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Traditional Clinical Leadership and Artificial Intelligence Readiness Among Hospital Nurses: Implications for a Digital Clinical Leadership Framework

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ABSTRACT

Background: Artificial intelligence is increasingly transforming healthcare delivery and creating new opportunities and challenges for nursing practice. Although clinical leadership is frequently associated with innovation, change management, and quality improvement, little empirical evidence exists regarding whether traditional clinical leadership competencies are associated with nurses' readiness to engage with AI-enabled practice. **Aim:** To examine the relationship between traditional clinical leadership and artificial intelligence (AI) readiness among Jordanian hospital nurses and explore implications for a Digital Clinical Leadership (DCL) framework.

Methods:
Design: Cross-sectional survey.
Methods: In 2025, a cross-sectional survey was conducted among nurses working in governmental, military, private, and teaching hospitals in Jordan. Clinical leadership was measured using validated attributes, skills, and action scales, whereas AI-related knowledge, attitudes, and literacy preferences were assessed using a standardized instrument. Descriptive analyses, group comparisons, and multivariable regression analyses were conducted.
Results: CL was widely demonstrated among nurses ($M = 3.99$, $SD = 0.68$). However, CL did not significantly differentiate AI adopters ($n = 152$) from non-adopters ($n = 194$) across attributes ($p = 0.098$), skills ($p = 0.513$), actions ($p = 0.899$), or overall CL ($p = 0.784$). Furthermore, CL was not a significant predictor of AI readiness ($\beta = 0.13$, $p = 0.206$). Educational attainment, professional experience, hospital sector, and shift patterns demonstrated significant associations with AI readiness.

Conclusions: Traditional clinical leadership was widely demonstrated among Jordanian nurses but was not associated with AI readiness. Educational and organizational factors appeared to play a more influential role. The findings suggest that competencies required for AI-enabled nursing practice may extend beyond those captured within existing clinical leadership frameworks.

Keywords: Artificial intelligence; Clinical leadership; Digital clinical leadership; Nursing leadership; Evidence-based nursing; Workforce readiness.

1 | Background

Clinical leadership (CL) in nursing is a foundational competency associated with safer care, effective teams, and better organizational performance (Cummings et al., 2021; Mianda & Voce, 2018). It is enacted through communication, clinical credibility, role modeling, ethical decision-making, change agency, and team influence (Cummings et al., 2021; Stanley, 2017). It has been linked to healthier work environments and improved clinical outcomes across settings (Cummings et al., 2021; Mianda & Voce, 2018; Daly et al., 2014). Despite this prominence, CL remains variably conceptualized. It is often conflated with managerial authority rather than understood as a distributed, values-driven, practice-embedded form of influence at the point of care (Stanley, 2017; Stanley & Stanley, 2018).

In parallel, artificial intelligence (AI) is reshaping nursing practice. AI-enabled tools, including predictive analytics, early-warning algorithms, and documentation automation, can streamline workflows and support earlier clinical intervention (Hassanein et al., 2025; Ronquillo et al., 2021). Editorial and roadmap contributions in nursing leadership emphasize that safe, effective AI integration requires strategic leadership, robust governance, workforce preparation, and equity-by-design approaches (Bourgault, 2025; Cary et al., 2025). Beyond clinical and workflow benefits, recent leadership commentary frames AI as a catalyst to strengthen modern nursing leadership capabilities, enabling data-driven decision-making, staff learning, and leadership self-efficacy, provided that governance and training mitigate ethical and workload risks (Roshanzadeh et al., 2025). At the same time, reviews and practice commentaries underscore persistent challenges around data privacy, ethical use, training, and scope-of-

practice evolution, highlighting the need for interpretability, human–AI teaming, and ethical oversight in nursing contexts (Brydges, 2025; Hassanein et al., 2025).

Although research is growing on nurses' views of AI and on leadership readiness at managerial levels, little is known about whether frontline nurses' CL profiles, including attributes, skills, and enacted actions, are associated with their AI readiness or early adoption behaviors. Evidence from nurse leaders indicates that readiness for AI varies with education, role, and experience (Kotp et al., 2025). Still, this focus on formal leadership roles leaves frontline nurses, who interact directly with AI tools, underrepresented in empirical analyses (Kotp et al., 2025). Moreover, despite calls for nurse-led strategies and governance for AI integration (Cary et al., 2025), few studies explicitly test whether CL differs between AI adopters and non-adopters among bedside nurses, and validated instruments targeting digital CL (e.g., algorithmic communication, data ethics, human–AI teamwork) remain scarce (Cary et al., 2025; Hassanein et al., 2025). These leadership perspectives remain largely conceptual and rarely linked to empirical tests of frontline leadership-adoption relationships (Roshanzadeh et al., 2025). Consequently, the relationship between traditional CL and AI readiness/adoption in frontline nursing is underexplored, particularly in Middle Eastern contexts such as Jordan (Cary et al., 2025; Hassanein et al., 2025).

More importantly, the existing literature has largely assumed that leadership competencies associated with quality improvement, change management, and professional influence naturally extend to digital innovation. However, this assumption has rarely been tested empirically among frontline nurses. As AI becomes increasingly embedded in clinical workflows, leadership responsibilities now include engagement

with algorithm-supported decision-making, digital safety, data governance, and human–AI collaboration (Brydges, 2025; Cary et al., 2025; Ronquillo et al., 2021). Whether these emerging responsibilities are adequately captured within traditional CL frameworks remains unclear.

To address this knowledge gap, this study examined whether traditional CL competencies are associated with nurses' readiness for AI-enabled practice. Because digital transformation is introducing new leadership responsibilities related to data stewardship, ethical oversight, technology-supported decision-making, and human-AI collaboration, findings from the study were subsequently used to inform a preliminary Digital Clinical Leadership (DCL) framework. Rather than replacing traditional CL, the DCL is proposed as a complementary extension intended to guide future investigation of leadership competencies relevant to increasingly digital healthcare environments.

1.1 | Purpose, Significance, and Regulatory Relevance

Building upon established CL frameworks and addressing a recognized gap, this study integrates two national initiatives: a CL program of work and an AI survey. With the increasing integration of AI into clinical workflows, a notable gap has emerged between existing leadership frameworks and the requirements of algorithm-supported care. Although CL is frequently associated with innovation and organizational change, there is limited empirical evidence demonstrating that traditional leadership attributes, skills, and actions differentiate nurses who engage with AI from those who do not. Addressing this gap has implications not only for leadership theory but also for workforce preparation, regulatory oversight, and organizational readiness for AI-enabled healthcare.

Therefore, the objectives of this study are to: (a) describe nurses' CL attributes, skills, and actions; (b) examine AI knowledge, attitudes, and literacy preferences; (c) assess whether CL differs between AI adopters and non-adopters; and (d) identify demographic and organizational predictors of AI readiness among frontline nurses in Jordan. To address emerging measurement needs, the DCL-11 instrument is introduced as a preliminary tool for assessing technology-enabled leadership competencies necessary for ethical and effective AI integration (Brydges, 2025; Cary et al., 2025).

The rapid expansion of AI within healthcare has intensified regulatory attention on workforce readiness, competency assurance, governance structures, and ethical oversight in clinical settings (Brydges, 2025; Cary et al., 2025; Hassanein et al., 2025; Ronquillo et al., 2021). Despite this heightened regulatory focus, empirical research rarely examines the relationship between frontline CL and AI readiness. Regulators continue to face challenges in evaluating nurses' preparedness for AI-enabled practice due to limited evidence and the lack of structured assessment methodologies (Alruwaili et al., 2024; Kotp et al., 2025; Sommer et al., 2024; Teng et al., 2022).

1.2 | Theoretical Framework

CL in nursing is grounded in well-established models, such as Stanley's CL Characteristics and related competency frameworks (Stanley, 2017; Stanley & Stanley, 2018). These frameworks conceptualize CL as a values-driven, practice-embedded form of influence expressed through personal attributes, professional skills, and observable leadership actions. In this study, these domains were assessed through 54 attributes, 10 skills, and 8 actions, reflecting foundational characteristics (e.g., integrity, visibility, credibility), operational competencies (e.g., communication, risk-taking, teamwork), and

behavioral enactments of leadership (e.g., influencing care delivery, leading change, supporting staff) among Jordanian nurses.

Although these frameworks have demonstrated relevance in explaining leadership effectiveness within clinical environments, they were developed before the widespread adoption of digital health technologies and AI-enabled healthcare systems (Stanley, 2017; Stanley & Stanley, 2018). Consequently, they focus predominantly on interpersonal influence, professional credibility, communication, advocacy, and team coordination, while offering limited attention to technology-enabled care, digital governance, algorithm-supported decision-making, data stewardship, and human-AI collaboration.

The accelerating digital transformation of healthcare has altered both the context and demands of nursing leadership. As AI increasingly becomes integrated into clinical workflows, nurses are expected not only to demonstrate traditional leadership competencies but also to engage with technology implementation, ethical oversight, data-informed practice, digital communication, and AI-supported decision-making (Brydges, 2025; Cary et al., 2025; Ronquillo et al., 2021). These emerging responsibilities raise important questions regarding whether traditional CL frameworks alone are sufficient to explain nurses' readiness for AI-enabled practice.

Accordingly, the present study proposes DCL as a complementary extension of traditional CL. DCL does not replace established CL frameworks; rather, it builds upon them by incorporating leadership competencies required within increasingly digital healthcare environments. Conceptually, DCL emerges from the intersection of traditional CL and ongoing digital transformation, recognizing that effective leadership in AI-

enabled settings requires competencies that extend beyond conventional leadership domains.

The resulting conceptual framework suggests that traditional CL provides the foundational attributes, skills, and actions upon which digitally oriented leadership capabilities are developed. As digital transformation progresses and AI becomes embedded within healthcare delivery, new leadership demands emerge, giving rise to DCL. The instrument was therefore developed as a preliminary operationalization of these evolving competencies and as an initial mechanism for assessing leadership readiness within AI-enabled healthcare environments. Figure 1 presents the proposed DCL framework.



FIGURE 1 | Digital Clinical Leadership (DCL) framework

1.3 | Research Questions

This study answers the following research questions:

1. What CL attributes, skills, and actions do nurses report?
2. How do nurses define AI, what are their attitudes toward AI in nursing, and what are their literacy preferences?
3. Do CL profiles differ between AI adopters and non-adopters?

4. What factors predict overall CL and AI readiness?

2 | Methods

2.1 | Study Design

This study employed a quantitative cross-sectional online survey to obtain data from Jordanian nurses at a single point in time. The design was selected because it enables efficient, cost-effective collection of information from diverse clinical environments without manipulation of study variables, making it well-suited for examining relationships between variables and exploring nurses' perceptions and attitudes (Polit & Beck, 2019). The survey incorporated both quantitative and narrative components. It included validated measures assessing CL-spanning attributes, skills, and leadership actions, as well as nurses' perceived knowledge, attitudes, and literacy preferences related to AI. The study followed the STROBE (Strengthening the Reporting of Observational Studies in Epidemiology) guidelines for cross-sectional research.

2.2 | Sample and Settings

The minimum required sample size was estimated using Thorndike's rule ($N \geq 10k + 50$), where *k* denotes the number of independent variables (Polit & Beck, 2019). Given approximately 17 predictors in this study, including demographic variables, CL subscales, and AI-related measures, the calculated minimum sample size was 220. The final sample consisted of 395 Jordanian nurses employed across governmental, teaching, military, and private hospitals; however, after data cleaning, 389 nurses were retained in the final sample. The excluded surveys included missing data of more than 20%.

Participants were recruited using a combination of purposive and convenience sampling. Nurses working in partner hospitals were invited directly. At the same time, additional participants were reached through announcements circulated on social media

platforms such as Facebook and WhatsApp, as well as QR codes posted in clinical units. All registered and practical nurses working in governmental, military, private, and teaching hospitals in Jordan were eligible to participate. Nurses were required to be actively engaged in clinical practice, able to read English, and willing to provide informed consent. Nursing students, retired nurses, nurses employed exclusively in academic or administrative positions, duplicate submissions, and substantially incomplete questionnaires were excluded from the study.

2.3 | Ethical Considerations

The study was conducted following the principles of the Declaration of Helsinki. The Institutional Review Board (IRB) of XXX university in XXX approved the study (IRB No. XXX, dated XXX). Participation was voluntary, and the completion of the online survey constituted informed consent. Anonymity and confidentiality were maintained through numerical coding of surveys, and all data were stored securely in a password-protected institutional Google Drive. Only aggregated findings were shared with hospital administrators to ensure the privacy of participating nurses.

2.4 | Data Collection Procedures

Data collection was conducted using an English-language Google Forms instrument, consistent with the language used in nursing documentation and education in Jordan. A pilot test confirmed that the instrument required no modification. Data were collected in 2025 over 20 days, with reminder messages issued midway to enhance response rates. The survey platform allowed participants to pause and resume completion, and settings

were configured to permit only one submission per respondent. Survey links were distributed through faculty channels, professional networks, and QR codes displayed in hospital units. A preliminary pilot study conducted in 2020 to test the CL items supported the appropriateness of the CL measures for use within Jordanian healthcare settings.

2.5 | Instruments

2.5.1 | Clinical Leadership

CL was assessed using Stanley's Clinical Leadership Questionnaire, a validated instrument widely applied in studies of nurses and paramedics in the United Kingdom and Australia (Stanley, 2006a; 2006b; 2006c; Stanley et al., 2012; 2014; Stanley & Stanley, 2018). The tool demonstrated strong construct validity, with Cronbach's alpha coefficients of 0.87 reported in prior work and 0.88 observed in the present study. Although the original questionnaire includes both quantitative and qualitative components, qualitative responses in the current study were incomplete and thus excluded from analysis. Only quantitative items measuring CL attributes, skills, and actions were analyzed. The first author developed additional demographic items relevant to the Jordanian nursing context.

Overall reliability of CL (composite of attributes, skills, and actions). Internal consistency was evaluated at both the subscale and composite levels. The CL Attributes checklist (54 dichotomous items) showed KR-20 = 0.86, acknowledging potential ceiling effects due to near-universal endorsement. The CL Skills scale (10 items) demonstrated $\alpha = 0.89$, and the CL Actions scale (8 items) demonstrated $\alpha = 0.91$, indicating excellent reliability for both subscales. To derive an overall CL score, the attribute, skills, and actions subscales were first transformed to a common metric. The 54 dichotomous

attribute items were converted to a percentage score (0-100), while skill and action scores were computed as mean item ratings. Each subscale was subsequently standardized (z-scores) to account for different measurement ranges. The standardized subscale scores were then averaged, and the resulting composite was rescaled to a 1-5 metric to facilitate interpretation. Higher scores reflected stronger overall CL.

2.5.2 | AI-related Perceptions and Attitudes

AI-related perceptions and attitudes were measured using a publicly available survey developed by Teng et al. (2022). This instrument includes multiple-choice items, ranking tasks, slider-scale ratings and narrative responses. Constructs measured included perceived understanding of AI, attitudes toward the impact of AI on professional practice, preferred methods for acquiring AI literacy, and the amount of time respondents were willing to invest in AI education. Nurses rated their support for AI on a 0–10 scale and indicated agreement with six attitudinal statements concerning AI's impact, ethical implications, hopefulness, worry, and perceived need for careful management. The current study added one additional item assessing overall positivity toward AI in nursing on a 5-point scale.

Because no standardized nursing definition of AI adoption currently exists, operational thresholds were developed a priori to distinguish respondents demonstrating positive attitudes and/or direct AI exposure from those reporting limited engagement. AI adopters were defined as respondents who expressed strong support for AI ($\geq 7/10$) and a positive overall attitude ($\geq 4/5$), or who reported direct workplace use of AI. Non-adopters were those demonstrating low support ($\leq 3/10$), non-positive attitudes ($\leq 3/5$), or explicitly stating no workplace exposure to AI. Participants not meeting either definition

were classified as Undetermined and excluded from subgroup analyses. Reliability analysis of the AI attitudes scale (five items) yielded Cronbach's $\alpha = 0.580$, indicating moderate internal consistency but acceptable composite reliability.

2.6 | Data Analyses

All statistical analyses were conducted using the Statistical Package for the Social Sciences (SPSS) Version 25.00 (IBM, 2017), with statistical significance set at $\alpha = 0.05$. Descriptive statistics were computed for all variables: frequencies and percentages for categorical variables and means and standard deviations (SDs) for continuous variables. Group differences in continuous outcomes were evaluated using Welch's t-tests (unequal variances), with corresponding two-sided p-values reported. Consumer-favored and least-favored AI items were identified from item-level means (Polit & Beck, 2019). To address the study's research questions, descriptive analyses summarized CL attributes, skills, and actions, as well as nurses' definitions of AI, attitudes toward AI, and literacy preferences.

To examine predictors of overall CL and AI readiness, Ordinary Least Squares (OLS) regression models were fitted with demographic and professional characteristics as predictors. Ordinary Least Squares (OLS) regression was used to examine predictors of the continuous outcome variables—overall CL and AI readiness (Polit & Beck, 2019). OLS estimates linear associations by identifying regression coefficients that minimize the sum of squared differences between observed and predicted values (Polit & Beck, 2019). Model assumptions (linearity, normality of residuals, independence, and homoscedasticity) were examined and found acceptable; to mitigate potential heteroscedasticity, HC3 robust standard errors were applied to all OLS estimates (Polit & Beck, 2019). This approach is widely used in health-services and behavioral research due

to its interpretability, statistical efficiency, and suitability for evaluating continuous leadership and attitude measures (Polit & Beck, 2019).

3 | Results

3.1 | Sample Profile

Of the 395 collected sample, the analytic sample included N = 389 nurses with broad demographic and organizational diversity. Women comprised 65.00% and men 35.00%. Age groups were ≤ 25.00 years (17.50%), 25.00–34.00 (40.90%), 35.00–44.00 (38.30%), and 45.00–54.00 (3.30%). Education included Associate (6.40%), Baccalaureate (35.50%), Diploma (50.10%), and Master's (8.00%). Participants worked across government (43.20%), military (21.10%), private (14.70%), and teaching (21.10%) hospitals. Shift patterns included day 8 h (46.80%) and rotating (24.70%), among others (Table 1). These variables formed the covariate structure in subsequent OLS analyses.

(Insert Table 1 Here)

3.2 | Scoring Criteria Used in the Study

CL was operationalized across three components. CL Attributes were captured with a 54-item binary forced-choice checklist; responses were converted to a percentage endorsed (0.00–100.00%). CL Skills comprised 10 Likert-type items (1–5; higher indicates stronger perceived capability). CL Actions comprised 8 Likert-type items (1–5; higher indicates more frequently enacted leadership behaviors).

AI perceptions were assessed using a 0- 10 scale for support, ethics, hopefulness, worry, and need for careful management, and a 1.00–5.00 scale for overall positivity. AI adopters were defined as support ≥ 7 and positivity ≥ 4 or explicit workplace use; non-

adopters were support ≤ 3, positivity ≤ 3, or explicit non-use. These definitions govern all analyses that follow.

3.3 | CL Attributes, Skills, and Actions Nurses Reported and Differences in CL Between AI Adopters and Non-Adopters

3.3.1 | Whole-Sample Summary

At the domain level, the CL Attributes checklist demonstrated very high endorsement across participants, indicating strong agreement with traditional leadership characteristics. Because the attribute measure consisted of dichotomous items and demonstrated substantial ceiling effects, attribute scores were interpreted descriptively rather than as indicators of meaningful between-person variation. Consequently, greater emphasis was placed on skills, actions, and overall CL scores

CL Skills and CL Actions were both high (Skills: M = 3.99, SD = 0.70; Actions: M = 3.99, SD = 0.73), yielding an Overall CL that was similarly elevated (M = 3.99, SD = 0.68). At the item level, top skills included recognizing optimal performance (M = 4.10, SD = 0.92), communication (M = 3.98, SD = 1.11), and visibility in the clinical environment (M = 3.90, SD = 1.07); risk-taking remained favorable (M = 3.95, SD = 1.01). For actions, prominent behaviors were leading to change and service improvement (M = 4.08, SD = 0.85), initiating innovations (M = 4.06, SD = 0.94), and participating in staff development (M = 4.06, SD = 0.96). These results indicate a high baseline of CL across the workforce.

3.3.2 | Adopter Vs. Non-Adopter Comparisons

Group contrasts showed no statistically significant differences between AI adopters (*n* = 152) and non-adopters (*n* = 194) on any CL domain (Table 2). The near-complete

endorsement of leadership attributes across both groups reflects substantial ceiling effects within the attribute checklist. It supports interpretation of this measure as a descriptive indicator of professional leadership values rather than a highly discriminative measure of individual leadership variation. CL Attributes were 99.98% versus 100.00% (Welch's $t(151.00) = -1.67$, $p = 0.10$); CL Skills were 3.96 (SD = 0.67) versus 4.01 (SD = 0.73) ($t(335.40) = -0.66$, $p = 0.51$); CL Actions were 4.00 (SD = 0.69) versus 3.99 (SD = 0.76) ($t(337.30) = 0.13$, $p = 0.90$); and Overall CL was 3.98 (SD = 0.64) versus 4.00 (SD = 0.71) ($t(337.10) = -0.28$, $p = 0.78$). Effect sizes were trivial ($d \leq 0.08$), indicating no practically meaningful differences by adoption status.

(Insert Table 2 Here)

3.3.3 | Items of CL Attributes

Whole sample. Endorsement of CL attributes was consistently high across participants, indicating broad agreement with traditional leadership characteristics. Because many attributes were endorsed by most respondents, item-level variability was limited, and evidence of ceiling effects was observed. Adopter versus non-adopter comparisons identified a small number of statistically significant but practically negligible differences, including "Is artistic/imaginative," "Inspires confidence," and "Is articulate." In all instances, effect sizes were trivial and showed no meaningful pattern favoring either group (Table 3).

(Insert Table 3 Here)

3.3.4 | Items of CL Skills

Whole-sample. Skills were consistently favorable (domain: M = 3.99, SD = 0.70). Key items included recognizing optimal performance (M = 4.10, SD = 0.92), communication

(M = 3.98, SD = 1.11), and visibility in the clinical environment (M = 3.90, SD = 1.07). Risk-taking remained positive (M = 3.95, SD = 1.01). The item-level pattern was similar across groups (see Table 4), and no domain-level differences were detected except for being willing to take risks for something they believe in (t = -4.09, p= 0.001; non-adopters had a higher mean score) (Table 4).

3.3.5 | Items of CL Actions

Whole-sample. Actions reflected frequent leadership enactment (domain: M = 3.99, SD = 0.73), with high ratings for leading change and service improvement (M = 4.08, SD = 0.85), initiating innovations (M = 4.06, SD = 0.94), and participating in staff development (M = 4.06, SD = 0.96). Item-level patterns were comparable between groups (see Table 5), aligning with the non-significant domain-level results (Table 2).

(Insert Table 5 Here)

3.4 | AI Readiness Indicators and Literacy Preferences

3.4.1 | AI Knowledge and Attitudes

Across the full sample, nurses reported moderately positive orientations toward AI. Support for AI averaged M = 6.97 (SE = 0.11), perceived impact on career was M = 6.36 (SE = 0.14), need for AI basics was M = 7.33 (SE = 0.14), and AI requires careful management was M = 7.88 (SE = 0.13). Overall positivity toward AI on the 1.00–5.00 scale was M = 3.29 (SE = 0.07). Table 6 reports the means, standard errors, and 95.00% confidence intervals for each indicator.

(Insert Table 6 Here)

3.4.2 | AI Literacy Preferences

Preferences emphasized practical, iterative learning. The most favored format was multiple workshop series (43.80%), followed by graduate-level education (31.90%), with short 1.00–2.00-hour workshops (17.10%) also common. Respondents prioritized appropriate clinical context + ethics + quality improvement (14.40%), with additional interest in interpreting results + communicating how technology works + understanding processes (5.00%). Distributional details, including curriculum placement and anticipated time to impact, appear in Table 7.

(Insert Table 7 Here)

3.5 | Predictors of CL

The OLS model predicting Overall CL demonstrated modest explanatory power (R^2 = 0.12). The AI total score was not a significant predictor (b = 0.03, p = 0.21). Significant positive coefficients were observed for male gender (b = 0.22, p = 0.04), team nursing vs. primary (b = 0.34, p = 0.02), and total patient care vs. primary (b = 0.41, p = 0.01). A significant negative coefficient was observed for military/other vs. public hospitals (b = −0.40, p = 0.02). Full estimates with HC3-robust SEs and 95.00% confidence intervals are presented in Table 8.

(Insert Table 8 Here)

3.6 | Predictors of AI Readiness

The model predicting AI readiness explained a larger share of variance (R^2 = 0.31). CL total was not a significant predictor (b = 0.13, p = 0.21). Strong positive predictors included education (Bachelor: b = 1.83, $p < 0.001$; Master: b = 1.97, $p < 0.001$) and selected experience bands (1.00–3.00 years: b = 1.71, p = 0.00; 3.00–5.00 years: b = 2.61,

$p = 0.00$; > 10.00 years: $b = 1.25$, $p = 0.04$). Negative predictors included private ($b = -1.32$, $p < 0.001$) and teaching ($b = -1.42$, $p < 0.001$) hospital sectors, and rotating/evening shifts (both $p < 0.001$). These patterns indicate that structural and educational determinants, rather than leadership, primarily shape nurses' AI orientations. Full estimates are provided in Table 9**.**

(Insert Table 9 Here)

4 | Discussion

This study examined whether traditional CL is associated with nurses' readiness to engage with artificial intelligence in clinical practice. While participants reported high levels of CL, no significant differences were observed between AI adopters and non-adopters, and CL was not a significant predictor of AI readiness. These findings suggest that factors influencing AI readiness may differ from those traditionally associated with CL. This finding is particularly important because CL is frequently assumed to facilitate innovation uptake, change implementation, and professional adaptation. The absence of an observed association suggests that readiness for AI-enabled practice may involve competencies and contextual influences that are not adequately represented within existing leadership models.

An important implication of this study is the possibility that emerging digital healthcare environments require leadership competencies that extend beyond those assessed in traditional CL frameworks. Traditional CL focuses on interpersonal influence and professional credibility, whereas DCL additionally encompasses digital stewardship, algorithmic accountability, ethical AI oversight, and human-AI collaboration. This finding is noteworthy because CL has traditionally been viewed as a key driver of

innovation, change implementation, and professional influence within healthcare organizations (Cummings et al., 2021; Daly et al., 2014; Stanley, 2017). Contrary to these expectations, the present findings indicate that nurses with similar leadership profiles may differ substantially in their readiness to engage with AI, which suggests that competencies influencing AI adoption extend beyond those measured by traditional CL frameworks.

Jordan represents an important setting for this investigation because healthcare institutions are increasingly adopting digital health technologies while evidence regarding nurses' preparedness for AI-enabled practice remains limited. Understanding readiness for AI in this context may help inform workforce preparation efforts in Jordan and similar healthcare systems undergoing digital transformation. For example, Canadian healthcare students similarly demonstrated moderate positivity toward AI readiness paired with uncertainty about ethical implications (Teng et al., 2022), while German nurses in a national survey reported openness to AI but focused on the need for ethical guidance and structured education (Sommer et al., 2024). Likewise, a recent study in Saudi Arabia showed nurses were generally aware of AI but expressed concerns related to training and preparedness (Alruwaili et al., 2024). These convergent patterns strengthen the argument that AI readiness is shaped less by leadership traits and more by systemic factors such as education, governance, training access, and workflow design. This contextualizes the current findings within a broader international trend of optimism mixed with structural barriers.

These findings point to a conceptual gap between established leadership frameworks and the realities of digitally mediated care. Traditional CL models were

designed to explain leadership through values, communication, credibility, role modelling, and interpersonal influence (Stanley, 2017; Stanley & Stanley, 2018). While these competencies remain essential, they do not explicitly address many of the leadership responsibilities emerging within AI-enabled healthcare environments, including algorithmic accountability, digital safety, data governance, ethical oversight, and management of human–AI interactions (Brydges, 2025; Cary et al., 2025; Ronquillo et al., 2021). The inability of traditional CL measures to differentiate adopters from non-adopters suggests that leadership competencies relevant to AI integration may not be adequately represented within existing leadership frameworks.

4.1 | DCL as a Complementary Leadership Domain

The present findings suggest a need to further examine whether leadership competencies relevant to AI-enabled practice extend beyond those assessed by existing CL frameworks. One possible interpretation is that additional digitally oriented leadership competencies may be important within technology-enabled healthcare environments. Consequently, the DCL framework is proposed as a preliminary conceptual model requiring further empirical evaluation. Unlike traditional CL models, DCL explicitly incorporates competencies related to algorithmic accountability, digital communication, data governance, AI safety surveillance, and human-AI collaboration. Importantly, the argument is not that traditional CL is no longer relevant. Rather, the findings suggest that existing leadership competencies may be necessary but insufficient for explaining readiness to engage with AI-enabled practice. CL remains essential for patient advocacy, teamwork, communication, and quality improvement (Stanley, 2017; Stanley & Stanley, 2018). However, AI implementation introduces additional expectations related to

technology stewardship, digital governance, algorithmic transparency, and ethical oversight that may not be fully reflected within traditional leadership models (Cary et al., 2025; Ronquillo et al., 2021). Consequently, DCL is proposed as an extension that complements rather than replaces established CL frameworks.

4.2 | Integration with the CL Framework

This study was guided by Stanley's Clinical Leadership Characteristics and related competency frameworks (Stanley, 2017; Stanley & Stanley, 2018), which conceptualize leadership as a constellation of attributes, skills, and actions enacted at the point of care and grounded in values, integrity, communication, clinical credibility, and influence rather than formal authority (Stanley, 2017; Stanley & Stanley, 2018). Two implications follow. First, because CL is practice-embedded and role-modeled, it forms a stable professional identity—consistent with the near-universal endorsement of attributes and the elevated skills and actions observed across the sample (current study; Stanley, 2017). Second, although CL facilitates change and shapes work environments positively, the framework anticipates stability across settings and individuals; thus, competencies may not vary simply because a new technology is introduced (Stanley, 2017; Stanley & Stanley, 2018). The absence of differences between adopters and non-adopters, therefore, aligns with the framework's values-based stability and underscores that contextual levers (education, sector, shift, experience) are more influential during early AI adoption.

Operationally, the CL framework implies that existing leadership strengths can be mobilized to create psychological safety, transparent communication about algorithmic limitations, and reliable escalation when human judgment diverges from AI recommendations—functions that gain importance as organizations move from

exploration to implementation and scale-up (Cary et al., 2025; Ronquillo et al., 2021; Stanley, 2017).

4.3 | CL Attributes

CL attributes were endorsed almost universally, suggesting strong adherence to traditional professional leadership values. However, substantial ceiling effects limited the ability of the attribute scale to distinguish between participants. This finding supports the interpretation that traditional leadership values are broadly embedded within nursing practice (Mianda & Voce, 2017; Stanley & Stanley, 2018) but may have limited utility for explaining variation in AI readiness (Cary et al., 2025).

4.4 | CL Skills

Strengths in recognition, communication, and visibility are precisely the skills required to translate complex information into shared understanding and sustain team learning during change (Daly et al., 2014; Stanley, 2017). Rather than generic leadership training, the implication is to situate these skills in digital use cases—for example, structured briefings that rehearse when to question an algorithm, how to explain limitations to patients, and how to escalate when clinical judgment diverges from model output (Hassanein et al., 2025; Ronquillo et al., 2021).

Interestingly, non-adopters reported a higher willingness to take risks than adopters, challenging assumptions that innovation adoption is driven by individual risk orientation. This finding suggests that engagement with AI may be shaped less by personal traits such as risk-taking and more by structural, contextual, or educational factors. Given that no differences were observed across other leadership domains, this

isolated finding should be interpreted cautiously and is unlikely to reflect a meaningful distinction in overall CL.

4.5 | CL Actions

High-frequency actions (e.g., leading change, initiating innovations, and developing staff) indicate that nurses are already doing the work of improvement. The discussion pivot is to bind these actions to AI governance: use existing change agency to co-design safer digital workflows, establish psychologically safe debriefs after AI-related incidents, and nominate peer champions who normalize human–AI teaming on every shift (Brydges, 2025; Cary et al., 2025).

4.6 | AI Readiness Indicators and Literacy Preferences

Moderately positive attitudes combined with strong calls for ethics, appropriate use, interpretability, and quality improvement point to a workforce that is open yet cautious—seeking rules of the road more than persuasion (Hassanein et al., 2025; Ronquillo et al., 2021). Educationally, respondents favored multi-session workshops and advanced study, implying that capacity building should be applied and scaffolded rather than one-off (Sommer et al., 2024; Teng et al., 2022). Strategically, this argues for role-anchored microlearning (e.g., charge nurse modules on escalation protocols; bedside simulations on accepting/overriding recommendations) that embeds literacy within routine work (Cary et al., 2025).

4.7 | Differences in CL Between AI Adopters and Non-Adopters

The absence of group differences indicates that early attitudes toward or exposure to AI do not stratify leadership in this context. Interpreted through the CL framework, this is

expected: when leadership is a stable, values-based construct, it should remain broadly expressed across the workforce regardless of short-term technology preferences (Stanley, 2017; Stanley & Stanley, 2018). Methodologically, ceiling effects in attributes further constrain detectable variance, a known limitation for highly endorsed measures; conceptually, the result suggests that context (e.g., policies, training access, shift design) is more decisive than individual leadership profile during initial AI integration (Cary et al., 2025).

4.8 | Predictors of CL

Consistent with the CL model, organizational role and local care design (e.g., team versus primary models; sector differences) explained only modest variation in perceived leadership, and AI readiness was not predictive. For practice, the message to leaders is to mobilize—not manufacture—leadership: channel the broadly shared CL capacity into digital safety routines (huddles, escalation, transparent documentation) and unit-level coaching rather than attempting to raise already saturated CL scores (Cary et al., 2025).

4.9 | Organizational and Educational Determinants of AI Readiness

Educational attainment, professional experience, hospital sector, and shift pattern emerged as significant predictors of AI readiness, whereas traditional CL did not. These findings align with previous studies demonstrating that workforce preparedness for AI is shaped by education, exposure, resources, and organizational support structures (Alruwaili et al., 2024; Kotp et al., 2025; Sommer et al., 2024). Thus, efforts to strengthen readiness for AI-enabled practice should extend beyond conventional leadership development and prioritize AI literacy, digital health education, governance frameworks, and equitable access to training opportunities across sectors and shifts. The

findings further suggest that structural and contextual influences play a more prominent role in shaping AI readiness than individual leadership profiles alone.

More details about the DCL Framework and Preliminary Evaluation of the DCL-11 instrument are provided as supplementary material (Appendix A, Tables S1 and S2). Also, the tools used to collect data, as well as the proposed DCL-11 instrument, are supplied in Appendix B.

(Insert Supplementary Material and Tables S1 and S2 Here)

4.10 | Study's Strengths and Limitations

A key strength is the large, heterogeneous sample (N = 389) spanning major sectors (governmental, military, private, teaching) and shift patterns, which enhances generalizability across Jordan's hospital settings. Rigorous statistics were used—Welch's t for unequal variances and OLS with HC3 robust errors for modeling—and reliability for skills and actions was excellent (IBM Corp., 2017; Polit & Beck, 2019). Whole-sample reporting (means, SDs) was prioritized before group contrasts, clarifying the baseline leadership context.

Limitations include the ceiling effect in attribute endorsement, which reduces the instrument's discriminative power and restricts the ability to detect meaningful variability across groups (Polit & Beck, 2019). The checklist format used for the CL attributes section may have contributed to ceiling effects by encouraging endorsement of socially desirable professional characteristics. Future studies should consider alternative scaling approaches capable of generating greater score variability. This ceiling effect is unsurprising given the culturally embedded and professionally socialized nature of CL attributes, which tend to be uniformly endorsed in high-commitment clinical

environments (Stanley, 2017; Stanley & Stanley, 2018). This ceiling compression restricts the instrument's ability to detect meaningful differences between subgroups and attenuates associations with other variables. These findings highlight that, while the attributes reflect deeply socialized professional values, they function descriptively rather than analytically in this dataset. Future studies should therefore consider complementary tools or revised response formats with greater sensitivity to variation in contemporary clinical settings.

The cross-sectional design further limits inference because temporal ordering cannot be established; thus, differences in AI readiness or leadership scores cannot be interpreted causally (Polit & Beck, 2019). As a result, the observed associations, for example, between education and AI readiness, must be understood as correlational patterns rather than indicators of developmental pathways. A third limitation concerns the non-probability sampling strategy, which, although practical, may reduce the representativeness of the sample, especially in systems where workforce composition varies across sectors and regions. Nurses with a stronger interest in leadership or AI may have been more likely to respond, introducing potential volunteer bias (Polit & Beck, 2019).

Because all variables were measured using self-report questionnaires collected at a single time point, common-method variance cannot be excluded. For example, the survey relied on self-report measures of AI readiness and AI exposure. Such measures are susceptible to social desirability tendencies, recall inaccuracy, and aspirational responding—particularly in domains such as leadership, where professional identity and organizational expectations are salient (Hassanein et al., 2025). Self-report exposure to

AI may also be inaccurate because many nurses work with algorithmic systems (e.g., triage tools, risk scores) without always recognizing them as AI (Ronquillo et al., 2021).

Traditional CL instruments, including those derived from Stanley's framework, were not originally designed to assess competencies relevant to digital, data-driven workflow environments. As AI becomes more embedded in routine care, leadership behaviors increasingly include tasks such as explaining algorithmic uncertainty, identifying model–workflow mismatches, and escalating digital safety risks. These behaviors fall outside the scope of conventional CL scales, underscoring the need for a concise and dedicated DCL measure (Cary et al., 2025; Ronquillo et al., 2021).

Finally, the AI readiness measure demonstrated relatively low internal consistency ($\alpha = 0.58$), indicating that responses may contain substantial measurement error. Consequently, findings involving AI readiness should be interpreted cautiously and viewed as exploratory. Although the instrument has been used in previous research and captures important conceptual domains of AI readiness, future studies should refine and expand AI readiness measures to improve reliability and construct representation within nursing populations.

4.11 | Implications

4.11.1 | Implications for Clinical Practice and the Workforce

Findings indicate that traditional CL competencies alone may not be sufficient to prepare nurses for AI-enabled healthcare environments. Healthcare organizations should supplement leadership programs with AI literacy, digital safety competencies, data stewardship, ethical decision-making, and structured governance mechanisms. The

proposed DCL framework offers a preliminary foundation for workforce development initiatives supporting safe AI integration in clinical practice.

Given the uniformly high CL baseline, organizations should leverage existing leadership strengths rather than attempt to increase already saturated scores. The priority is to translate CL capacities into digital safety behaviors. Embedding brief AI-related huddles, where teams verbalize concerns and clarify algorithmic uncertainty, fosters psychological safety and supports shared situational awareness (Cary et al., 2025). Likewise, establishing explicit escalation pathways when AI recommendations conflict with clinical judgment strengthens clinical accountability and mitigates automation bias (Brydges, 2025). Peer-to-peer coaching, particularly during real-time documentation and decision-making, helps normalize the integration of AI into routine practice and reduces the perceived threat of adoption (Cary et al., 2025).

4.11.2 | Implications for Education and Capacity Building

Because AI readiness correlates strongly with education and experience, professional development should emphasize applied AI literacy that covers ethics, appropriate use, model interpretability, and quality improvement principles (Hassanein et al., 2025; Ronquillo et al., 2021). Educational programming should move beyond conceptual awareness toward hands-on demonstrations, scenario-based simulations, and workflow-aligned micro-learning. The strong preference for multi-session workshops and micro-credentialing supports a scaffolded learning model in which staff progress from foundational knowledge to more advanced practice-integrated competencies (Sommer et al., 2024; Teng et al., 2022).

4.11.3 | Implications for Organizational Policy, Governance, and Regulatory Practice

At the policy level, these findings suggest that regulatory bodies and healthcare organizations should reconsider the definition and assessment of leadership competencies in the context of AI integration. Existing frameworks frequently emphasize traditional interpersonal leadership, which may overlook essential domains such as digital safety, algorithmic accountability, and data ethics. Incorporating digital leadership competencies into nursing standards, educational curricula, accreditation processes, and competency frameworks is essential to promote the safe and equitable adoption of AI.

The present findings also suggest that workforce readiness for AI implementation should not be evaluated solely through traditional leadership assessments. Although CL remains important for professional practice, the absence of associations between CL and AI readiness indicates that existing leadership measures may overlook competencies required for safe and effective technology implementation. Future competency frameworks should therefore integrate digital leadership capabilities alongside traditional leadership expectations.

Sector, shift pattern, and model of care were identified as significant correlates of AI readiness. Therefore, organizations should establish clear protocols for AI use, override procedures, documentation standards, and digital hazard reporting, while ensuring equitable training access across all shifts and sectors (Cary et al., 2025). Leadership recognition, allocation of protected time, and appointment of designated AI champions can address contextual barriers, particularly in private and teaching hospitals where readiness was lower (Hassanein et al., 2025). These findings are also relevant to

nursing regulatory bodies responsible for competency assurance and public protection, suggesting that regulators should prioritize minimum AI-related competencies, equitable training access, and transparent governance structures for algorithmic oversight.

4.11.4 | Implications for Measurement, Evaluation, and Directions for Future Research

The findings support a two-stage perspective: traditional CL establishes a foundation for ethical decision-making and team coordination, but does not differentiate early AI adopters. As organizations progress toward broader AI integration, leadership is expected to play a critical role in resolving conflicts between algorithmic outputs and human judgment (Stanley, 2017; Cary et al., 2025). Given the ceiling effects and the digital-specific demands of contemporary practice, this study recommends further development and validation of the DCL-11 instrument to assess competencies such as communicating AI limitations, identifying workflow misalignments, recognizing digital safety concerns, and facilitating human-AI collaboration (Cary et al., 2025; Ronquillo et al., 2021).

Most existing CL tools were developed for pre-digital practice environments and do not adequately address algorithmic transparency, digital ethics, human-AI collaboration, or technology-related safety risks. Future research should evaluate the reliability, dimensionality, and criterion validity of the DCL-11 instrument using objective measures of AI exposure, including system logs, interaction frequency, and override rates (Teng et al., 2022). Furthermore, research should support the development of policy playbooks and implementation pathways that institutionalize human-AI collaboration through standardized escalation processes, transparent communication, and

comprehensive oversight mechanisms (Cary et al., 2025; Hassanein et al., 2025; Ronquillo et al., 2021).

5 | Conclusions

This study demonstrated that traditional CL was widely present among Jordanian nurses but did not differentiate AI adopters from non-adopters, nor did it explain variability in AI readiness. Although CL remains an essential component of nursing practice, the findings suggest that the attributes, skills, and actions traditionally associated with effective CL may not be sufficient to account for engagement with AI-enabled healthcare technologies.

The findings therefore highlight a potential gap between established CL frameworks and the emerging leadership demands associated with digital transformation and artificial intelligence integration in healthcare. As AI becomes increasingly embedded within clinical practice, nurses may be required to demonstrate additional competencies related to digital stewardship, technology-enabled decision-making, ethical oversight, data-informed practice, and human-AI collaboration.

Consequently, the DCL framework is proposed as a complementary extension of traditional CL, reflecting leadership requirements that may not be fully captured by existing frameworks. The preliminary DCL-11 instrument provides an initial operationalization of this construct and a foundation for future psychometric evaluation and refinement.

In conclusion, traditional CL was widely demonstrated among Jordanian hospital nurses; however, it was not associated with AI readiness in this sample. Educational and organizational factors appeared to be more influential determinants of AI readiness.

These findings suggest that readiness for AI-enabled nursing practice may involve competencies extending beyond those captured by existing CL frameworks. The proposed DCL framework provides a preliminary basis for future research exploring leadership competencies relevant to increasingly digital healthcare environments.

Declarations:

CRediT Authorship Contribution Statement

Dr. Ahmad, K., Alomari: Conceptualization, abstract, methodology, investigation, data analysis and writing, limitations, original draft preparation, writing, review, editing.

Prof. Dr. Majd Mrayyan: Conceptualization, abstract, methodology, investigation, data analysis and writing, limitations, original draft preparation, writing, review, editing, and supervision.

Dr. Ali Elmasarawa: Review, and editing of discussion, and implications.

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Declaration of Generative AI And AI-Assisted Technologies in the Writing Process

During the preparation of this work, the author used Grammarly and Copilot to edit language. After using these tools, the author reviewed and edited the content as needed and took full responsibility for the content of the publication.

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Ethics Statement

The study was conducted following the principles of the Declaration of Helsinki. The Institutional Review Board (IRB) of The Hashemite University, Jordan, approved the study; the IRB number is 1/1/2020/2021, dated Oct 18th, 2020. Informed consent was obtained before participation. Anonymity, confidentiality, voluntary participation, and the ability to withdraw at any time without consequences were assured. All questionnaires were completed anonymously, and no identifiable information was collected. Data were password-protected, and access was restricted to the researcher. All analyses were conducted on aggregated data; no individual participant or institution could be identified. The study posed no physical or psychological risks to the participants. No rewards were provided to the participants or the researcher.

Consent

The invitation letter informed the participants that their participation in the survey constituted their consent to participate in the study.

Conflicts of Interest

The author declares no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available on reasonable request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

Patient or Public Contribution

Patients, service users, caregivers, and members of the public were not involved in the design, conduct, analysis, interpretation, or reporting of this study because the research focused exclusively on hospital nurses.

Reporting Method

The author of this manuscript have adhered to the Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) checklist, which was used to guide the study.

Supporting Material

Details about the DCL Framework and Preliminary Evaluation of the DCL-11 instrument are provided as supplementary material (Appendix A). Tools used to collect data and the proposed DCL-11 instrument are supplied in Appendix B.

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TABLE 1 | Nurses' demographics (*N*=389).

Variable	Category	*N*	%
Gender	Female	253	65.0
	Male	136	35.0
Marital status	Married	268	68.9
	Separated/Widowed	2	0.5
	Single	119	30.6
Age	25–34	159	40.9
	35–44	149	38.3
	45–54	13	3.3
	≤25	68	17.5
Education	Associate	25	6.4
	Baccalaureate	138	35.5
	Diploma	195	50.1
	Master	31	8.0
Years of nursing experience	1–2	28	7.2
	3–4	38	9.8
	5–9	74	19.0
	<1 year	56	14.4
	≥10	193	49.6
Years of experience in the current area	1–2	57	14.7
	3–4	84	21.6
	5–9	71	18.3
	<1 year	50	12.9
	≥10	127	32.6
Work area	Units	217	55.8
	Wards	172	44.2
Hospital type	Governmental	168	43.2
	Military	82	21.1
	Private	57	14.7
	Teaching	82	21.1
Shift worked	Day (12h)	41	10.5
	Day (8h)	182	46.8
	Evening (12h)	48	12.3
	Evening (8h)	8	2.1
	Night (8h)	14	3.6
	Rotating (A, B, C)	96	24.7
Average daily census	11–15 patients	75	19.3
	16–20 patients	18	4.6
	1–5 patients	115	29.6
	6–10 patients	90	23.1
	>20 patients	91	23.4
Model of nursing care	Functional	48	12.3
	Primary	96	24.7
	Team	166	42.7
	Unclear	79	20.3
Decision-making style	Authoritative-unilateral	85	21.9
	Mixed	188	48.3
	Participating-bilateral	100	25.7
	Unclear	16	4.1
University graduated from	Governmental	352	90.5
	Private	37	9.5

395 Jordanian nurses were recruited; however, after data cleaning, 389 nurses were retained in the final sample.

TABLE 2 | Group means and standard deviations (SDs) related to CL.

	AI adopter			**AI non-adopter**			**Test**	**Sig.**
Measure	*N*	Mean	SD	*N*	Mean	SD	t (Welch)	*p* (two-sided)
CL Attributes (% endorsed)	152	99.98	0.14	194	100.00	0.00	-1.667 (df=151.0)	0.098
CL Skills (1–5)	152	3.96	0.67	194	4.01	0.73	-0.655 (df=335.4)	0.513
CL Actions (1–5)	152	4.00	0.69	194	3.99	0.76	0.127 (df=337.3)	0.899
Overall CL (1–5)	152	3.98	0.64	194	4.00	0.71	-0.275 (df=337.1)	0.784

SD computed as SE × √N for each group (N1 = 152, N2 = 194). Welch t-test based on group means and SDs; two-sided p-value; 95% CI of differences available on request; df = degrees of freedom.

TABLE 3 | Group means and standard deviations (SDs) of CL attributes using the t-test.

Items	AI Adopters			AI Non-Adopters			Test	Sig.
Attributes (code)	***N***	**Means**	**SD**	***N***	**Means**	**SD**	**t**	***p***
VAR1.1	152	1.07	0.25	194	1.09	0.29	-0.93	0.353
VAR1.2	152	1.12	0.33	194	1.09	0.29	0.95	0.345
VAR1.3	152	1.10	0.30	194	1.15	0.36	-1.57	0.117
VAR1.4	152	1.09	0.29	194	1.08	0.27	0.49	0.627
VAR1.5	152	1.09	0.29	194	1.13	0.34	-1.09	0.276
VAR1.6	152	1.12	0.33	194	1.14	0.35	-0.52	0.601
VAR1.7	152	1.10	0.32	194	1.13	0.34	-0.99	0.324
VAR1.8	152	1.15	0.36	194	1.15	0.36	-0.09	0.932
VAR1.9	152	1.12	0.33	194	1.17	0.38	-1.18	0.238
VAR1.10	152	1.18	0.38	194	1.18	0.39	-0.07	0.947
VAR1.11	152	1.10	0.30	194	1.12	0.33	-0.74	0.461
VAR1.12	152	1.18	0.38	194	1.21	0.41	-0.67	0.503
VAR1.13	152	1.12	0.33	194	1.10	0.30	0.79	0.432
VAR1.14	152	1.11	0.32	194	1.15	0.36	-1.04	0.300
VAR1.15	152	1.14	0.35	194	1.12	0.32	0.54	0.591
VAR1.16	152	1.15	0.36	194	1.18	0.38	-0.60	0.550
VAR1.17	152	1.20	0.40	194	1.15	0.36	1.16	0.247
VAR1.18	152	1.27	0.45	194	1.26	0.44	0.14	0.887
VAR1.19	152	1.11	0.32	194	1.12	0.33	-0.34	0.734
VAR1.20	152	1.12	0.32	194	1.12	0.33	-0.15	0.881
VAR1.21	152	1.15	0.36	194	1.22	0.41	-1.57	0.118
VAR1.22	152	1.15	0.36	194	1.14	0.35	0.18	0.857
VAR1.23	152	1.16	0.37	194	1.15	0.36	0.08	0.934
VAR1.24	152	1.23	0.42	194	1.18	0.38	1.25	0.211
VAR1.25	152	1.12	0.33	194	1.14	0.35	-0.52	0.601
VAR1.26	152	1.19	0.39	194	1.25	0.43	-1.27	0.205
VAR1.27	152	1.11	0.32	194	1.13	0.34	-0.48	0.629
VAR1.28	152	1.16	0.37	194	1.14	0.35	0.48	0.629
VAR1.29	152	1.15	0.36	194	1.20	0.40	-1.09	0.276
VAR1.30	152	1.20	0.40	194	1.18	0.39	0.55	0.584
VAR1.31	152	1.14	0.35	194	1.11	0.32	0.68	0.494
VAR1.32	152	1.16	0.37	194	1.14	0.35	0.48	0.629
VAR1.33	152	1.11	0.32	194	1.18	0.38	-1.69	0.092
VAR1.34	152	1.06	0.24	194	1.14	0.35	-2.54	**0.011**
VAR1.35	152	1.11	0.32	194	1.12	0.33	-0.34	0.734
VAR1.36	152	1.07	0.26	194	1.14	0.35	-2.05	**0.041**
VAR1.37	152	1.11	0.32	194	1.18	0.39	-1.82	0.070
VAR1.38	152	1.14	0.35	194	1.21	0.41	-1.50	0.133
VAR1.39	152	1.05	0.22	194	1.14	0.35	-2.94	**0.003**
VAR1.40	152	1.12	0.32	194	1.13	0.34	-0.29	0.770
VAR1.41	152	1.07	0.25	194	1.13	0.34	-2.01	0.046
VAR1.42	152	1.08	0.27	194	1.14	0.35	-1.95	0.052
VAR1.43	152	1.13	0.34	194	1.15	0.36	-0.61	0.543
VAR1.44	152	1.17	0.38	194	1.21	0.41	-0.95	0.343
VAR1.45	152	1.11	0.31	194	1.10	0.30	0.07	0.948
VAR1.46	152	1.11	0.31	194	1.12	0.32	-0.39	0.697
VAR1.47	152	1.07	0.26	194	1.13	0.34	-1.76	0.079
VAR1.48	149	1.10	0.30	193	1.10	0.30	0.07	0.946
VAR1.49	152	1.07	0.26	194	1.11	0.31	-1.17	0.244
VAR1.50	152	1.14	0.35	194	1.15	0.36	-0.43	0.667
VAR1.51	152	1.11	0.31	194	1.15	0.36	-1.37	0.172
VAR1.52	152	1.11	0.32	194	1.09	0.29	0.58	0.565
VAR1.53	152	1.11	0.31	194	1.20	0.40	-2.51	0.013
VAR1.54	152	1.09	0.29	194	1.08	0.28	0.31	0.754

See the whole instrument attached as a supplementary online file (Appendix B).

TABLE 4 | Group means and standard deviations (SDs) of CL skills, using the t-test.

Skills	**AI Adopters**			**AI Non-Adopters**			**Test**	**Sig.**
Item	***N***	**Means**	**SD**	***N***	**Means**	**SD**	**t**	***p***
Have the skills and resources necessary to perform tasks effectively	152	4.00	1.08	194	3.93	1.07	0.62	0.54
Being in a management position to be effective	152	3.88	1.04	194	3.80	1.14	0.60	0.55
Be able to work within the team	152	4.03	0.98	194	4.09	1.03	-0.50	0.61
Be visible in the clinical environment	152	3.88	1.09	194	3.92	1.05	-0.31	0.76
Recognize optimal performance and express appreciation in a timely manner	152	4.11	0.87	194	4.10	0.96	0.09	0.93
Initiate interventions and lead actions and procedures	152	4.12	0.80	194	3.97	0.98	1.57	0.12
Have high moral character, know what is right and wrong and act accordingly	152	3.99	1.07	194	4.15	0.98	-1.46	0.15
Be willing to take risks for something they believe in	152	3.70	1.10	194	4.14	0.88	-4.09	**0.001**
Be able to communicate well, presenting ideas logically and effectively	152	3.91	1.14	194	4.04	1.09	-1.06	0.29
Be flexible, able to improvise and respond with appropriate skills and interventions	152	4.01	0.88	194	4.05	0.85	-0.42	0.67

TABLE 5 | Group means and standard deviations (SDs) of CL actions, using the t-test.

Actions	**AI Adopters**			**AI Non-Adopters**			**Test**	**Sig.**
Item	***N***	**Means**	**SD**	***N***	**Means**	**SD**	**t**	***p***
Influence organizational policy	152	3.86	1.06	194	3.94	0.99	-0.74	0.46
Influence the way clinical care is delivered	152	3.89	1.00	194	3.94	1.00	-0.45	0.65
Participate in staff development education	152	4.08	0.87	194	4.05	1.02	0.27	0.79
Provide valuable staff support	152	4.01	0.87	194	4.05	0.91	-0.47	0.64
Initiate innovations in practice	152	4.11	0.89	194	4.02	0.97	0.89	0.37
Lead change and service improvement	152	4.12	0.79	194	4.05	0.90	0.74	0.46
Encourage initiative, involvement and innovation from co-workers	152	3.95	0.85	194	4.03	0.89	-0.82	0.41
Encourage and lead service improvement	152	3.99	0.95	194	3.91	0.99	0.76	0.45

TABLE 6 | Descriptives of AI readiness using means, standard errors, and 95% confidence intervals (CI) for the whole sample (*N*=389).

Item	Mean	SE	95% CI (Lower)	95% CI (Upper)
Support AI development (0–10)	6.97	0.112	6.75	7.19
AI will impact my career (0–10)	6.36	0.144	6.08	6.64
The need for AI basics (0–10)	7.33	0.141	7.05	7.61
Understand ethics of AI (0–10)	5.83	0.132	5.58	6.09
Hopeful about AI (0–10)	6.35	0.120	6.11	6.59
Worried about AI (0–10)	5.58	0.127	5.33	5.83
AI requires careful management (0–10)	7.88	0.125	7.63	8.13

Overall positivity toward AI in the nursing profession (1–5): Mean = 3.29, SE = 0.067, 95% CI = 3.16–3.42

TABLE 7 | Descriptives of AI knowledge, attitudes, literacy preferences, and priorities using the sample size and frequencies for the whole sample (*N*=389).

Category	***N***	**%**
AI Knowledge		
Accurate / mostly accurate definition	147	36.5
Do not know	145	35.9
Scattered opinions/pros & cons	112	27.6
AI Attitude Narratives	*N*	%
Positive (overall)	247	61.8
Negative	128	31.0
Neutral	29	7.2
AI Literacy Preferences & Settings Preference	*N*	%
Want AI basics in the curriculum	233	57.7
Prefer outside curriculum	162	40.1
Other	9	2.2
Learning format		
Multiple workshop series	177	43.8
Graduate-level education	129	31.9
1–2-hour workshop	69	17.1
One-day course	17	4.2
Anticipated time to AI impact		
In 10 years	216	53.5
In 5 years	122	30.2
In 20 years	49	12.1
Not in a lifetime	17	4.2
Priorities in AI Literacy (Top groupings)	*N*	%
Appropriate tech. context + ethics + quality improvement	58	14.4%
Interpret results + communicate how technology works + understand processes	20	5.0%

TABLE 8 | Predictors of CL using ordinary least squares.

Predictor	*b*	SE (HC3)	t	*p*	95% CI	*β* (std)
Constant	3.46***	0.43	8.07	<0.001	[2.62, 4.30]	—
AI total	0.03	0.03	1.26	0.209	[-0.02, 0.09]	0.07
Gender: Male (vs. Female)	0.22*	0.11	2.08	0.038	[0.01, 0.43]	0.15
Age: 25–29 (vs <25)	0.32	0.45	0.71	0.479	[-0.56, 1.19]	0.21
Age: 30–39 (vs <25)	0.24	0.45	0.52	0.600	[-0.65, 1.13]	0.16
Age: 40+ (vs <25)	0.02	0.49	0.04	0.965	[-0.94, 0.99]	0.01
Education: Bachelor's (vs Diploma/Associate)	0.28	0.38	0.74	0.457	[-0.46, 1.02]	0.19
Education: Master's (vs Diploma/Associate)	0.55	0.37	1.51	0.132	[-0.17, 1.27]	0.36
Education: Doctorate/Other (vs Diploma/Associate)	0.73	0.39	1.85	0.064	[-0.04, 1.50]	0.27
Years Exp: 1–3 years (vs <1 year)	-0.44	0.44	-1.00	0.318	[-1.31, 0.42]	-0.16
Years Exp: 3–5 years (vs <1 year)	-0.49	0.44	-1.11	0.266	[-1.35, 0.37]	-0.20
Years Exp: 5–10 years (vs <1 year)	-0.53	0.46	-1.15	0.251	[-1.44, 0.38]	-0.29
Years Exp: >10 years (vs <1 year)	-0.79	0.43	-1.84	0.066	[-1.63, 0.05]	-0.54
Hosp Type: Private (vs Public/Government)	-0.26	0.15	-1.75	0.081	[-0.55, 0.03]	-0.13
Hosp Type: Teaching/University (vs Public/Government)	-0.13	0.14	-0.96	0.337	[-0.41, 0.14]	-0.08
Hosp Type: Military/Other (vs Public/Government)	-0.40*	0.17	-2.34	0.019	[-0.74, -0.07]	-0.23
Shift: Fixed Evening (vs Fixed Day)	0.28	0.19	1.43	0.152	[-0.10, 0.65]	0.13
Shift: Rotating (vs Fixed Day)	0.02	0.18	0.11	0.916	[-0.33, 0.36]	0.01
Shift: Fixed Night (vs Fixed Day)	0.31	0.31	1.00	0.319	[-0.30, 0.92]	0.06
Shift: 12h Day (vs Fixed Day)	-0.72	0.38	-1.88	0.060	[-1.46, 0.03]	-0.18
Shift: 12h Night (vs Fixed Day)	0.09	0.19	0.45	0.651	[-0.29, 0.46]	0.05
Model of Care: Team Nursing (vs Primary Nursing)	0.34*	0.14	2.38	0.017	[0.06, 0.62]	0.23
Model of Care: Functional (vs Primary Nursing)	0.25	0.17	1.45	0.148	[-0.09, 0.59]	0.11
Model of Care: Total Patient Care (vs Primary Nursing)	0.41**	0.15	2.68	0.007	[0.11, 0.71]	0.23

N = 389; $R^2 = 0.117$. Coefficients are unstandardized β with Heteroskedasticity-consistent standard errors (HC3); standardized β reported only for continuous predictors. Significance: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

TABLE 9 | Predictors of integration of AI in the nursing profession using ordinary least squares.

Predictor	*b*	SE (HC3)	t	*p*	95% CI	*β* (std)
Constant	6.56***	0.52	12.67	<0.001	[5.55, 7.58]	—
CL total	0.13	0.10	1.27	0.206	[-0.07, 0.32]	0.06
Gender: Male (vs Female)	-0.82***	0.20	-4.20	<0.001	[-1.20, -0.44]	-0.25
Age: 25–29 (vs <25)	-1.36	0.78	-1.74	0.082	[-2.89, 0.17]	-0.42
Age: 30–39 (vs <25)	-0.61	0.81	-0.75	0.452	[-2.21, 0.98]	-0.19
Age: 40+ (vs <25)	-0.80	0.87	-0.92	0.357	[-2.51, 0.91]	-0.09
Education: Bachelor's (vs Diploma/Associate)	1.83***	0.39	4.65	<0.001	[1.06, 2.60]	0.58
Education: Master's (vs Diploma/Associate)	1.97***	0.43	4.64	<0.001	[1.14, 2.81]	0.59
Education: Doctorate/Other (vs Diploma/Associate)	0.25	0.66	0.38	0.701	[-1.05, 1.55]	0.04
Years Exp: 1–3 years (vs <1 year)	1.71**	0.58	2.92	0.004	[0.56, 2.85]	0.28
Years Exp: 3–5 years (vs <1 year)	2.61***	0.71	3.67	<0.001	[1.21, 4.00]	0.49
Years Exp: 5–10 years (vs <1 year)	0.55	0.77	0.71	0.476	[-0.96, 2.05]	0.14
Years Exp: >10 years (vs <1 year)	1.25*	0.61	2.06	0.040	[0.06, 2.44]	0.39
Hosp Type: Private (vs Public/Government)	-1.32***	0.27	-4.91	<0001	[-1.85, -0.79]	-0.29
Hosp Type: Teaching/University (vs Public/Government)	-1.42***	0.31	-4.64	<0.001	[-2.02, -0.82]	-0.37
Hosp Type: Military/Other (vs Public/Government)	0.36	0.36	1.00	0.316	[-0.35, 1.07]	0.09
Shift: Fixed Evening (vs Fixed Day)	-1.13***	0.29	-3.93	<0.001	[-1.69, -0.57]	-0.23
Shift: Rotating (vs Fixed Day)	-1.13***	0.26	-4.37	<0.001	[-1.63, -0.62]	-0.35
Shift: Fixed Night (vs Fixed Day)	0.41	0.34	1.22	0.223	[-0.25, 1.08]	0.04
Shift: 12h Day (vs Fixed Day)	-0.13	0.70	-0.18	0.856	[-1.51, 1.25]	-0.02
Shift: 12h Night (vs Fixed Day)	-1.22***	0.26	-4.68	<0.001	[-1.73, -0.71]	-0.33
Model of Care: Team Nursing (vs Primary Nursing)	-1.32***	0.26	-5.11	<0.001	[-1.83, -0.81]	-0.41
Model of Care: Functional (vs Primary Nursing)	-0.29	0.30	-0.96	0.337	[-0.87, 0.30]	-0.06
Model of Care: Total Patient Care (vs Primary Nursing)	-0.55	0.31	-1.74	0.081	[-1.16, 0.07]	-0.14

N = 389; $R^2 = 0.308$. Coefficients are unstandardized β with Heteroskedasticity-consistent standard errors; standardized β reported only for continuous predictors. Significance: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- AppendixAandBSupplementaryDCLMaterial18APA.docx