

Governing Artificial Intelligence in Nursing Practice in Low- and Middle-Income Countries: A Critical Integrative Review and Nurse-Centred Sociotechnical Framework

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Abstract

Background: Artificial intelligence (AI) is increasingly promoted as a means of strengthening clinical decision-making, documentation, triage, surveillance, remote monitoring, and health-system efficiency. In low- and middle-income countries (LMICs), where nurses often sustain frontline care amid workforce shortages, fragile infrastructure, limited specialist access, and constrained public resources, AI could support safer and more timely care. Yet its implementation also risks reproducing inequity when tools are imported, poorly validated, culturally mismatched, weakly regulated, or introduced without meaningful nursing participation. **Aim:** To synthesize current evidence and policy guidance on barriers and enabling conditions for AI implementation in LMIC nursing practice and to develop a nurse-centred sociotechnical governance framework for safe, equitable, and context-responsive adoption. **Design:** Critical integrative review with framework synthesis. **Methods:** Peer-reviewed literature, AI reporting standards, implementation science frameworks, nursing workforce evidence, and authoritative global policy documents were synthesized. Sociotechnical systems theory provided the primary analytic lens, supported by value-sensitive design, technology acceptance constructs, implementation outcomes, and prior nurse-centred AI readiness scholarship. Evidence was charted across infrastructure, workforce, data, governance, cultural-linguistic, and workflow domains and interpreted at micro, meso, and macro levels. **Results:** Six interdependent implementation domains were identified: digital infrastructure and health information systems; nursing AI literacy and professional agency; data quality, representativeness, and sovereignty; ethical, legal, and regulatory governance; cultural-linguistic localization; and human-AI collaboration within nursing workflows. The synthesis shows that AI risk in LMIC nursing is not reducible to technical error. It emerges from interactions among infrastructure instability, constrained labour conditions, imported or poorly validated models, data asymmetries, weak procurement safeguards, regulatory gaps, and the marginalization of nurses from design and oversight. **Conclusion:** AI implementation in LMIC nursing should be governed as sociotechnical health-system transformation, not technology transfer. Safe adoption requires local validation, nurse participation, data justice, accountable procurement, proportional regulation, cultural-linguistic adaptation, and post-deployment learning governance. **Impact:** The proposed framework offers policymakers, nursing leaders, educators, regulators, developers, funders, and global health partners a practical structure for integrating AI without weakening nursing judgement, patient dignity, or health equity.

Keywords: artificial intelligence; nursing; low- and middle-income countries; global health; sociotechnical systems; AI ethics; implementation science; data justice; health equity

Accepted: April 03, 2026

Published: May 15, 2026

CITATION

Mutabazi P. & Sangwa, S. (2026). *Governing Artificial Intelligence in Nursing Practice in Low- and Middle-Income Countries: A Critical Integrative Review and Nurse-Centred Sociotechnical Framework*. Open Journal of Transformative Education & LifeLong Learning, 2(2). Open Christian Press.

DOI:

[10.65655/openchristianpres.s.2026.118](https://doi.org/10.65655/openchristianpres.s.2026.118)

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1. Introduction

Artificial intelligence has moved rapidly from experimental health informatics into clinical decision support, imaging, triage, remote monitoring, documentation, surveillance, and administrative optimization. In policy and investment discourse, AI is often framed as a corrective to scarcity: a way to extend expertise, accelerate diagnosis, reduce documentation burden, and bring decision support to settings where specialists are scarce. This promise is especially attractive in LMICs, where nurses often serve as the most continuously present health professionals and where the pressures of workforce shortages, rural access barriers, weak referral systems, fragmented data systems, and constrained public budgets are severe.

The nursing workforce context makes this question urgent. WHO describes nurses as the largest occupational group in health and as an indispensable force for achieving universal health coverage, reducing inequities in access, and advancing health-related Sustainable Development Goals (World Health Organization [WHO], 2025a). World Bank data likewise show wide cross-country variation in nurses and midwives per 1,000 population and document how many LMICs remain far below the densities observed in high-income health systems (World Bank, 2026). In such settings, AI could support nurses through early warning scores, triage prompts, medication safety checks, maternal and neonatal risk identification, infectious disease surveillance, remote monitoring, clinical documentation, patient education, and supply-chain forecasting. Yet these benefits cannot be assumed simply because an algorithm performs well in a laboratory, a private tertiary hospital, or a dataset from a high-income country.

This article argues that the barriers to AI implementation in LMIC nursing practice cannot be understood as isolated technical or organizational deficits. Infrastructure instability, limited AI literacy, weak legal and ethical governance, algorithmic bias, cultural-linguistic mismatch, and fragile procurement

systems interact as mutually reinforcing conditions that shape whether AI becomes a tool for nursing empowerment or a mechanism for reproducing inequity. Building on this premise, the article develops a nurse-centred sociotechnical governance framework that links implementation readiness with professional accountability, data justice, cultural responsiveness, and clinical safety. The framework is intended to guide policy formation, nursing education, procurement decisions, regulatory oversight, and responsible clinical implementation in resource-constrained health systems.

The paper makes three contributions. First, it synthesizes implementation barriers and enabling conditions for AI in LMIC nursing through a theoretically explicit sociotechnical lens. Second, it develops a nurse-centred governance framework that integrates infrastructure, workforce, data, regulation, culture, workflow, and clinical accountability. Third, it offers practical implications for nursing education, health ministries, regulators, technology developers, hospital leaders, funders, and international partners. The argument is deliberately critical but not anti-technological. AI may support nurses and patients, but only when it is locally validated, ethically governed, clinically accountable, and designed with the people who must use it.

This manuscript extends prior nurse-centred AI readiness scholarship by shifting the analytic focus from general clinical practice to the distinctive implementation conditions of LMIC health systems. Mutabazi and Sangwa (2026) conceptualized nurse AI readiness as a distributed socio-technical capability shaped by technical reliability, educational preparation, ethical and legal safeguards, professional autonomy, organizational support, and equity-oriented governance. The present review builds on that readiness logic but advances a more context-specific LMIC governance argument: in resource-constrained health systems, safe AI adoption depends not only on whether nurses are prepared to use AI, but also on whether infrastructure, data systems, procurement arrangements, regulatory safeguards, local validation processes, and

cultural-linguistic conditions are capable of supporting accountable nursing practice.

2. Aim and Review Questions

This manuscript aims to synthesize current evidence and policy guidance on the implementation of AI in nursing practice in LMICs and to develop a nurse-centred sociotechnical governance framework. The review was guided by three questions. First, what

barriers and enabling conditions shape the implementation of AI in LMIC nursing practice? Second, how do these barriers interact across infrastructure, workforce, data, governance, cultural-linguistic, and workflow domains? Third, what framework can guide ethically aligned, locally responsive, and clinically accountable AI adoption in LMIC nursing contexts?

Table 1. Population-Concept-Context eligibility logic and analytic questions.

Element	Operational definition	Rationale for inclusion
Population	Nurses, midwives where nursing care overlaps, nurse educators, nursing students, nursing leaders, nursing regulators, nurse-led services, and multidisciplinary contexts in which nurses are expected to use or be affected by AI.	AI in health literature frequently treats nurses as downstream users. A nurse-centred frame is necessary because nurses operationalize clinical workflows, documentation, patient education, surveillance, and relational care.
Concept	AI-enabled or algorithmic tools, including machine learning, predictive analytics, clinical decision support, natural language processing, generative AI, computer vision, robotics, remote monitoring, algorithmic triage, and AI-enabled public health surveillance.	The review addresses implementation and governance rather than one technology class; the relevant risk is the entry of algorithmic systems into nursing work and accountability structures.
Context	LMIC health systems and settings are classified by the World Bank income group, with attention to public-sector facilities, rural and fragile settings, regional variation, and global health partnerships.	AI transferability is strongly context-dependent. LMIC settings differ in infrastructure, data systems, regulation, language ecology, workforce distribution, and procurement power.
Primary question	What barriers and enabling conditions shape AI implementation in LMIC nursing practice?	Maps the evidence base and identifies conditions for safe adoption.
Framework question	How can these barriers be organized into a nurse-centred sociotechnical governance framework?	Moves beyond listing barriers to explaining interaction, accountability, and implementation pathways.

3. Methods

3.1 Design and Reporting Approach

A critical integrative review with framework synthesis was used. This design was selected because the evidence base on AI in LMIC nursing is heterogeneous and includes empirical studies, conceptual papers, technical reports, global policy documents, regulatory guidance, implementation commentaries, and reporting standards. A narrow effectiveness review would be premature because many AI interventions relevant to LMIC nursing are

pilots, imported tools, health-system-level digital initiatives, or policy proposals that have not generated comparable outcome data. The integrative approach allowed synthesis of empirical evidence, normative guidance, and implementation knowledge while retaining critical attention to power, equity, professional accountability, and health-system feasibility.

The reporting approach was informed by scoping review standards and evidence synthesis principles. PRISMA-ScR contains 20 essential reporting items and 2 optional items for scoping reviews and is intended to support transparent mapping of evidence

and identification of knowledge gaps (Tricco et al., 2018). JBI guidance also emphasizes clear eligibility criteria, transparent source identification, data charting, and explicit presentation of evidence characteristics in scoping reviews (Peters et al., 2020). Because this manuscript develops a conceptual governance framework rather than estimating intervention effects, no meta-analysis, pooled effect estimate, or formal risk-of-bias grading was conducted.

3.2 Search Strategy and Source Selection

Sources were identified through a structured, iterative search of peer-reviewed literature, reporting standards, and authoritative policy repositories. Searches combined terms for AI, nursing, LMICs, digital health, governance, algorithmic bias, implementation science, and health equity. Indicative search strings included: ("artificial intelligence" OR "machine learning" OR "clinical decision support" OR algorithm* OR "predictive analytics" OR "generative AI") AND (nurs* OR "nursing practice" OR "nursing education" OR "nurse-led care") AND ("low- and middle-income countries" OR LMIC* OR "global south" OR Africa OR "South Asia" OR "Latin America"). Searches were supplemented by targeted retrieval of WHO, UNESCO, ITU, World Bank, IMF, Oxford Insights, and nursing professional guidance. Priority was given to literature from 2018 to 2026, with older foundational works retained when theoretically necessary.

The review was deliberately inclusive because AI implementation in LMIC nursing is a cross-disciplinary problem. Eligible sources addressed at least one of the following: AI in health care; nursing workforce capacity or professional accountability; digital health readiness; AI ethics and regulation; data quality, bias, or sovereignty; cultural-linguistic localization; AI reporting and validation standards; implementation science; or LMIC health-system constraints. Sources were excluded when they addressed digital health without an AI or algorithmic component, AI without relevance to health or nursing work,

high-income-country examples with no transferability insight, or purely technical model-development papers that did not discuss implementation, clinical workflow, ethics, governance, or equity.

3.3 Data Charting and Synthesis

Data were charted by source type, country or region where applicable, AI function, nursing relevance, implementation barrier, enabling condition, ethical issue, data concern, regulatory implication, and contribution to the emerging framework. Evidence was coded deductively into six domains drawn from sociotechnical systems theory and the existing draft synthesis: infrastructure and digital readiness; nursing workforce capacity; data quality and algorithmic bias; ethics, law, and governance; cultural and linguistic localization; and human-AI collaboration in workflows. Inductive coding was then used to identify cross-domain dependencies, especially the ways in which infrastructure, data, culture, labour conditions, procurement, and regulation interact in LMIC settings.

Sociotechnical systems theory provided the primary analytic lens because AI implementation is not merely the insertion of software into clinical practice. It is an interaction among people, technologies, tasks, organizational routines, data infrastructures, regulation, resources, values, and political economy. Value-sensitive design and nurse-centred AI readiness scholarship were used to examine whether AI tools embed or neglect dignity, autonomy, fairness, privacy, inclusiveness, professional agency, and cultural plurality (Friedman et al., 2006; Mutabazi & Sangwa, 2026). Technology acceptance constructs, especially perceived usefulness, ease of use, trust, and professional autonomy, were used to interpret nurse adoption and resistance (Davis, 1989; Venkatesh et al., 2003). Implementation outcomes such as acceptability, appropriateness, feasibility, fidelity, sustainability, and equity impact were used to translate the synthesis into measurable implementation concerns (Proctor et al., 2011).

3.4 Trustworthiness and Reflexive Safeguards

Several safeguards were used to strengthen analytic trustworthiness. First, the synthesis distinguished empirical evidence, reporting standards, and policy guidance rather than treating all sources as equivalent. Second, the framework was tested against counterexamples: AI tools that may be accurate but unusable, culturally inappropriate, legally ambiguous, or harmful to nursing workflow. Third, the analysis

avoided two common errors: technological determinism, which assumes AI adoption is inevitable and beneficial, and institutional fatalism, which assumes LMIC constraints make responsible AI impossible. Fourth, the framework was made testable through propositions and measurable indicators rather than being presented only as a descriptive diagram.

Table 2. Core source categories and their contribution to the synthesis.

Source category	Examples	Contribution to framework synthesis
Global AI and digital health guidance	WHO AI ethics guidance; WHO regulatory considerations; WHO digital health strategy; WHO LMM guidance; UNESCO Recommendation on AI Ethics.	Defined normative principles for autonomy, safety, transparency, accountability, inclusiveness, sustainability, human rights, and post-deployment governance.
Nursing workforce and professional guidance	WHO State of the World's Nursing; American Nurses Association AI position statement; World Bank nurses and midwives indicator.	Established the workforce rationale for centring nurses and connected AI adoption to education, professional accountability, staffing pressure, and scope of practice.
Nurse-centred AI readiness scholarship	Mutabazi and Sangwa's nurse-centred socio-technical AI readiness framework.	Provided a prior conceptual basis for treating AI readiness as distributed across technical, educational, ethical/legal, professional, organizational, and equity/governance domains, later adapted in this manuscript to LMIC nursing implementation conditions.
AI validation and reporting standards	CONSORT-AI, SPIRIT-AI, DECIDE-AI, FUTURE-AI, and health AI evaluation literature.	Supported claims that clinical AI must be evaluated across development, validation, early deployment, and post-market monitoring, not only model accuracy.
Implementation science and sociotechnical theory	NASSS, implementation outcomes, technology acceptance, value-sensitive design.	Provided analytic categories for adoption, non-adoption, abandonment, feasibility, sustainability, workload, and fit with organizational routines.
Algorithmic bias and data justice literature	Obermeyer et al.; Panch et al.; Vyas et al.; data colonialism and data feminism scholarship.	Grounded analysis of representativeness, bias, data extraction, data sovereignty, and epistemic injustice.
LMIC and global readiness data	ITU Facts and Figures; Oxford Insights Government AI Readiness Index; IMF AI Preparedness Index; World Bank health workforce data.	Supported regional comparison and showed why AI readiness is uneven across infrastructure, human capital, innovation, regulation, and public-sector capacity.

Structured evidence identification and framework synthesis pathway

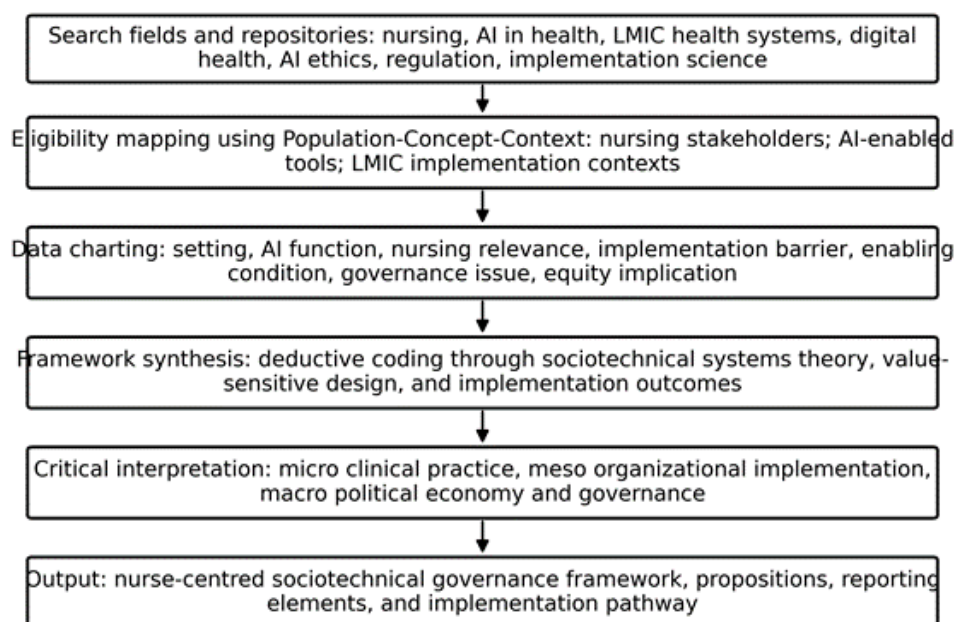


Figure 1. Structured evidence identification and framework synthesis pathway. The pathway summarizes the review logic used to connect source identification, eligibility mapping, data charting, theory-informed coding, critical interpretation, and framework development. Source: Author synthesis informed by PRISMA-ScR and JBI scoping review guidance (Peters et al., 2020; Tricco et al., 2018).

4. Results: Six Interdependent Implementation Domains

4.1 Infrastructure and Digital Public Goods

AI cannot function as a reliable clinical support system where electricity, connectivity, hardware, electronic health records, interoperability, cybersecurity, and maintenance capacity remain unstable. In many LMIC settings, nursing work still depends on paper records, fragmented registers, intermittent power, and uneven internet access. WHO's Global Strategy on Digital Health emphasizes that digital health requires coordinated strategy, governance, investment, human resources, and interoperable infrastructure rather than isolated tools (WHO, 2021a). ITU's 2024 connectivity evidence similarly shows that internet use continues to grow globally, but universality remains elusive, especially in low-income regions and in urban-rural divides (International Telecommunication Union [ITU], 2024).

The clinical significance of infrastructure gaps is often underestimated. AI systems can fail quietly when data are missing, delayed, or entered under pressure. Cloud-based decision support may become unavailable during power or network interruption. Predictive models trained on electronic health record data may be unusable in facilities without reliable digital records. Even when devices are donated, sustainability may fail because budgets do not cover maintenance, software updates, cybersecurity, local language support, or replacement parts. For nurses, this means AI can become an additional burden rather than a support, especially if it requires duplicate documentation or forces clinical judgement into poorly designed digital forms.

The implementation implication is clear: AI readiness must be evaluated as health-system readiness. Ministries and hospital leaders should not procure AI as isolated software. They should assess digital public goods, facility-level infrastructure, data flows, procurement conditions, cybersecurity, human resources, and maintenance arrangements before

deployment. In low-resource settings, offline-capable tools, solar-supported systems, low-bandwidth design, open standards, and integration with existing health information systems may be more appropriate than high-compute, cloud-dependent products.

4.2 Nursing Workforce AI Literacy and Professional Agency

Nurses cannot safely use AI tools they do not understand at a practical level. AI literacy does not require every nurse to become a data scientist, but it does require competence in interpreting algorithmic outputs, recognizing uncertainty, identifying possible bias, questioning recommendations, documenting overrides, and communicating AI-supported decisions to patients. Without this competence, two opposite risks emerge. Nurses may reject useful tools because they distrust opaque systems, or they may over-trust AI outputs because institutional hierarchy and vendor authority make the algorithm appear more objective than clinical judgement.

The workforce challenge must be situated within broader labour realities. The global nursing shortage, maldistribution of nurses, migration pressures, unsafe staffing ratios, and weak professional voice in digital procurement mean that AI may be introduced into environments where nurses are already overburdened. In such conditions, technology marketed as support may function as surveillance or productivity intensification if not governed carefully. AI literacy must therefore include professional agency. Nurses need the authority to question, override, and report problems with AI systems without fear of blame.

Nursing councils, universities, and employers should integrate AI competencies into pre-service curricula, continuing professional development, leadership training, and specialist nursing informatics roles. These competencies should include data ethics, model limitations, bias recognition, explainability, documentation of disagreement, patient communication, cybersecurity, and incident reporting. AI education should not be framed as technological compliance alone; it should prepare nurses to act as

critical clinical interpreters and governance participants.

4.3 Data Quality, Representativeness, and Sovereignty

AI systems inherit the limits of the data from which they learn. In health care, those limits are not merely technical. They are historical, institutional, and political. Many advanced models are developed using datasets from high-income countries, private hospitals, or populations with better access to care. When transferred into LMIC nursing contexts, such systems may misread disease prevalence, comorbidity patterns, skin tone, language, health-seeking behaviour, medication availability, referral pathways, and documentation practices. WHO warns that AI trained on narrow or unrepresentative data can produce biased, unsafe, or inequitable outcomes (WHO, 2021b).

Algorithmic bias is not hypothetical. Obermeyer et al. (2019) demonstrated that a widely used health care algorithm systematically underestimated the needs of Black patients because it used health care costs as a proxy for health need. Vyas et al. (2020) showed that clinical algorithms can encode racial correction in ways that shape diagnosis, referral, and treatment. Panch et al. (2019) argue that algorithmic bias is a health-system problem, not only a model-development problem, because biased data, inequitable access, and institutional routines can reinforce each other. In LMIC nursing, analogous risks arise when imported models encode assumptions about populations, facilities, staffing, language, and care pathways that do not hold in the deployment context.

Data scarcity in LMICs has several causes: weak electronic health record infrastructure, fragmented public and private systems, limited data governance capacity, under-documentation of rural and marginalized groups, and legitimate concerns about privacy and extraction. These weaknesses create a paradox. LMICs are told they need AI to compensate for scarcity, but the AI systems available to them often depend on data infrastructures they do not yet

possess. Worse, global technology partnerships may extract data from LMIC populations without building durable local analytic capacity or returning meaningful benefits. Data sovereignty must therefore be treated as a nursing and public health issue, not only an IT issue.

Responsible AI implementation requires local validation before clinical use. Validation should assess accuracy, calibration, subgroup fairness, usability, explainability, and effect on nursing workflow. It should include nurse participation because nurses can identify mismatches between algorithmic assumptions and bedside realities. Where data sharing is necessary, governance should define consent, de-identification, access, benefit sharing, storage location, secondary use, audit rights, and procedures for withdrawal or community oversight. Federated learning, privacy-preserving analytics, and regional data collaboratives may help, but they are not substitutes for public accountability.

4.4 Ethical, Legal, and Regulatory Governance

AI in nursing raises familiar bioethical questions in unfamiliar forms. Autonomy is implicated when patients do not know AI is influencing care. Beneficence and non-maleficence are implicated when models perform unevenly across populations or degrade under local conditions. Justice is implicated when AI tools benefit urban tertiary facilities while rural clinics remain offline. Accountability is implicated when a nurse follows an AI recommendation that harms a patient, or overrides it and is blamed for not following institutional protocol. Privacy is implicated when clinical data are used to train or improve commercial products.

WHO identifies six ethical principles for AI in health: protecting autonomy; promoting human well-being, safety, and the public interest; ensuring transparency, explainability, and intelligibility; fostering responsibility and accountability; ensuring inclusiveness and equity; and promoting responsive and sustainable AI (WHO, 2021b). WHO's regulatory guidance further emphasizes

documentation, risk management, data quality, validation, transparency, and post-market surveillance across the AI product lifecycle (WHO, 2023). UNESCO's Recommendation on the Ethics of AI, adopted by Member States, emphasizes human rights, dignity, fairness, transparency, human oversight, and the need to include underrepresented contexts in AI ethics and governance (UNESCO, 2021).

For LMIC nursing practice, these principles must be institutionalized. Procurement contracts should require disclosure of model purpose, intended users, training data limitations, validation evidence, cybersecurity measures, update procedures, audit rights, and liability arrangements. Hospitals should establish AI governance committees that include nurses, patients, ethicists, legal experts, informaticians, community representatives, and procurement officers. Regulators should classify AI tools by risk, require contextually relevant validation, and mandate incident reporting. Professional bodies should clarify that AI recommendations do not eliminate the nurse's duty of judgement, while also protecting nurses from being made legally vulnerable for upstream failures in procurement, validation, supervision, or governance.

4.5 Cultural and Linguistic Localization

AI tools are never culturally neutral. They are shaped by the language, data, clinical norms, moral assumptions, and institutional environments in which they are built. In LMIC nursing, cultural and linguistic mismatch is especially consequential because nurses often mediate between biomedical systems and patients' families, communities, beliefs, fears, and local idioms of illness. A chatbot, triage assistant, or patient education system that works in English may fail in Kiswahili, Kinyarwanda, Luganda, Wolof, Hindi, Bengali, Nepali, Quechua, or local dialects. Even accurate translation may not be sufficient if metaphors, symptom descriptions, family decision-making norms, stigma, spiritual beliefs, or gender dynamics are ignored.

Cultural localization is not a decorative final step. It is part of safety. An AI system that cannot recognize

how patients describe pain, fever, pregnancy complications, mental distress, medication use, domestic violence, or neonatal danger signs in local language may generate unsafe advice. A decision support tool built around treatment options unavailable in rural facilities may create false expectations or increase moral distress among nurses. A system that assumes individual consent where family decision-making dominates may undermine trust. Nurses are indispensable in localization because they understand how formal protocols meet lived realities.

A philosophically serious account of AI in nursing must therefore begin with persons-in-context rather than abstract users. Patients and nurses are not endpoints in a digital pipeline. They are moral agents embedded in histories, communities, languages, institutions, vulnerabilities, and forms of practical wisdom. When AI enters nursing practice, it enters this moral field. It must therefore be judged not only by predictive accuracy but also by whether it strengthens or weakens the conditions for humane, equitable, and accountable care.

4.6 Human-AI Collaboration and Nursing

Workflow

The most ethically defensible use of AI in nursing is augmentation, not replacement. Nursing practice is relational, interpretive, embodied, and context-sensitive. It includes surveillance, coordination, advocacy, education, comfort, moral judgement, and presence. AI may support some cognitive and administrative tasks, but it cannot assume the full moral responsibilities of nursing care. The danger is not only that AI may replace nurses. The subtler danger is that AI may reshape nursing around machine-readable tasks, privileging what can be predicted, scored, and audited over what patients actually need.

Responsible human-AI collaboration requires explicit workflow design. Nurses must know when AI is advisory, when it is mandatory, when override is allowed, how disagreement is documented, who

reviews alerts, and how false positives or alert fatigue are managed. AI tools should be evaluated not only for accuracy but also for their effect on workload, communication, documentation time, patient trust, professional judgement, and liability. A tool that is statistically impressive but increases nursing burden, fragments patient interaction, or shifts accountability downward is not a successful implementation.

Reporting standards for clinical AI reinforce this point. SPIRIT-AI, CONSORT-AI, and DECIDE-AI emphasize that AI interventions require transparent reporting of intended use, users, intervention context, human-AI interaction, performance monitoring, and implementation conditions (Liu et al., 2020; Rivera et al., 2020; Vasey et al., 2022). In LMIC nursing, these standards should be extended to include workload effects, local validation, language adaptation, facility readiness, professional override, and patient communication.

Table 3. Implementation domains, risks, and nurse-centred safeguards for AI in LMIC nursing practice.

Domain	Implementation risk	Clinical consequence for nursing	Nurse-centred safeguard
Infrastructure	Unreliable power, connectivity, devices, interoperability, cybersecurity, and maintenance.	AI tools become unavailable, duplicate work, produce delayed recommendations, or fail silently.	Facility readiness assessment; offline-capable tools; open standards; maintenance budget; cybersecurity plan; integration with existing systems.
Workforce capacity	Low AI literacy, limited informatics training, weak professional agency, and unsafe staffing.	Misuse, overreliance, resistance, inability to challenge unsafe outputs, or technology-mediated work intensification.	Curriculum integration; continuing professional development; nurse super-users; protected override rights; professional incident reporting.
Data ecosystem	Incomplete, biased, imported, extractive, or non-representative datasets.	Misclassification, unsafe triage, inequitable recommendations, and loss of trust.	Local validation; representative data; data stewardship; fairness audits; benefit-sharing agreements; audit rights.
Governance	Unclear liability, weak procurement rules, limited regulation, and poor post-market surveillance.	Nurses carry downstream risk for upstream failures in design, procurement, validation, or deployment.	Risk-based regulation; AI governance committees; vendor transparency; incident reporting; post-market monitoring.
Culture and language	Lack of local language support and cultural adaptation.	Miscommunication, low trust, unsafe patient education, exclusion of marginalized groups, and moral distress.	Co-design with nurses and communities; translation plus cultural adaptation; local usability testing; culturally competent patient communication.
Workflow	Poor integration into nursing routines and accountability structures.	Alert fatigue, documentation burden, erosion of judgement, fragmented patient relationship, and unclear responsibility.	Human-AI protocols; override procedures; workload monitoring; participatory implementation; regular review of clinical and equity outcomes.

5. Regional and System-Level Differences

LMICs are not a single implementation environment. Readiness varies by income level, region, political commitment, health system structure, data infrastructure, regulation, language ecology, nursing education capacity, and local AI expertise. Sub-Saharan Africa faces severe infrastructure and workforce pressures in many countries, although countries such as Rwanda, Kenya, Ghana, South Africa, Nigeria, and others have growing digital health and AI policy activity. South Asia includes both highly constrained settings and countries with substantial AI talent, mobile connectivity, and public digital infrastructure, especially India. Latin America has comparatively stronger connectivity and health-system digitization in some middle-income countries, but inequality and fragmented public-private systems remain major concerns. These

differences matter because an AI implementation strategy suitable for a tertiary hospital in São Paulo, Bengaluru, Nairobi, Kigali, or Cape Town may not translate to a rural district clinic without adaptation.

The digital divide is not only about access. It is about quality, reliability, affordability, data governance, cybersecurity, local language support, maintenance, procurement power, and meaningful use. ITU's 2024 connectivity evidence shows continuing global progress in internet use while emphasizing persistent inequalities in low-income settings (ITU, 2024). AI readiness indices evaluate national preparedness across digital infrastructure, human capital, innovation, and regulation and continue to show that lower-income countries face structural disadvantages in the inputs required for safe AI adoption (International Monetary Fund, 2023; Oxford Insights, 2025). Therefore, the ethical question is not whether LMICs should use AI. It is under what conditions AI can be introduced without converting technological dependence into clinical risk.

Table 4. Regional implementation emphasis for AI in LMIC nursing practice.

Region or setting	Readiness pattern	Likely nursing use cases	Primary risks	Strategic priority
Sub-Saharan Africa	Highly uneven infrastructure; growing AI policy interest in some countries; persistent rural digital exclusion.	Maternal risk screening, infectious disease surveillance, triage, community health support, clinical documentation, supply forecasting.	Power/connectivity gaps, imported models, weak regulation, workforce shortages, data extraction, vendor dependency.	Invest in infrastructure, nursing informatics, local validation, regional governance, and data stewardship.
South Asia	Large digital markets and AI talent in some countries; persistent rural and public-sector inequalities; high linguistic diversity.	Decision support, imaging support, language tools, telehealth triage, maternal and neonatal care, chronic disease support.	Urban-rural divide, fragmented public-private provision, language mismatch, uneven accountability.	Scale validated pilots through public systems with equity monitoring and language adaptation.
Latin America	Stronger connectivity in many middle-income countries; health-system fragmentation and social inequality.	Administrative automation, imaging, public health surveillance, chronic disease support, patient communication.	Inequitable access between private and public sectors; data governance variation; proprietary vendor lock-in.	Regulate procurement, interoperability, public-sector deployment, and independent evaluation.
Small states and fragile settings	Limited specialist capacity; dependence on external vendors, donors, or regional partners.	Remote consultation support, triage, outbreak alerts, stock management, referral decision support.	Vendor lock-in, data sovereignty risks, sustainability failures, limited regulatory capacity.	Use open standards, pooled regional expertise, procurement safeguards, and phased implementation.

6. Nurse-Centred Sociotechnical Governance Framework

The synthesis indicates that safe AI implementation in LMIC nursing requires a framework that connects ethical commitments with practical implementation conditions. Figure 2 presents a nurse-centred sociotechnical governance framework. The framework places safe, equitable, nurse-centred AI use at the centre, surrounded by clinical workflow, human oversight, professional judgement, data justice, infrastructure, AI literacy, localization, regulation, procurement, sovereignty, sustainability, and accountability. These domains are not sequential stages. They are mutually dependent conditions. Weak infrastructure compromises data quality. Weak data governance undermines trust. Poor localization reduces usability. Limited AI literacy weakens human oversight. Unclear liability makes nurses vulnerable.

Defective workflow integration converts AI from support into burden.

The framework also adapts and extends the recent general nurse AI readiness model (Mutabazi and Sangwa, 2026). Whereas that earlier model organized readiness around technical, educational, ethical/legal, professional, organizational, and equity/governance domains, the present framework specifies how readiness must be reconfigured for LMIC nursing contexts, where infrastructure instability, externally developed models, data sovereignty concerns, weak procurement safeguards, regulatory gaps, cultural-linguistic plurality, and public-sector resource constraints shape whether AI can be used safely and justly.

Nurse-centred sociotechnical governance framework for AI in LMIC nursing

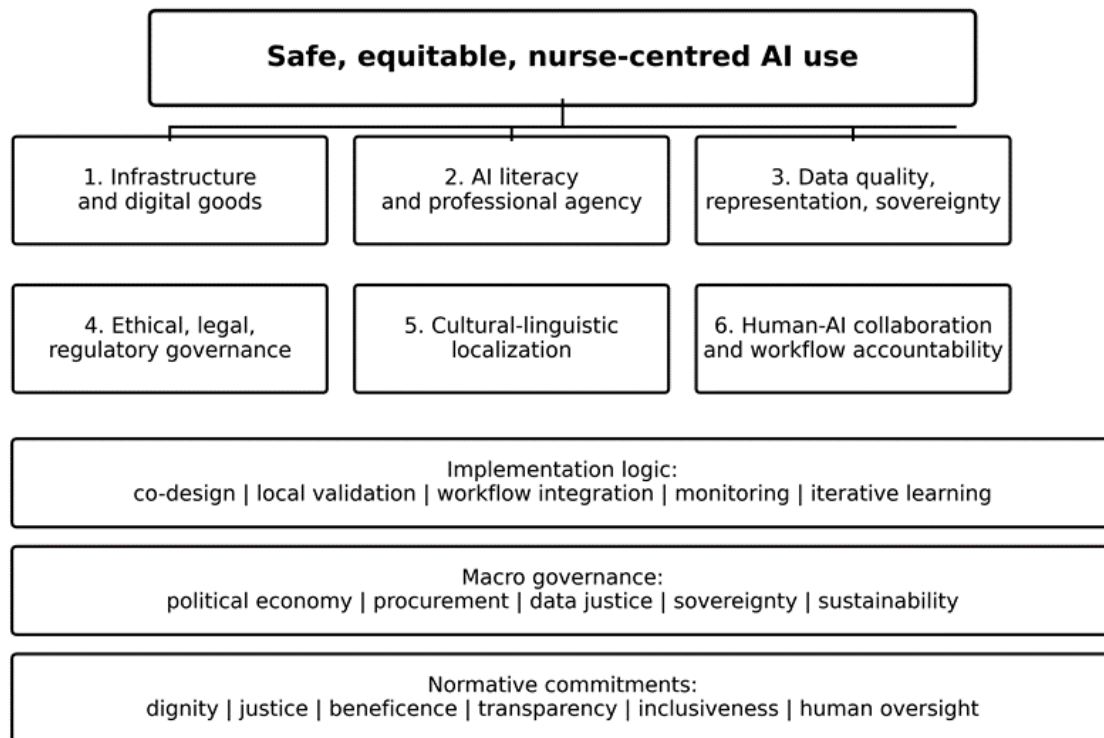


Figure 2. Nurse-centred sociotechnical governance framework for AI in LMIC nursing practice. The framework synthesizes sociotechnical systems theory, value-sensitive design, implementation outcomes, and global AI ethics guidance to identify conditions required for safe, equitable, and clinically accountable implementation. Source: Author synthesis adapted and extended from Mutabazi and Sangwa's (2026) nurse-centred AI readiness framework, with additional grounding in UNESCO (2021), WHO (2021a, 2021b, 2023, 2025a), and implementation science literature.

6.1 Framework Propositions

For a framework to contribute to Q1-level scholarship, it must do more than organize concepts. It should generate propositions that can be tested,

refined, or challenged through empirical implementation research. The propositions below translate the synthesis into researchable claims and policy-relevant indicators.

Table 5. Framework propositions and measurable indicators for future research.

Proposition	Rationale	Possible indicators
P1. AI tools deployed in LMIC nursing contexts without local validation are more likely to produce unsafe, inequitable, or unusable recommendations.	Algorithmic performance depends on data distribution, disease prevalence, language, facility resources, and workflow fit.	Calibration, subgroup performance, local validation accuracy, clinical override rates, adverse recommendation reports.
P2. Nurse participation in needs assessment, procurement, workflow design, and monitoring increases acceptability and reduces unsafe use.	Nurses understand documentation burden, patient communication, practical constraints, and moral consequences of AI-supported care.	Nurse involvement in governance committees, usability scores, acceptance, workload, override documentation, incident reporting quality.
P3. Infrastructure instability mediates the relationship between model performance and clinical usefulness.	A high-performing model may fail when electricity, connectivity, devices, records, or maintenance are unreliable.	Downtime, delayed alerts, incomplete data, duplicate documentation, network dependency, maintenance response time.

P4. Cultural-linguistic localization moderates patient trust and nurse adoption.	Language and cultural fit affect comprehension, acceptability, patient disclosure, and safe interpretation of recommendations.	Language coverage, patient comprehension, trust scores, cultural usability testing, error reports related to translation or communication.
P5. Clear liability, audit, and incident-reporting mechanisms reduce inappropriate risk transfer to frontline nurses.	Nurses should not carry legal or moral responsibility for upstream failures in design, procurement, validation, or system governance.	Defined accountability protocols, incident reports, audit logs, vendor obligations, governance review frequency.
P6. Post-deployment learning governance is essential because AI performance and workflow effects change over time.	Clinical data drift, model updates, staffing changes, policy shifts, and patient behaviour can alter safety and effectiveness.	Model drift metrics, periodic fairness audits, workload trends, user feedback cycles, adverse event review, retraining decisions.

Responsible implementation pathway from need assessment to learning governance

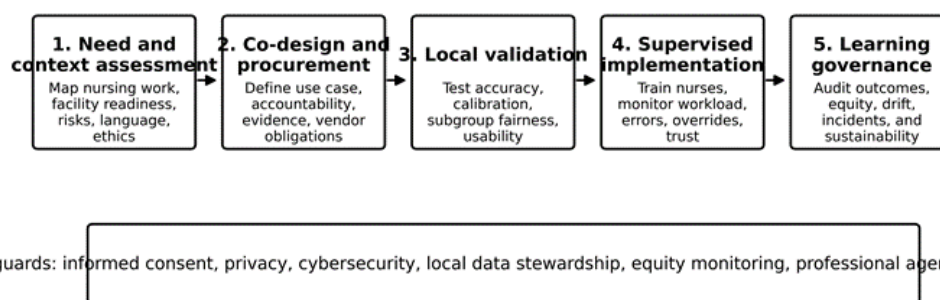


Figure 3. Responsible implementation pathway from pilot to scale. This pathway operationalizes the framework by converting ethical and sociotechnical requirements into staged implementation decisions. Source: Author synthesis based on WHO regulatory considerations and digital health implementation guidance (WHO, 2021a, 2023).

7. Discussion

7.1 From Technology Transfer to Health-System Transformation

The dominant risk in AI implementation is not that LMICs will be excluded from AI altogether, although exclusion remains serious. A deeper risk is that LMIC health systems will be included on unequal terms: as markets for imported products, sites for pilot projects, or sources of under-governed data, without sufficient investment in local capacity, nursing leadership, public accountability, and durable infrastructure. This pattern would reproduce the logic of technology transfer without health-system transformation. AI would then become another layer of dependency rather than a means of professional empowerment or patient benefit.

A sociotechnical perspective clarifies why narrow pilot success can be misleading. A model may perform well in a short study yet fail when scaled into facilities with different staffing patterns, languages, disease profiles, documentation practices, drug formularies, referral pathways, and accountability structures. Similarly, a tool may reduce one task while increasing total workload through alerts, data entry, troubleshooting, or patient explanation. For nurses, the central question is not whether AI is innovative, but whether it is usable, safe, just, and clinically meaningful within actual care conditions.

7.2 The Hidden Political Economy of AI in Nursing

AI in LMIC nursing must also be examined through political economy. Data, compute, software ownership, cloud infrastructure, regulatory expertise, and procurement power are unequally distributed.

Many LMIC institutions lack bargaining power when negotiating with multinational vendors or donor-funded technology initiatives. Procurement may prioritize novelty over need, and evaluation may emphasize adoption metrics over patient outcomes, nursing workload, equity, or sustainability. If not corrected, these dynamics can produce a form of digital dependency in which LMIC nurses become users of systems they did not design, cannot audit, and cannot meaningfully contest.

This is why data justice and procurement governance belong in nursing scholarship. Couldry and Mejias (2019) describe data colonialism as a political economy of extraction, while D'Ignazio and Klein (2020) emphasize that data systems embed power relations and can reproduce inequity unless designed and governed with justice in view. In nursing, these concerns become immediate and practical. Nurses operationalize AI at the bedside, absorb patient questions, manage errors, and reconcile algorithmic outputs with clinical realities. Yet nurses are often absent from AI design, procurement, and regulatory decision-making. A Q1-level nursing contribution must therefore insist that nurses are not merely end-users. They are epistemic contributors who understand care work, patient context, and the practical consequences of automation.

7.3 Ethical Tension: Non-Adoption Can Also Be Harmful

A critical position should not romanticize manual systems or treat technological caution as sufficient ethics. In settings where preventable morbidity and mortality remain high, refusing useful AI because of imperfect conditions may also be ethically problematic. If validated decision support can help detect postpartum haemorrhage risk, sepsis deterioration, medication interactions, tuberculosis, diabetic retinopathy, hypertensive emergencies, neonatal danger signs, or stock-out risks, then non-adoption may preserve avoidable harm. The ethical task is therefore not to choose between adoption and rejection. It is to define the conditions

under which adoption is justified, accountable, and equity-enhancing.

This balanced stance is important for policy. Overregulation can freeze innovation in health systems that need support. Underregulation can expose vulnerable patients and nurses to unsafe tools. The governance goal should be proportionate regulation: higher-risk AI tools require stronger evidence, local validation, explainability, human oversight, incident reporting, and post-deployment monitoring, while lower-risk administrative tools may require lighter but still meaningful safeguards. The central principle is not maximal regulation, but accountable fit between risk, evidence, context, and use.

7.4 Contribution to Nursing Science and Implementation Science

This review contributes to nursing science by reframing AI implementation as a matter of professional judgement, relational care, data justice, and governance rather than only digital modernization. This contribution builds on prior work that framed nurse AI readiness as a distributed professional capability rather than a simple function of individual willingness, digital competence, or exposure to AI tools (Mutabazi & Sangwa, 2026). It also contributes to implementation science by identifying LMIC nursing as a setting in which adoption outcomes cannot be separated from infrastructure, political economy, cultural-linguistic fit, and procurement accountability. The NASSS framework reminds researchers that non-adoption, abandonment, and challenges to scale-up, spread, and sustainability are predictable when technologies are complex, organizations are unready, user work is disrupted, or wider systems are unstable (Greenhalgh et al., 2017). The framework developed here extends that insight by centring nursing practice and LMIC implementation realities.

8. Implications for Policy, Practice, Education, Development, and Research

8.1 Health Ministries and Regulators

Health ministries and regulators should develop risk-based AI governance for health care that explicitly includes nursing. Policies should define AI categories, validation requirements, data protection expectations, liability arrangements, procurement standards, and post-market surveillance. AI tools should not be deployed in public facilities solely on the basis of vendor claims or high-income-country validation. Minimum action set: establish a national or regional health AI governance body; require contextually relevant validation for higher-risk tools; mandate procurement transparency and audit rights; define incident-reporting pathways; and align AI policy with nursing workforce strategy.

8.2 Nursing Councils, Professional Bodies, and Educators

Nursing councils and educators should define AI competency standards, integrate AI ethics into licensure and continuing professional development, and clarify the scope of professional accountability in AI-supported care. Nursing curricula in LMICs should include AI literacy, data ethics, digital documentation, interpretation of algorithmic outputs, bias recognition, patient communication about AI, cybersecurity basics, and human-AI collaboration. Advanced nursing informatics pathways should prepare nurse leaders who can participate in procurement, evaluation, policy, and research.

8.3 Hospitals and Nursing Leadership

Nursing leaders should ensure that AI implementation is tied to real clinical needs rather than institutional fascination with digital transformation. Nurse participation should be required in needs assessment, workflow redesign, training, pilot evaluation, governance committees, and post-deployment review. Implementation should protect nurses' right to understand, question, and override AI outputs. Incident reporting systems should distinguish individual misuse from system-level design, procurement, staffing, or governance failures.

8.4 Developers and Vendors

Developers should treat LMIC settings as design contexts, not merely deployment markets. This requires participatory design with nurses and patients, local language support, transparent documentation, low-resource usability testing, offline or low-bandwidth functionality where needed, and disclosure of model limitations. Vendors should provide model cards, dataset documentation, validation evidence, cybersecurity documentation, update procedures, audit rights, and clear allocation of responsibilities for incidents and performance drift.

8.5 Funders and International Partners

Funders and international partners should avoid pilot-driven AI projects that demonstrate novelty without building local capacity. Investment should support digital public goods, nursing informatics education, local validation studies, regional data stewardship, policy capacity, and independent evaluation. Partnerships should include benefit-sharing agreements and protect LMIC institutions from extractive data arrangements or vendor lock-in.

8.6 Future Research

Future research should move beyond general attitudes toward AI and examine clinical safety, workload effects, patient trust, cost-effectiveness, equity outcomes, professional judgement, and implementation sustainability. Studies should include rural and public-sector facilities, not only urban tertiary centres. More LMIC-led and nurse-led research is needed, including local validation studies, comparative policy analyses, implementation trials, and evaluations of AI literacy interventions. Journals and funders should prioritize studies that build local analytic capacity rather than merely extracting data.

Table 6. Minimum reporting elements for AI implementation studies in LMIC nursing contexts.

Reporting element	Why it matters	Expected detail
Context	AI performance depends on setting.	Country income category, facility type, infrastructure, staffing, language, patient population, digital maturity, and care pathway.
Use case	Prevents vague AI claims.	Clinical or administrative task, intended user, workflow location, decision authority, risk category, and human oversight model.
Data provenance	Determines bias and transferability.	Training data source, local validation data, missingness, representativeness, de-identification, governance approvals, and benefit-sharing terms.
Model evidence	Supports safety and accountability.	Performance metrics, calibration, subgroup analysis, limitations, update plans, explainability, and drift monitoring.
Nursing workflow effects	Measures real-world usefulness.	Workload, documentation time, alert fatigue, trust, override patterns, patient communication, moral distress, and professional accountability.
Equity and ethics	Addresses justice, privacy, and agency.	Consent, privacy, cybersecurity, cultural adaptation, language support, human oversight, adverse event reporting, and equity monitoring.
Sustainability	Prevents failed pilots.	Costs, maintenance, training, procurement terms, local ownership, support model, replacement plan, and scale-up criteria.

9. Limitations

This manuscript is a critical integrative review and framework synthesis. Although the reporting approach was informed by scoping review standards, the review does not estimate prevalence of barriers, conduct meta-analysis, or claim comprehensive retrieval of every relevant source across subscription databases. The evidence base remains uneven, with more literature on AI in health generally than on AI in nursing practice specifically, and more data from middle-income and urban settings than from low-income, rural, and fragile health systems. This unevenness is itself a substantive finding: nursing remains under-centred in much of the AI-in-health literature.

The pace of AI development also means that regulatory and technological conditions are changing rapidly. New foundation models, local language tools, national AI strategies, and health AI regulations may alter implementation conditions. The framework should therefore be treated as a living analytic structure, open to empirical testing and revision. Despite these limitations, the synthesis draws on authoritative global guidance, implementation science, nursing workforce evidence, AI reporting standards, and current policy data to develop a framework that can guide empirical testing, policy

design, procurement, education, and implementation research.

10. Conclusion

AI may become a valuable ally for nurses in LMICs, but only if it is implemented under conditions that respect nursing judgement, patient dignity, local knowledge, cultural plurality, and health-system realities. The strongest argument for AI in LMIC nursing is not technological enthusiasm. It is the possibility of using carefully governed tools to extend care, reduce preventable harm, support overburdened nurses, and strengthen public health systems. The strongest argument against careless AI implementation is equally clear: imported, opaque, poorly validated, culturally mismatched, weakly regulated, and vendor-controlled systems can deepen inequity while shifting risk onto nurses and patients.

The path forward is neither uncritical adoption nor defensive rejection. It is nurse-centred sociotechnical governance: co-design, local validation, accountable regulation, transparent procurement, data justice, culturally responsive implementation, professional agency, and continuous monitoring. Under those conditions, AI can support nursing practice without displacing the human judgement, compassion, and relational accountability at the heart of care.

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Appendix A. Reproducible Search Strings for Database Replication

The following sample strings can be adapted for PubMed/MEDLINE, CINAHL, Scopus, Web of Science, Embase, IEEE Xplore, ACM Digital Library, Global Index Medicus, and Google Scholar.

Journal-specific syntax should be adjusted by the submitting author or information specialist.

Core search: ("artificial intelligence" OR "machine learning" OR "clinical decision support" OR algorithm* OR "predictive analytics" OR "generative AI" OR "natural language processing" OR "computer vision") AND (nurs* OR "nursing practice" OR "nursing education" OR "nurse-led care" OR midwi*) AND ("low- and middle-income countries" OR LMIC* OR "global south" OR Africa OR "South Asia" OR "Latin America" OR "resource-limited").

Governance search: (AI OR "artificial intelligence" OR algorithm*) AND (health* OR clinical OR

nursing) AND (ethic* OR govern* OR regulat* OR liability OR privacy OR accountability OR bias OR fairness OR "data sovereignty").

Implementation search: (AI OR "artificial intelligence" OR "machine learning") AND (implementation OR adoption OR feasibility OR acceptability OR workflow OR scale-up OR sustainability) AND (nurs* OR clinician*) AND (LMIC* OR "low-income" OR "middle-income" OR rural OR public sector).

Appendix B. PRISMA-ScR-Informed Reporting Alignment

Appendix Table B1. *Alignment with selected PRISMA-ScR reporting expectations.*

Reporting item	Where addressed	Notes
Title and abstract	Title page and Abstract	The abstract identifies design, aim, synthesis approach, major findings, and framework contribution.
Rationale and objectives	Sections 1 and 2	The rationale centres LMIC nursing as a neglected implementation and governance context.
Eligibility criteria	Sections 2 and 3.2; Table 1	Population-Concept-Context logic is used to define inclusion boundaries.
Information sources and search	Sections 3.2 and Appendix A	The strategy is transparent and reproducible; full database counts should be added if the authors conduct a registered formal scoping review.
Data charting and synthesis	Sections 3.3 and 3.4; Table 2	Charting categories and analytic domains are stated explicitly.
Characteristics of sources	Table 2	Sources are characterized by evidence category and contribution to synthesis.
Synthesis of results	Sections 4-8; Tables 3-6; Figures 1-3	Results are synthesized into domains, regional considerations, framework propositions, and implementation implications.
Limitations and conclusions	Sections 9 and 10	The manuscript is transparent about the limits of a critical integrative review and does not claim meta-analytic inference.

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