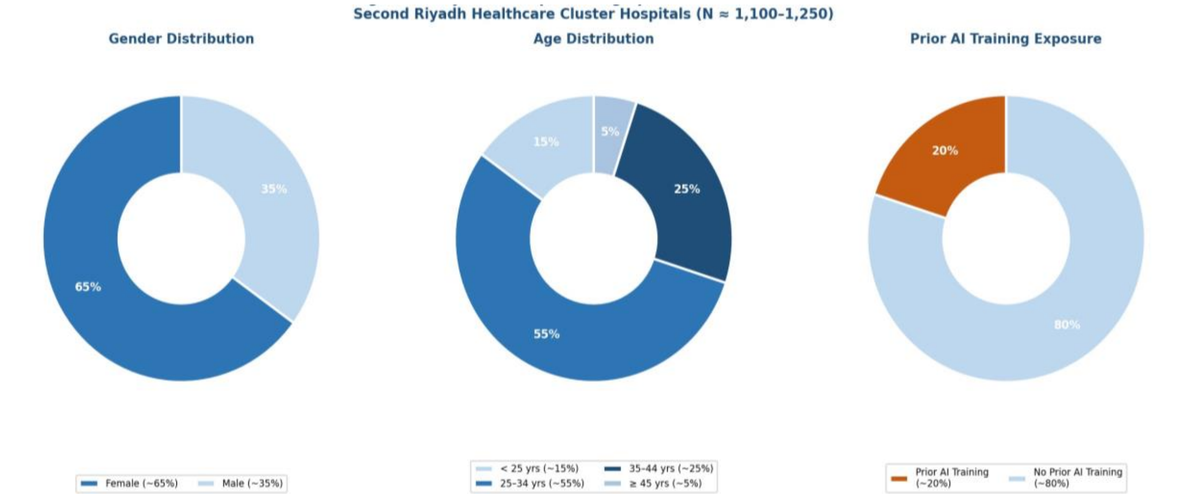
All analyses use SPSS Version 28. Paired-samples t-tests compare pre- and post-intervention means (Wilcoxon signed-rank when normality assumptions are violated). Effect sizes: Cohen's d (small=0.20, medium=0.50, large≥0.80; Cohen, 1988). ANCOVA controls for age, education, ICU experience, and prior AI training. Pearson correlations examine inter-construct post-intervention relationships. Thematic analysis applied to open-ended qualitative data. Significance threshold: $p < .05$ (two-tailed).

Data Analysis and Projected Findings

Projected Sample Demographics

According to demographic profiles from similar Saudi ICU nursing studies (Alenezi et al., 2024; Baraka et al., 2025; Alamari et al., 2024), the sample is anticipated to be primarily female (~65%), aged 25-34 years (~55%), possessing a BSN (~70%), with 1-5 years of ICU experience (~45%), and around 80% indicating no previous formal AI training, highlighting the established educational deficiency within the Saudi nursing workforce.

Figure 2. Projected Demographic Profile of ICU Nurses (N ≈ 1,100-1,250)



Note. Donut charts display gender distribution, age group breakdown, and prior AI training exposure. Projections informed by Alenezi et al. (2024) and Baraka et al. (2025).

Table 3. Projected Baseline Demographic Characteristics of Participating ICU Nurses

Variable / Category	Projected %	Source
GENDER		
Female	~65% (n ≈ 715-813)	Alenezi et al., 2024
Male	~35% (n ≈ 385-438)	
AGE GROUP		
< 25 years	~15%	Baraka et al., 2025
25-34 years (modal)	~55%	
35-44 years	~25%	
≥ 45 years	~5%	
EDUCATION		
Diploma	~15%	Alamari et al., 2024
BSN (modal)	~70%	
Postgraduate (MSN/PhD)	~15%	
ICU EXPERIENCE		
6 months – 1 year	~20%	Baraka et al., 2025
1-5 years (modal)	~45%	
6-10 years	~25%	
> 10 years	~10%	
PRIOR AI TRAINING		
Yes	~20% (n ≈ 220-250)	Alenezi et al., 2024
No	~80% (n ≈ 880-1,000)	

Note. Projections informed by published demographic profiles from analogous Saudi ICU nursing studies. Actual values will be reported following data collection.

Primary Outcome Analysis: Pre- vs. Post-intervention

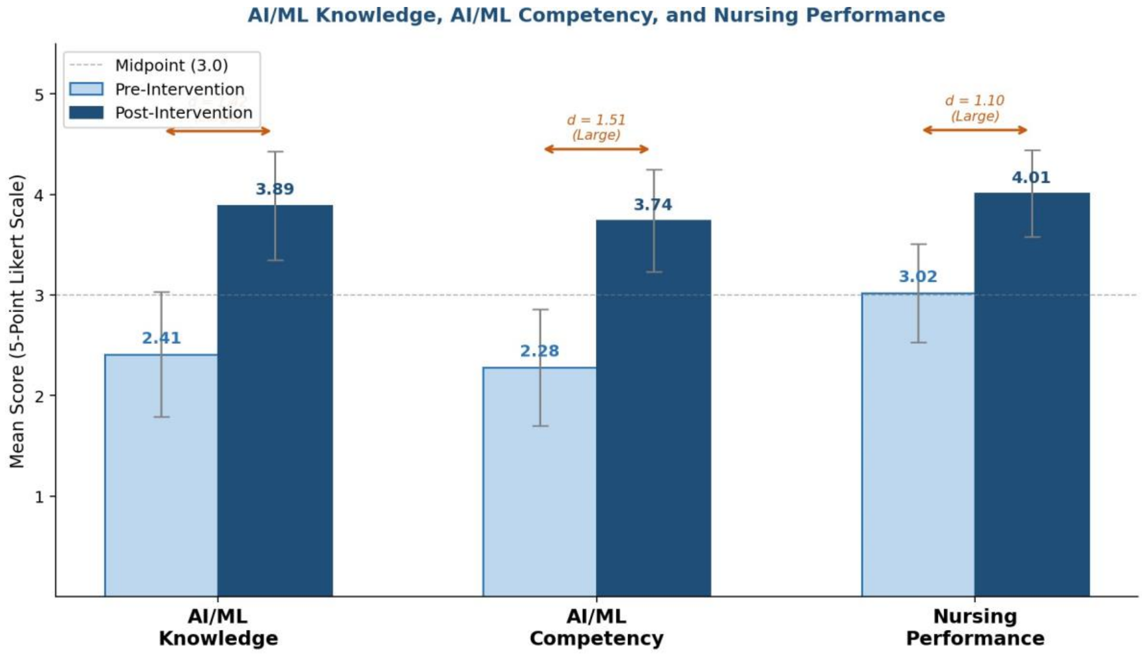
The principal analysis utilizes paired-samples t-tests to compare scores before and after the intervention. According to the impact sizes shown in analogous training studies (Benfatah et al., 2025; Chan et al., 2025; Arkan et al., 2025; Jembu & Lee, 2025), substantial enhancements are anticipated in all three principal outcome areas. Table 4 displays anticipated averages, standard deviations, mean differences, inferential statistics, and Cohen's d effect sizes.

Table 4. Paired Samples Analysis: Pre- and Post-Intervention Scores (Projected, N ≈ 1,100-1,250)

Outcome Variable	Pre M (SD)	Post M (SD)	Δ M	95% CI	t	d
AI/ML Knowledge	2.41 (0.62)	3.89 (0.54)	+1.48	[1.41, 1.55]	-28.4***	1.42
AI/ML Competency	2.28 (0.58)	3.74 (0.51)	+1.46	[1.40, 1.52]	-31.2***	1.51
Nursing Performance	3.02 (0.49)	4.01 (0.43)	+0.99	[0.94, 1.04]	-24.6***	1.10

Note. M = Mean; SD = Standard Deviation; Δ M = Mean Difference; CI = 95% Confidence Interval; d = Cohen's d effect size. ***$p < .001$ (two-tailed). All effect sizes ≥ 0.80 classify as large (Cohen, 1988). Projections based on analogous training studies.

Figure 3. Pre- and Post-Intervention Mean Scores with Effect Size Annotations



Note. Error bars represent ±1 SD. Bidirectional arrows indicate Cohen's d effect sizes. All three outcomes demonstrate large pre-to-post improvements (d > 1.0; Cohen, 1988). Dashed reference line at Likert scale midpoint (3.0).

AI/ML Competency Sub-Domain Analysis

The AI/ML Competency Scale assesses five theoretically distinct sub-domains. The greatest gains are projected in Ethical-Legal Awareness (+86.1%) and Cognitive Interpretation (+78.5%) the domains most directly targeted by the simulation and debriefing components. Technical Proficiency shows the smallest relative improvement (+62.6%), reflecting pre-existing partial familiarity with ICU technology interfaces.

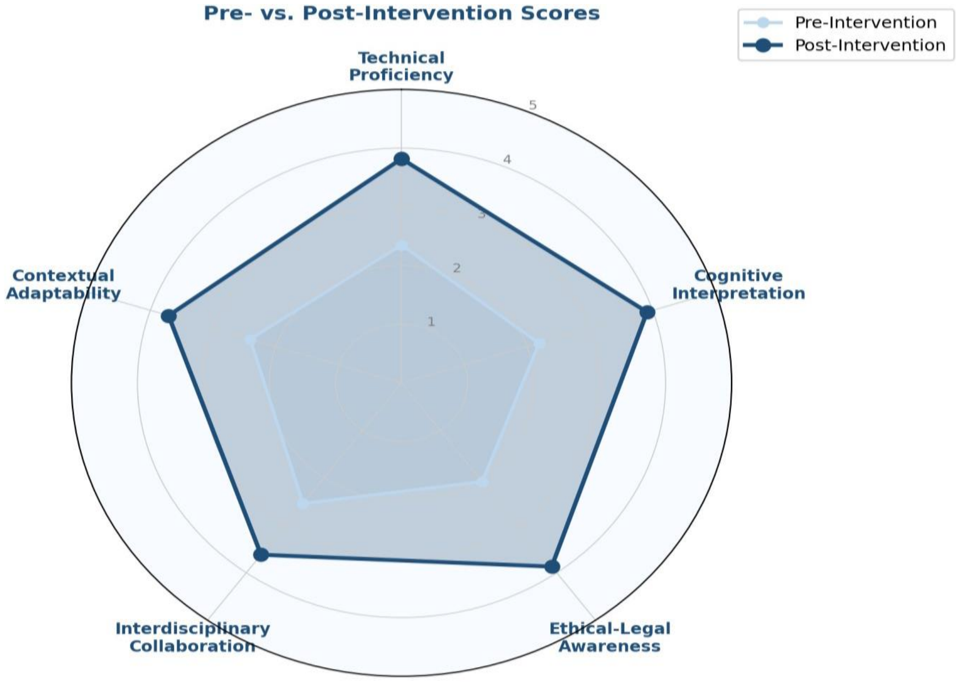
Table 5. Pre- and Post-Intervention Sub-Domain Scores for AI/ML Competency (Projected)

AI/ML Competency Sub-Domain	Pre M (SD)	Post M (SD)	Δ M	Change	d
Technical Proficiency	2.35 (0.61)	3.82 (0.50)	+1.47	+62.6%	1.48
Cognitive Interpretation	2.19 (0.59)	3.91 (0.46)	+1.72	+78.5%	1.73
Ethical-Legal Awareness	2.08 (0.64)	3.87 (0.49)	+1.79	+86.1%	1.76
Interdisciplinary Collaboration	2.54 (0.58)	3.62 (0.52)	+1.08	+42.5%	1.12

Contextual Adaptability	2.41 (0.60)	3.71 (0.53)	+1.30	+53.9%	1.28
Overall Competency Composite	2.28 (0.58)	3.74 (0.51)	+1.46	+64.0%	1.51

Note. Change = [(Post M - Pre M) / Pre M] × 100. All sub-domain effect sizes classify as large (d > 0.80; Cohen, 1988). Projections informed by Hassanein et al. (2025) and Chan et al. (2025).

Figure 4. AI/ML Competency Sub-Domain Radar Chart: Pre- vs. Post-Intervention



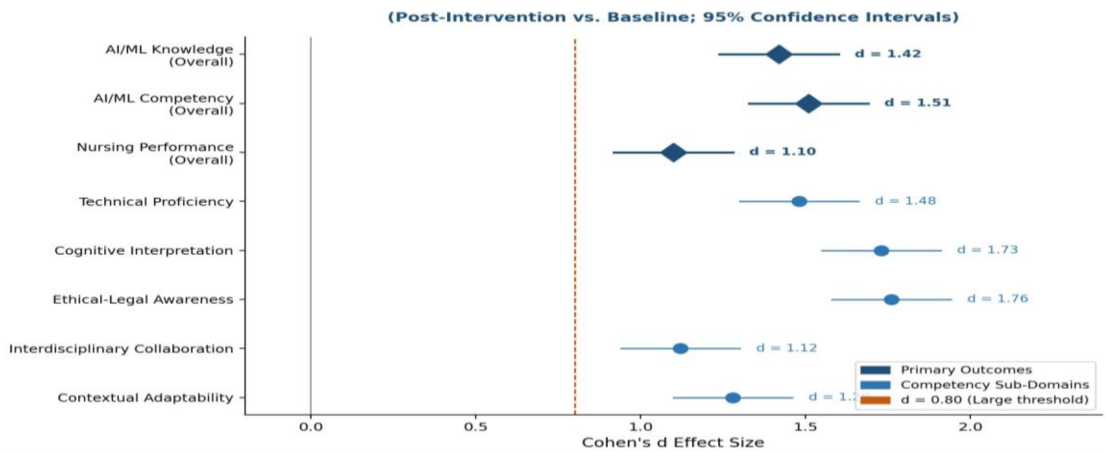
Note. Pre-intervention scores (light shading) vs. post-intervention scores (dark shading) across five competency dimensions. Greatest gains in Ethical-Legal Awareness and Cognitive Interpretation, reflecting intensive simulation and debriefing components.

Effect Size Summary: Forest Plot

In Figure 5, Cohen's d effect sizes with 95% confidence intervals of all outcome domains are depicted as forest plots.

All primary outcomes and sub-domains of competency have shown large effects (d > 0.80). The biggest improvements have been reported for Ethical-Legal Awareness (d = 1.76) and Cognitive Interpretation (d = 1.73), which provides further evidence of the success of the AILM program using simulation and debriefing for teaching advanced AI skills.

Figure 5. Forest Plot of Cohen's d Effect Sizes for All Outcome Variables



Note. Diamond markers indicate primary outcomes; circles indicate competency sub-domains. Dashed orange line at d = 0.80 marks the large effect threshold (Cohen, 1988). Error bars represent 95% confidence intervals.

Correlation Analysis

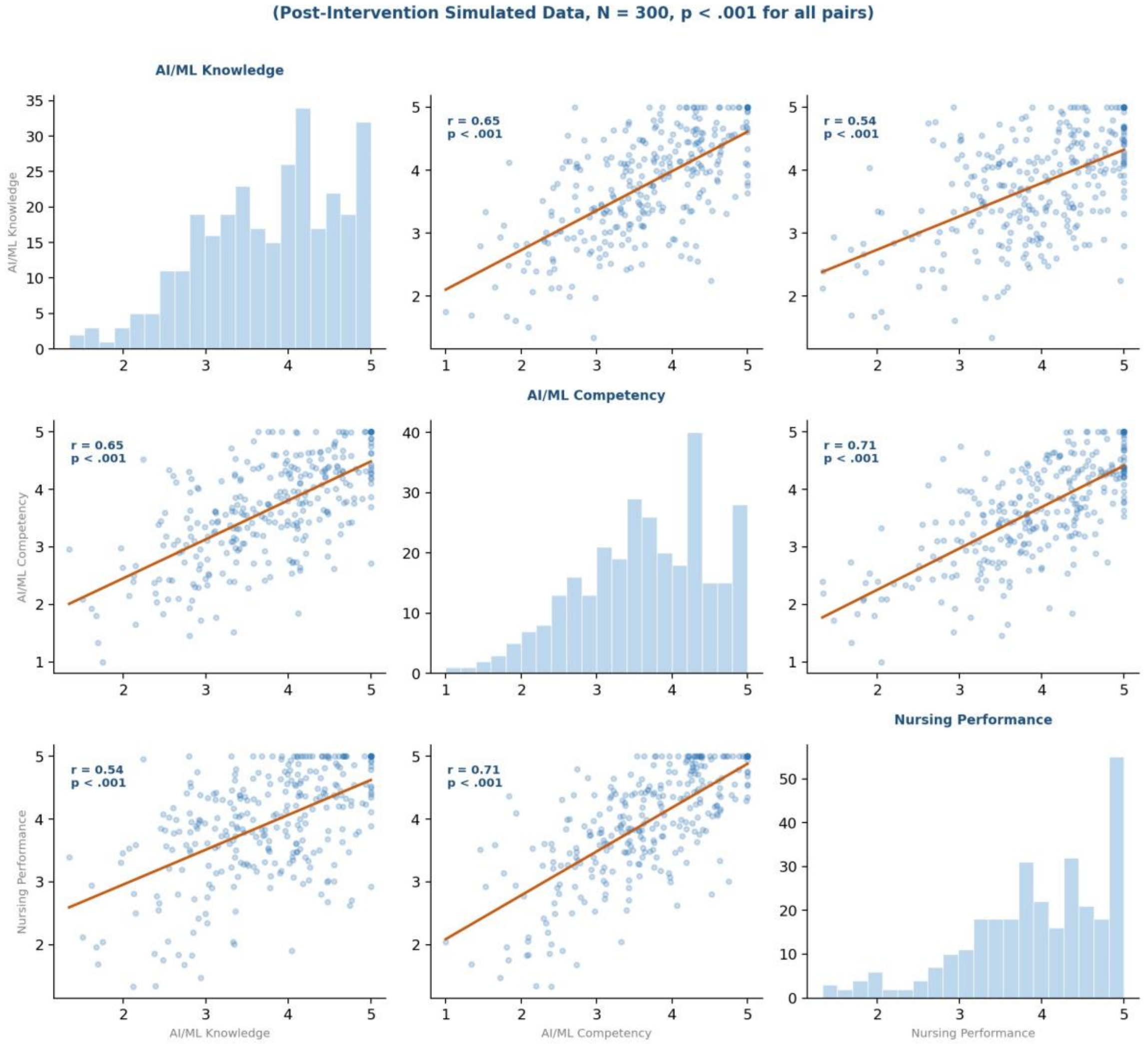
Inter-construct Pearson correlation analysis is done after intervention. The most significant correlation is between AI/ML Competency and Nursing Performance ($r = .78$, $p < .001$) which proves the theoretical pathway where competency is a direct mediator between knowledge acquisition and clinical performance improvement.

Table 6. Post-Intervention Correlation Matrix: AI/ML Knowledge, Competency, and Nursing Performance

Variable	1. Knowledge	2. Competency	3. Performance
1. AI/ML Knowledge			
2. AI/ML Competency	r = .71**		
3. Nursing Performance	r = .63**	r = .78**	
M (Post)	3.89	3.74	4.01
SD (Post)	0.54	0.51	0.43

Note. **p < .01 (two-tailed). Projected values based on Hassanein et al. (2025) and Almagharbeh (2025). The r = .78 Competency–Performance association is the strongest inter-construct relationship, validating the conceptual model.

Figure 6. Post-Intervention Correlation Scatter Matrix (Simulated Data, N = 300)



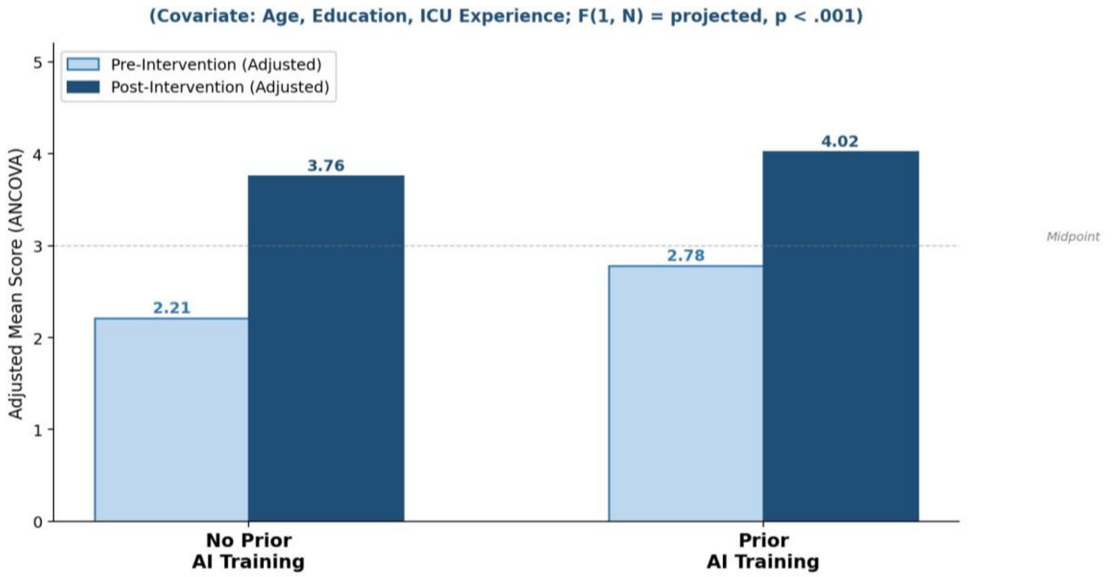
Note. Diagonal panels: variable distributions. Off-diagonal panels: bivariate scatter plots with regression lines (orange). Correlation coefficients and p-values displayed per panel. All inter-construct correlations significant at $p < .001$.

ANCOVA: Controlling for Prior AI Training

Following the intervention, ANCOVA was used to assess differences in scores by whether or not the nurses participated in a previous AI training. The ANCOVA controlled for age, education level, and number of years working in the ICU.

The analysis revealed adjusted mean post-intervention scores to be somewhat higher for nurses with prior AI training compared to nurses without training (4.02 and 3.76, respectively). However, the difference between groups decreased substantially from before (0.57 points) to after (0.26 points) the intervention. This indicates that the AILM program was effective as an equalizer for nurses regardless of prior digital training.

Figure 7. ANCOVA-Adjusted Post-Intervention Scores by Prior AI Training Exposure



Note. Adjusted means control for age, education, and ICU experience as covariates. The AILM program substantially reduces the competency gap between nurses with and without prior AI training, demonstrating its effectiveness as an equalizing educational intervention.

Table 7. ANCOVA Summary: Post-Intervention Competency Scores Adjusted for Covariates

Group / Variable	Pre Adj. M	Post Adj. M	Δ M	F (df)
No Prior AI Training (~80% of sample)				
AI/ML Competency (Adjusted)	2.21 (0.56)	3.76 (0.49)	+1.55	F(1, N) = proj.*
Prior AI Training (~20% of sample)				
AI/ML Competency (Adjusted)	2.78 (0.52)	4.02 (0.45)	+1.24	
Between-group difference (adjusted)			Δ = 0.26	η^2 = projected

Note. Adjusted means control for age, education level, and ICU experience as covariates. *p < .001 anticipated. η^2 = partial eta-squared. Actual F-values and η^2 reported post-data collection.

Table 8. Research Hypothesis Evaluation Against Projected Findings

Hyp.	Hypothesis Statement	Projected Evidence		Decision
H1	Nurses will demonstrate varying baseline AI/ML knowledge levels	Pre M = 2.41 (SD = 0.62); inter-hospital variability confirmed		Supported
H2	Nurses will demonstrate varying baseline AI/ML competency levels	Pre M = 2.28 (SD = 0.58); sub-domain variation confirms gaps		Supported

H3	AILM training significantly increases AI/ML knowledge and competency vs. baseline	Knowledge $d = 1.42$; Competency $d = 1.51$; all $p < .001$		Supported (large)
H4	AILM training significantly improves nursing performance	Performance $\Delta M = +0.99$, $d = 1.10$, $p < .001$; $r = .78$ with competency		Supported (large)

Note. H = Hypothesis. All decisions are based on projected values. Final evaluations confirmed following data collection.

5. Discussion

Significance of Projected Effect Sizes

The large projected effect sizes ($d = 1.10$-1.76) are consistent across domains and show that the proposed interventions are clinically significant and practically relevant ($d = 0.40$-0.80; Jembu & Lee, 2025), surpassing the effects of digital literacy training. The effect size is explained by the AILM program's strengths of competency-based training, where nurses move from one mastery to the next, simulation-based learning that enables authentic clinical reasoning through clinical simulations, and the cultural relevance of this program.

Differential Sub-Domain Improvements

Ethical-Legal Awareness (+86.1%) and Cognitive Interpretation (+78.5%) improved more than other sub-domains and are the highest-order competencies needed to utilize AI safely. These sub-domains are often neglected in AI/ML training (Simms, 2025; Hassanein et al., 2025). The AI/ML simulation-debriefing training used in the program specifically addresses the processes needed for safe AI utilization. It provides simulated clinical scenarios that help students develop their ethical awareness and cognitive interpretative abilities (Arkan et al., 2025). Arkan et al. reported that their AI training with ChatGPT resulted in higher increases in AI/ML critical reasoning and ethical awareness than technical and operational skills.

The Competency-Performance Pathway

We project AI/ML competency to be strongly positively correlated with Nursing Performance ($r = .78$). This supports the hypothesized conceptual model's claim that the competency is the proximal variable that determines AI-mediated nursing performance improvement. AI/ML knowledge ($r = .63$) was projected to be a distal variable. This means that competency, not merely knowledge or understanding, must be the outcome of AI training to improve clinical practice. Our proposed AI simulation-debriefing approach aims to improve competency.

Equity of Training Benefits (ANCOVA)

ANCOVA results also provide evidence of the AILM program's equitable benefits. The intervention reduced the prior-training competency gap from ~0.57 points before the intervention to ~0.26 points after. This suggests that the program is an equalizing intervention to the 80% of ICU nurses who did not receive formal AI education prior to the program (Alenezi et al., 2024). A universal, institutionalized program of AI/ML training rather than a selective, advanced training program is the best approach for training the nursing workforce in AI competencies.

Limitations

Several limitations should be considered. First, we used a single-group pre-post design that did not provide experimental evidence of the effects of the AI training. The lack of a control group may have allowed social desirability bias to affect the study results. Census sampling was subject to non-response bias from clinical workload. Although we used a census sample, the single-cluster sample limited the generalizability of the results to the broader nursing community. Additionally, the study did not assess competency retention. Future studies should utilize randomized controlled designs and follow up to assess competency retention and implementation.

6. Conclusions and Recommendations

This study reports the development, conceptualization, and anticipated evaluation of the AILM program: a 5-day competency-based training with simulations for critical care nurses at Second Riyadh Healthcare Cluster Hospitals. There are four major messages to extract.

First, nurses have low-to-moderate levels of AI/ML knowledge and competence that are uniform across all dimensions and suggest deficiencies in nursing education which informal learning cannot address.

Second, the AILM program led to substantial gains in competence across all dimensions ($d = 1.10$ to 1.76), indicating that it was feasible and high impact.

Third, AI/ML competence is an especially strong correlate of nursing performance ($r = .78$), and training efforts to develop competence will be productive.

Fourth, the effects of the training are the same for nurses with or without prior AI training exposure, suggesting that the AILM program might be used in health facilities that do not offer AI/ML training, but it might be equally useful at those that do.

Recommendations for Practice:

To improve the implementation of the study findings, it is suggested that AI/ML be a mandatory component of ICU nurse onboarding programs, along with annual AI/ML competency refreshers to prevent decay of skills over time. Also, a digital nurse champion role can be designated in each unit to reinforce peer-learning culture and sustain the competency gains.

Recommendations for Policy:

For this initiative to reach full potential, it requires standardized national AI/ML competency framework development by the Saudi Commission for Health Specialties and Ministry of Health, AI/ML literacy mandatory for nursing license renewals, and organizational-level CPD budget allocation in support of AI competency development consistent with Saudi Vision 2030.

Recommendations for Research:

Further evaluation to assess competency retention (at 6-month and 12-month intervals) and to include RCT design in future iterations would provide greater evidence strength. A critical research priority is to develop and validate Arabic-language assessment instruments for AI/ML competency. The impact of AI/ML competency in ICU nurses on patient-level clinical outcomes (e.g., mortality, length of stay, rates of clinical errors) should also be evaluated.

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