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The Human-Digital Nexus: Architecting a Future-Ready Healthcare Workforce through AI-Enabled Performance Intelligence and Empathetic Leadership

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Abstract

Background: In healthcare, artificial intelligence promises transformative capabilities to healthcare systems, but its effective implementation depends on the choice of institutional governance, systemized workforce training, and agreement with human value sets.

Methods: An integrative review was undertaken in compliance with the PRISMA guidelines. Four databases including PubMed, Scopus, Elsevier, and Google Scholar were searched with the help of three conceptual constructs future-ready healthcare workforce, AI-enabled performance intelligence, and empathetic leadership. The quality of paper was evaluated through the Critical Appraisal Skills Programme (CASP) checklist of 19 finalised cross-sectional studies.

Findings: Systematic and large discrepancies between awareness and operational preparedness of AI were found between clinical settings and professional groups which could be explained by poor pre-deployment institutional investments. Ethical decision-making and professional identity were the significant predictors of AI-ready organisational culture. AI-mediated empathy was linked to greater engagement of workforce and decreased attrition. Adoption was conditioned by an enabler-barrier dynamic that was complex as data privacy concerns could be interpreted as a kind of legitimate professional accountability, demographic and role-based variables played a significant role in mediating pattern of adoption. Certain ethical issues such as algorithmic bias, deskilling, liability, data governance need to be disaggregated to be addressed in the policy.

Conclusions: Preparation to integrate AI is not an individual task, but rather an institutional one. The sustainable adoption requires clear governance structures, undergraduate curriculum changes that make AI literacy and ethics become fundamental along with observable empathetic leadership that provides the psychological safety needed to allow actual workforce engagement. Hence, a model of three domains implementation is suggested.

Keywords: Artificial intelligence; healthcare workforce readiness; empathetic leadership; AI-enabled performance intelligence; data governance; clinical education; organisational readiness.

Introduction

Artificial intelligence (AI) has evolved exponentially in recent years and is no longer considered prospective feature for healthcare mainly because of its widespread operational integration in the form of clinical diagnosis, patient monitoring, resource allocation, documentation and administrative workflow (Hendrickson et al., 2025). The capacity of AI to process high-volume data sets, augmenting clinical decision making and reducing institutional inefficiency has positioned it as a defining instrument for healthcare delivery (Al Jnainati et al., 2025). The translation of AI capabilities into clinical benefit is not straightforward as it depends on the quality of institutional ecosystems into which AI is introduced, the governance frameworks that govern it and preparedness of the workforce that is expected to utilize it (George, 2025). However, considering the widespread applications and prominence of AI for the healthcare sector, the workforce readiness is also raised despite acknowledging the need for foundational governance (Muhyi et al., 2024). Within healthcare organizations, the decision to procure and deploy AI tools is often carried out by institutional executives, technology purchasing authorities and as well as organizational leadership rather than clinical or healthcare professionals who subsequently encounter the challenges in its exposure during point of care. Since

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frontline staff are implementers of decisions made by those above them, their relationship with AI is substantially a one compliance issue. The findings of Virgillito and Ledda (2025) have confirmed the fact that the effective deployment and usage of AI is encountered with structural challenges rather attitudinal.

As per Alami et al. (2021), AI readiness is understood as an organization's and workforce composite capacity comprises cognitive, technical and ethical aspects in order to effectively integrate and utilize AI tools within clinical setting. Further, this does not merely encompasses familiarity with AI systems however, at the same time it requires cultivation of ethical reasoning, adaptive professional identity along with digital literacy that functional AI-augmented practice demands. Moreover, AI-enabled performance intelligence is described as the capacity of AI systems in order to generate, analyse and act upon workforce and clinical performance data to facilitate decision making, optimal resource deployment and support continuous quality improvement (Cavadi & Cosenz, 2025). Another key aspect of the present review is empathetic leadership which is reflects the capacity of institutional leaders to understand, acknowledge and act on the concerns and development needs of the workforce during especially during technological transition hence, making it both interpersonal and structural in character (Guzmán et al., 2020).

However, the two critical dimensions of AI readiness discourse receive insufficient attention while reviewing the existing body of literature. At first, the potential of AI as a pedagogical instrument holds significant prominence as a training tool capable of facilitating high-fidelity clinical decision making simulation hence, presenting differential diagnostic reasoning and contextually responsive formative feedback to medical and nursing students at scale (Mateusz et al., 2025). Further, concerns about data privacy among clinicians is also identified as emerging theme in the existing literature which is considered as a significant adoption barrier. Specifically, existing electronic health records (EHR) systems and hospital information technology infrastructure share identical categories of vulnerability with AI platforms such as susceptibility to cyber intrusion, system failure, unauthorised access, and data breach (Ahmed et al., 2025). Moreover, AI does not merely introduce categorically new risk profiles; however, at the same time it suggests that clinicians who express concerns about AI data security exercise the same professional accountability obligation that is already applicable for the current digital systems (Smith, 2021). This suggests that an appropriate institutional response is transparent governance rather reassurance.

Further, at present, the simultaneous coexistence of data privacy concerns and limited understanding of broader ethical AI frameworks is not contradictory as clinicians appropriately recognise that patient data is sensitive and requires to be professionally protected by professionals having all necessary domain specific knowledge (Shoghli et al., 2024; Williamson & Prybutok, 2024). The issue of privacy awareness and ethical literacy is required to be considered and adequately adhered at policy level. Considering this gap, the present review is aimed at investigating the nexus of AI-enabled performance intelligence, empathetic leadership and healthcare workforce readiness while emphasizing how institutional governance promotes or impedes AI adoption and how it can leverage both operationally and educationally. A three domain implementation framework has also been proposed while investigating how empathetic leadership mediates the human dimensions of technological transition and what systemic conditions are required to cultivate a workforce which is both technically capable and ethically grounded.

Methodology

Research Design

The review employed an integrative methodology incorporating primary studies of different methodological designs such as quantitative, qualitative and mixed designs enabling comprehensive synthesis across diverse healthcare contexts. The integrative approach comprised of five structured stages in accordance with the findings of García-Peñalvo (2022), as problem identification, systematic literature search, data quality appraisal, thematic data analysis and interpretive synthesis. Thematic analysis was conducted through iterative data reduction and cross comparison with themes derived inductively from patterns across included studies and was reported in accordance with PRISMA guidelines.

Research Strategy and Search Terms

Systematic searches were performed across prominent database such as PubMed, Scopus, Elsevier, and Google Scholar. AI adoption, workforce management and leadership research were the key focus area for the search criteria. All the included studies were cross sectional primary studies in English. Published between 2016 and 2026 addressing AI adoption, workforce performance and leadership in healthcare setting. Table 1 presents the search terms used.

Table 1: Search Terms and Strings

Category	Search Terms
Core Terms	• ”AI” AND “healthcare”
	• "Artificial Intelligence" AND "clinical decision support"
	• "AI" AND "performance intelligence" OR "digital performance"
	• "AI" AND "workforce readiness"
	•"Empathetic leadership" AND "AI"
	• "AI adoption" AND "healthcare workers" OR "nurses" OR "doctors"
	• "AI" AND "employee performance" AND "leadership"
Supplementary Terms	• ”Healthcare workforce” AND “AI tools”
	• "Machine learning" AND "AI performance intelligence"
	• "AI empathy" AND "leadership styles"
	• "Artificial intelligence" AND "workforce performance metrics"

Eligibility Criteria

Eligibility criteria was considered for all three conceptual domains of this review as future-ready healthcare workforce, AI-enabled performance intelligence and empathetic leadership. The screening process was processed by searches including title and abstracts.

Table 2: Inclusion and Exclusion Criteria

Inclusion Criteria	Exclusion Criteria
Only primary research studies were included.	Secondary research and review-based studies were excluded.
Studies addressing healthcare workforce scope.	Studies outside the healthcare workforce domain.
Studies published between 2016 and 2026.	Studies published before 2016.
Full-text articles in English.	Abstracts only, or articles in languages other than English.

Screening and Study Selection

The PRISMA framework guided screening and visual representation of the selection process is highlighted in Figure 1. From total 245 identified records, 130 duplicates were identified and removed resulting in 115 records. Further, screening following abstract and titles were performed contributing to 45 studies for full-text eligibility. Amongst these, 26 were excluded due to inaccessibility, inconclusive findings and limited methodological relevance to the review constructs thereby resulting in finalized 19 studies.

Quality Assessment

The methodological quality of final 19 studies was also performing using Critical Appraisal Skills Programme (CASP) checklist for cross-sectional studies. Consistent with the cross-sectional design of all included articles, certain limitations such as inability to establish causal inference, reliance on convenience sampling and self-reporting bias were also acknowledged across the evidence base and were addressed in the limitations section.

Results

Nineteen studies representing insights from eight countries such as China, Saudi Arabia, Pakistan, India, Jordan, Bangladesh, Iraq, and the United States from hospital, primary care and academic settings were included. The population of study mainly comprised as physicians, nurses, nursing/medical students, allied health professionals and corporate leaders. A descriptive summary of each study is presented in Table 4. Three themes emerged from thematic analysis.

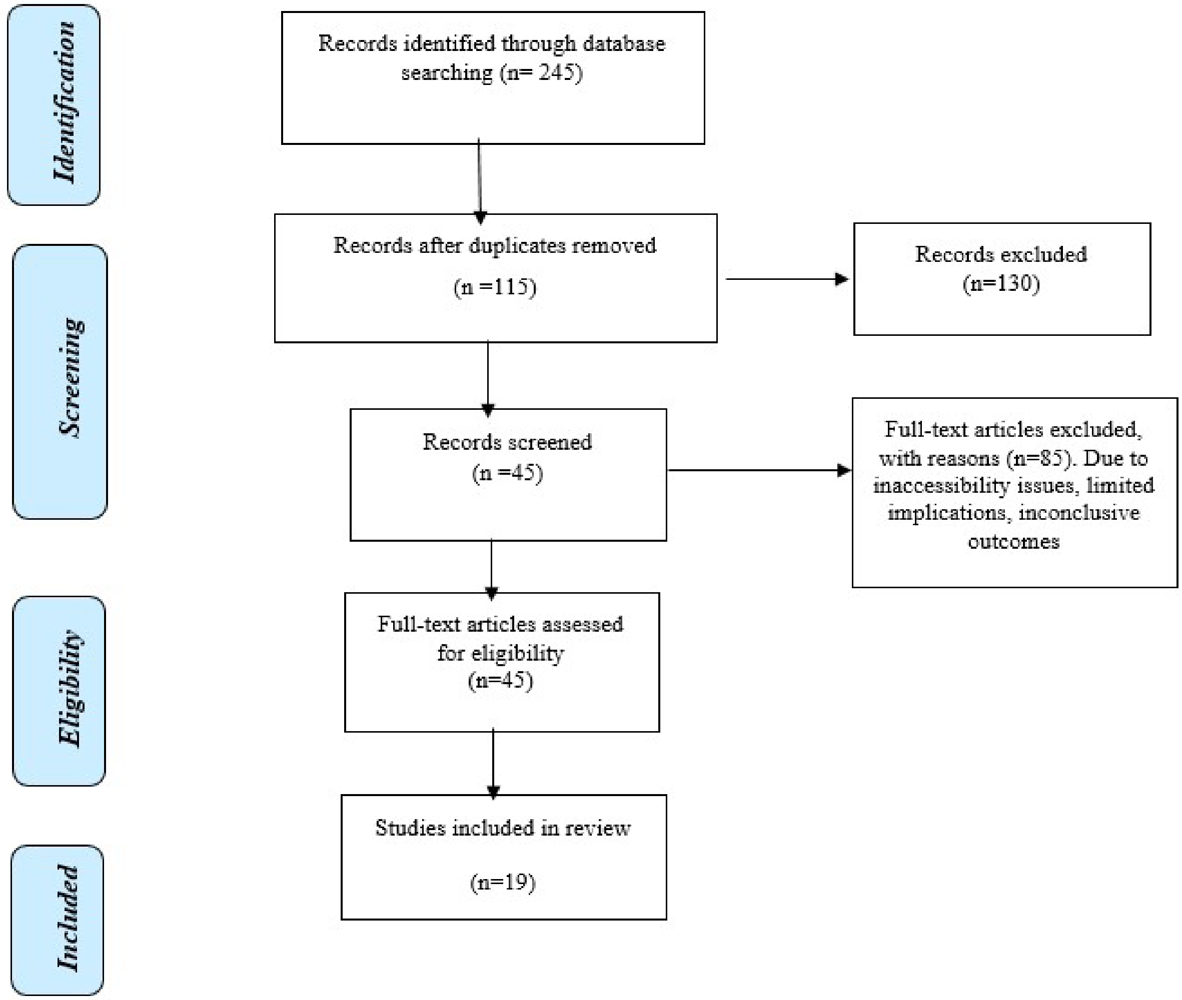

Figure 1: PRISMA Flow Diagram

Theme 1: The Awareness-Preparedness Disjunction: A Governance Deficit, Not a Workforce Deficit

Among different studies, a consistent and clinically significant gap was identified between awareness of AI and functional preparedness of using AI. The majority of findings summarized above suggest awareness-preparedness disjunction is primarily an institutional governance which as a result indicates the consequences of deploying AI systems into environments where no structured pre-deployment preparation is provided. Dai et al. (2025), comprising a large sample set of n=2,705 concluded that 92.4% of physicians and 84.2% of nurses were aware of medical AI applications where only 22.8% and 17% respectively reported intention which contradicts with the fact there has been attitudinal problem existed as well. Al-Kahtani et al. (2025) suggested that 68.3% familiarity with AI was reported however, only 41.2% active utilisation was found. Habib et al. (2024) studied 610 Pakistani healthcare professionals and found that 78.7% received no formal AI training indicating the defining variable as the absence of institutional provision rather than the individual reluctance. In addition, nearly 70.3% of the same sample acknowledged ethical importance of responsible AI use.

Further, studies indicate that among majority of newly qualified clinicians, the most likely was to be AI-native in their general digital habits comprising preparedness deficit as equally marked indicting the problem in educational system. Gupta et al. (2025) found that majority of Indian medical trainees rated their own AI knowledge as insufficient, as 84.6% reported no curricular exposure. Yang et al. (2026) found that newly qualified Chinese nurses nearly had moderate AI readiness indicating limited foundational AI knowledge and inadequate digital literacy.

Table 3: Quality Assessment-CASP-Cross sectional Studies:

S.No	Did the study address a clearly focused issue?	Did the authors use an appropriate method to answer their question?	Were the subjects recruited in an acceptable way?	Were the measures accurately measured to reduce bias?	Were the data collected in a way that addressed the research issue?	Did the study have enough participants to minimize the play of chance?	How the results presented and what are is the main result?	Was the data analysis sufficiently rigorous?	Is there a clear statement of findings?	Can the results be applied to the local population?	How valuable is the research?
Study 1	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Study 2	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Study 3	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Study 4	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Study 5	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Study 6	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Study 7	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Study 8	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Study 9	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Study 10	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Study 11	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Study 12	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Study 13	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Study 14	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Study 15	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Study 16	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Study 17	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Study 18	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Study 19	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Tariq et al. (2025) confirmed that 33.9% of Pakistani practitioners felt operationally confident with AI systems despite broadly positive attitudinal orientations. The findings indicate that the healthcare education pipeline especially at undergraduate and postgraduate levels has not been aligned with the evolving technology being embedded in clinical practice suggesting a systemic educational governance failure.

The findings also signify the importance to distinguish conceptual and empirically AI adoption and AI readiness. It has been discussed that constructs are related but not equivalent to adoption intention measured by instruments such as UTAUT, which captures psychological behavioural tendency (Dai et al., 2025). Moreover, readiness captures a systemic capacity comprising institutional, educational and structural aspects for the effective integration of AI. Hence, number of studies have suggested to measure intention and report the findings as evidence for AI readiness.

Theme 2: Ethical Grounding and Professional Identity as Foundational Predictors of AI-Ready Culture

The current theme addresses the human dimensions

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Table 4: Summary of Studies

S.No	Author(s) & Year	Study Design	Sample & Participants	Key Findings	Limitations & Critical Appraisal
Study 1	Randriamiary (2024)	Quantitative (PLS-SEM)	337 corporate leaders from various industries.	Ethical decision-making has a strong positive impact on AI-Ready Culture. AI-ready culture significantly predicted organizational performance whereas digital Competence has a significant negative impact on AI-Ready culture.	The sample only comprised corporate leaders instead of exclusively healthcare professionals.
Study 2	Ali and Pitafi (2025)	Quantitative (CB-SEM).	359 employees in China	AI-driven HRM empathy positively influences job engagement and organizational engagement which in turn enhances performance and reduces turnover intentions.	Single country study in China, limiting cross-cultural generalizability.
Study 3	Boyacı and Söyük (2025)	Cross-sectional descriptive study.	195 healthcare workers in a Turkish university hospital.	Significant but low-level positive relationship between medical AI readiness and openness to organizational change.	Single-center study in one Turkish university hospital, limiting generalizability.
Study 4	Dai et al. (2025)	Cross-sectional Survey	2,705 (991 physicians, 1,714 nurses) of China	Performance expectancy, effort expectancy, social influence, and AI facilitating conditions positively predict intention to use. Perceived risk negatively impacted nurses' willingness but not physicians'.	Cross-sectional design restricted causal inference. Convenience sampling via professional associations could further strengthen the scope and methodological rigor.
Study 5	Tariq et al. (2025)	451 medical and dental practitioners of Pakistan.	Positive attitudes but low confidence in operating AI systems were observed. Dental practitioners showed significantly higher willingness to incorporate AI into diagnosis/ treatment planning than medical practitioners.	Single-city study i.e. Lahore, Pakistan) through non-probability convenience sampling, restricted generalizability.	Single-city study i.e. Lahore, Pakistan) through non-probability convenience sampling, restricted generalizability.

Cont. Table 4

S.No	Author(s) & Year	Study Design	Sample & Participants	Key Findings	Limitations & Critical Appraisal
Study 6	Al-Kahtani et al. (2025)	Cross-sectional	Total 437 comprising 173 HCPs, 264 health science students of Saudi Arabia	The majority of the population was familiar with AI in documentation, but merely 41.2% actively used it. Students were more optimistic than professionals about AI's accuracy and efficiency. Key adoption factors included reliability, efficiency and data privacy.	Cross-sectional design involving single-country study with the limited sample and disparities in subgroup sizes was observed.
Study 7	Algunmeeyn and Mrayyan (2025)	Cross-sectional online survey	434 nursing students in Jordan	Students perceived high AI benefits alongside high risks, particularly liability issues, communication barriers and privacy concerns.	Single-country study i.e. Jordan and convenience sampling from only five universities, limits generalizability.
Study 8	Yang et al. (2026)	Cross-sectional	329 qualified nurses of China.	AI readiness was reported as moderate whereas significant predictors were measured as perceived ease of use, prior AI training and awareness of AI in nursing. Perceived usefulness and perceived barriers were not significant predictors. Barriers were as limited AI knowledge and inadequate computer skills.	Cross-sectional design involving convenience sampling from four tertiary hospitals in one Chinese province restricted generalizability.
Study 9	Habib et al. (2024)	Cross-sectional	610 healthcare students and professionals of Pakistan	Of the 610 survey participants, 78.7% never received formal AI training. Amongst this 70.3% believed AI would raise ethical challenges and 66.4% believed AI should be taught at undergraduate level. Conclusively, higher educational qualifications was associated with more positive attitudes.	Convenience sampling via social media could only access younger, tech-savvy respondents thereby introducing selection bias.

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Cont. Table 4

S.No	Author(s) & Year	Study Design	Sample & Participants	Key Findings	Limitations & Critical Appraisal
Study 10	Alsaedi et al. (2024)	Cross-sectional	610 healthcare students and professionals of Pakistan	Of the 610 survey participants, 78.7% never received formal AI training. Amongst this 70.3% believed AI would raise ethical challenges and 66.4% believed AI should be taught at undergraduate level. Conclusively, higher educational qualifications was associated with more positive attitudes.	Cross-sectional design comprising convenience sampling restricted generalizability. Also, Self-selection bias as over-representation was observed.
Study 12	Adithyan et al. (2024)	Cross-sectional	200 healthcare professionals comprising doctors, nurses and paramedics of India	Among 200 professionals, 52% had moderate knowledge while 48% had low attitude toward AI adoption confirming Significant association between knowledge and attitude. However, no significant association between attitude and perceived barriers.	Single tertiary-care hospital study in India and cross-sectional design prevented causal conclusions.
Study 13	Mariano et al. (2025)	Cross-sectional descriptive correlational design.	349 nurses and students in Saudi Arabia	Significant positive correlations between knowledge and attitudes, knowledge and practices and attitudes and practices were reported along with relatively patient data security and ethical concerns.	Convenience and snowball sampling possess biasness in results toward participants with positive attitudes whereas cross-sectional design limits validity.
Study 14	Salloma et al. (2026)	Cross-sectional.	366 healthcare providers in Saudi Arabia	Study found there is a high perception but predominantly neutral attitudes Significant associations between perception and gender, job type, position, age, education and experience was reported. Positive correlation between perception and attitude suggested enhancing knowledge may shift attitudes from neutrality to acceptance.	Convenience sampling from merely two governmental hospitals in Jeddah limits generalizability. Self-reported questionnaires also introduces response bias.

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Cont. Table 4

S.No	Author(s) & Year	Study Design	Sample & Participants	Key Findings	Limitations & Critical Appraisal
Study 15	Hussien and Mohammed (2025)	Cross-sectional	451 primary healthcare workers in Baghdad, Iraq.a	Positive attitude towards AI was reported, confirming significant positive correlations between attitudes and age, educational qualification and years of experience. It was also reported that AI diagnostic ability is superior to human clinical experience.	Single-city study i.e. Baghdad with non-probability purposive sampling, limited generalizability.
Study 16	Gupta et al. (2025)	Cross-sectional	194 medical students and resident doctors in India	Among 194 participants, 63.4% rated their AI knowledge as poor, while 84.6% reported no AI exposure in their curriculum. ChatGPT was observed as the most used tool.	Single tertiary-care center study in North India and predominance of male participants indicate limited generalizability and gender bias respectively.
Study 17	Rony et al. (2024)	Cross-sectional	431 healthcare workers in Dhaka, Bangladesh	Among 431 participants, 39.26% had reasonable knowledge, but 73.06% held positive attitudes. Strong positive correlation between knowledge and positive attitudes was reported.	Single-city study Dhaka, Bangladesh limited generalizability. While self-reported data likely introduce social desirability bias.
Study 18	Oweidat et al. (2025)	Descriptive Correlational Cross-sectional	116 nurses from Jordanian governmental hospitals.	AI attitudes and practices significantly predict intent to stay, whereas barriers to AI were negatively correlated with intent to stay.	Limited sample size (n=116) from only four governmental hospitals in Jordan restricts generalizability whereas cross-sectional design prevents causal inference.
Study 19	Muthukumar (2025)	Quasi-experimental that is Chatbot Compassion Quotient tool.	30 participants.	AI-generated responses were rated significantly more empathetic compared to human responses. Response length was also a significant predictor of compassion ratings.	Small sample size of n=30 limited generalizability whereas the focus was solely on text-based empathy, excluding non-verbal communication.

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of AI integration specifically concerning the role of ethical decision making, professional identity and AI-mediated empathy as a mediating dimension for AI deployment and organizational and clinical benefit. Randriamiary (2024) concluded that ethical decision making strongly predict AI-ready organizational culture based on the obtained t-statistics β=0.881, $p<0.001$ where digital competence carried a significant negative association with AI readiness. The aforementioned findings suggest that technical proficiency when deployed in the absence of ethical grounding impede AI ready culture by generating overconfidence, reducing reflective practice and diluting human oversight mechanism that safe AI deployment.

Ali and Pitafi (2025) demonstrated that AI-driven human resource management (HRM) empathy positively influence job engagement based on β=0.17, $p<0.01$ and organisational engagement (β=0.42, $p<0.001$) signifying downstream benefits for individual performance and reduced turnover intention. The aforementioned findings confirm that AI when deployed with leadership and HRM focused has proven to be a meaningful instrument for workforce retention provided it is implemented with empathetic institutional culture rather than surveillance on productivity monitoring tool. Muthukumar (2025) in a quasi-experimental study used Chatbot Compassion Quotient tool where he found that AI-generated responses were rated as more empathetic as compared to human responses. Though the sample size of aforementioned study lacks generalizability however, the findings raised important questions explaining the nature of AI mediated compassion and its appropriate role in clinical and organizational communication.

Studies indicate that professional identity is emerged as a robust moderator of AI receptivity. For instance, Oweidat et al. (2025) studying 116 Jordanian nurses found that positive AI attitudes (β=0.34, $p<0.001$) and practices (β=0.29, $p<0.001$) predict intention to stay while AI barriers correlated negatively with retention (r=-0.42), and professional identity. Moreover, Tariq et al. (2025) found that dental practitioners expressed substantially greater rate of AI adoption willingness compared to medical practitioners (68.5% vs. 57%, $p=0.004$) indicating difference attributes to earlier and more structured technological exposure in dental education suggesting the case for discipline-specific curricular integration of AI rather than generic digital literacy modules. Further, concerns about junior professionals losing clinical experiential knowledge through premature and poorly governed AI reliance as suggested by Alsaedi et al. (2024) and Algunmeeyn and Mrayyan (2025) are appropriate and deserve structural response. The aforementioned findings also indicate the potential of AI as a training instrument capable of simulated clinical reasoning supported by AI.

Theme 3: The Enabler-Barrier Dynamic: Governance, Data Ethics, and the Demographic Landscape of Adoption

The adoption of AI is not facilitated and hindered uniformly but instead is influenced by an interactive combination of enabling factors and structural challenges. Dai et al. (2025) who used UTAUT model established that performance expectancy, effort expectancy, social influence and facilitating conditions all had a positive significance on the adoption intention. The effect of perceived risk on the willingness of the nurses was negative (B=-0.041, $p=0.002$) and reported positive for willingness of physicians mainly due to the differences in accountability structures, scope of practice issues and interaction to direct patient care. Yang et al. (2026) found that strongest predictors of readiness are perceived ease of use (0.211), prior AI training (0.23) while found perceived usefulness as non-significant indicating that experiential exposure is a stronger predictor of adoption than are arguments regarding the usefulness of AI.

The challenge of data privacy needs to be re-contextualised as these have been discussed significantly in the existing body of literature. Al-Kahtani et al. (2025), Alsaedi et al. (2024), Mariano et al. (2025) and Algunmeeyn and Mrayyan (2025) have regularly classified AI adoption challenges as adoption barriers. The existing clinical systems, EHR platforms, laboratory information systems, radiology picture archiving systems possess the same underlying vulnerability profile as AI platforms, which includes exposure to cyber-attack, system downtime, unauthorised access and data corruption. AI is not a new form of digital risk as it simply expands an already existing one to other functional areas. A clinician, who is showing a concerned attitude towards AI data security is implementing a professional duty that they already have concerns over the current systems.

Further, as ethical implications of AI are presently vague to guide policy, the most fundamental literature is directed at a variety of different areas, including algorithmic bias and systemic unfairness in AI-generated clinical recommendations. Further, medico-legal responsibility in AI-assisted diagnosis, the possibility of downscaling in junior clinicians, patient data to train AI and AI-generated performance analytics used constitutes surveillance of staff. All these concerns are responded differently by institution, regulatory bodies and educational sector.

Further, the demographic variables was found to be a significant moderator of adoption patterns among studies. For instance, Salloma et al. (2026) in their study of 366 Saudi healthcare providers found that the perception and attitude towards AI were all related to gender, type of job, seniority, age, education and experience. The neutral attitudes and high perception scores indicate that education may change the neutral attitudes to informed acceptance. Moreover, Rony et al. (2024) involving younger workers suggested that better AI knowledge had among the studied participants. In addition, Hussien and Mohammed (2025) suggested that positive correlations exist between age and favourable attitude and is a subtle contrast to avoid the stereotypical age-based generalisation. This suggests that the greater level of educational achievement, the greater was the positive relationship between the two thereby highlighting the strategic value of undergraduate reform as an instrument of adoption.

Discussion

The present review can be seen as a step forward towards substantive reframing of the AI readiness conversation in healthcare. In the present review, it has been argued that present AI framing is analytically inadequate and practically misleading though it does produce useful descriptive data. The state of readiness is essentially an institutional and systemic fact and is the outcome of decisions of governance, investment in education and dedication by leaders and not the preferences of frontline workers. To handle the intention-behaviour gap which is the same disagreement that persists suggesting institutional and not attitudinal intervention is needed.

This review places itself in a context of integrative and scoping literature that has captured the potential of AI adoption in healthcare. According to a study conducted by Muhyi et al. (2024), AI implementations need obvious involvement of the executive, trust building and changing leadership capabilities. Virgillito and Ledda (2025) found that readiness is not consistent even when there is high awareness, making it difficult to assume that there is technology acceptance in workforce situations. The article has validated AI as a valuable resource in workforce management by highlighting the possible opportunities of AI in personalised risk prediction and targeted intervention in workplace health promotion (Lange et al., 2024). These findings are validated and complemented by the current review that introduces a perspective of governance framework where the locus of adoption authority should be stated and discussed directly in case the recommendations are going to the appropriate actors.

The findings by Lange et al. (2024) suggested that AI-ready culture is predicted by ethical decision-making and not by digital competence as an important and underestimated point. It implies that the prevailing institutional investment in AI preparedness that focuses on technical infrastructure and digital skills training is possibly solving a secondary determinant and not the primary one. Values-based leadership courses, ethics training and development of reflective professional practice are not soft skills to technical AI training.

The empathy as especially argued by Muthukumar (2025), Ali and Pitafi (2025) need to be framed with caution. The fact that the responses generated by AI have been rated more empathetic than the ones generated by human beings does not mean that AI is more compassionate. It is more realistic in considering that text-based asynchronous communication is a form of communication that limits human expression of empathy and that AI created to employ contextually sensitive language in a consistent manner can be calibrated to use. The argument in this review is not that AI must replace human relational care; it is that AI, used in a strategic manner can lessen the burden of administration and communication amongst clinicians, thus making capacity available to the high-order relational care that is irreducibly human. The difference between AI as a replacement of empathy and AI as an enabling technology is the key to responsible implementation.

The potential of AI as a training tool is worth highlighting as one of the underutilized strategic resources. Habib et al. (2024) also realized that 66.4% of respondents thought AI should to be taught in undergraduates whereas Gupta et al. (2025) established that 81.4% of AI users were not aware of the ethical issues, which can be resolved structurally by providing pre-qualification education. AI-assisted simulation may introduce clinical situations of graded difficulty, simulate diagnostic reasoning processes, deliver immediate formative feedback and expose learners to ethical challenges in a psychologically safe setting. The introduction of AI as a pedagogical aid in medical and nursing learning deals with the preparedness gap at the level of its origin.

The global nature of this review is worth commenting

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on. The limitations inherent in the individual included studies are the lack of multicounty recruitment, limiting the applicability of the study results in isolation. But, the aggregate synthesis is across eight countries in four continents with diverse healthcare systems structure, regulatory conditions, cultural and resource base. The fact that across the entire spectrum of contexts the results converge on these areas of awareness-preparedness gap, the importance of ethical foundation, the role of professional identity, the complexity of adoption dynamics, gives one the confidence that the themes are well bolstered and the inability of any given single study to be generalised across countries.

Proposed Implementation Framework

Based on the synthesised evidence on three themes and in keeping with the governance-based reframing that was promoted in this review, a Three-Domain Implementation Framework is suggested (Table 5). The model positions the governance, education and empathetic leadership constructs of governance and education on particular actors, actions and expected outcomes. It is aimed to give institutional leaders, curriculum developers and clinical managers a framework upon which to translate the findings of the review into practice.

Table 5: Three-Domain Implementation Framework for AI-Ready Healthcare Workforce Development

Domain	Primary Actor	Required Actions	Anticipated Outcome
I. Governance & Procurement	Executives / Procurement authorities	Establish AI governance frameworks, mandate pre-implementation workforce preparation thereby apply consistent data security standards across all digital systems.	Institutional readiness, reduced liability exposure and consistent data governance
II. Education & Curriculum Reform	Academic institutions / Postgraduate training bodies	Embed AI literacy as core competency in undergraduate medical and nursing curricula. Incorporate AI-assisted simulation for clinical decision-making and address algorithmic bias, informed consent for AI and data ethics.	Workforce prepared prior to clinical deployment, reduced deskilling risk, increased adoption confidence.
III. Empathetic Leadership & Cultural Enablement	Clinical leaders / Department managers	Model ethical AI use at leadership level, communicate transparent rationales for AI deployment and create psychologically safe environments for reporting AI concerns. Also, make use AI-mediated tools to reduce documentation burden and protect relational care capacity.	Staff retention, reduced intention-behaviour gap and AI-ready organisational culture

Conclusion

It is this review that states that to build a future-ready healthcare workforce in the AI era, there has to be a fundamental shift in responsibility not upon individual clinicians but upon institutions, educators and leadership structures. Although AIs are well-known to the frontline level, the biggest gap is systematic preparation, especially ethical backgrounding, professional identity development, and empathetic leadership. The results suggest that ethical decision-making is a stronger predictor of AI readiness compared to technical skill, which requires a deliberate change of the strategy to values-based education and leadership development. Moreover, the fact that clinicians are worried about the privacy of the data is an element of professional responsibility and an indication that strong institutional governing systems are required. Another potential of AI as a pedagogical instrument that has not been explored fully is also reported in the review to increase clinical reasoning and ethical competence. The three- domain framework suggested, namely, governance, education, and leadership, highlights the fact that the introduction of AI is an institutional task, and its outcomes have direct effects on patient safety, the wellbeing of the workforce, and the organisational performance.

Strengths and Limitations

The synthesis of 19 empirical studies in eight countries and various groups of healthcare professionals makes this review strong as it provides a solid international view of the field, which is frequently limited by the analysis of a single country. The rigor of the methodology is improved by the PRISMA compliance and quality appraisal based on CASP, transparency, and reproducibility. Nevertheless, there are a number of constraints that have to be taken into consideration. The vulnerability of cross-sectional designs to causal inference and the use of convenience sampling as the primary method of sampling could lead to selection bias and limit generalisability. It can also have social desirability bias as a result of reliance on self-reported measures. Moreover, the operationalisation of the construct of AI-enabled performance intelligence is still underdeveloped in the overall literature. Another weakness is that there is a relative lack of empirical evidence regarding empathetic leadership, which is a conceptual progress over measurement. Further studies ought to be based on longitudinal, multi-location design and target organisational level factors such as governance systems, executive decision making, and workforce preparation policies.

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