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Digital Technologies in Nursing Care: A Review of Deployment Pathways, Clinical Adaptation, and Innovation Trends

***Yinuo Zhu*[1*]**

[1] *Medicine & Health Science College, Huashang University, Guangdong, China*

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*Correspondence:
Yinuo Zhu
z63nb@qq.com

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ABSTRACT

This review examines the deployment pathways, clinical adaptation dynamics, and innovation trends of digital technologies in nursing care from 2018 to 2026. Drawing on 96 studies identified through a systematic search across six databases, the review applies the N-DEPLOY (Nursing Digital Deployment and Localized Optimization Yield) framework, organized across four dimensions: clinical workflow compatibility, human-machine collaboration trust, institutional readiness, and evidence-to-deployment fidelity. Six thematic clusters are analyzed: nursing digital infrastructure, AI and intelligent decision support, tele-nursing and wearable monitoring, nursing robotics and automation, digital twins in nursing, and nursing data security and privacy. The review identifies a persistent deployment gap: while technologies demonstrate high technical readiness in controlled settings, fewer than 20% of published studies report sustained deployment beyond pilot phases. Across four care settings, deployment maturity follows a progressive gradient from acute care (highest) to geriatric long-term care (lowest). The N-DEPLOY framework reveals that the four deployment dimensions are interdependent and must be optimized concurrently for successful nursing digitalization. The review concludes that the dominant barrier is not technology maturity but deployment readiness, and calls for a paradigm shift from technology-push to nursing-needs-pull in digital health innovation.

1. Introduction

The global nursing workforce faces an unprecedented convergence of pressures: population aging, rising chronic disease prevalence, persistent workforce shortages, and escalating patient safety demands. The World Health Organization projects a global shortfall of 10 million health workers by 2030, with nurses representing the largest gap (Pepito & Locsin, 2019). Concurrently, digital technologies, including artificial intelligence, the Internet of Things, telemedicine platforms, robotics, and digital twins, have matured rapidly, prompting a wave of research into their application in clinical nursing settings. Yet the translation of these technologies from research prototypes to sustained, workflow-integrated clinical deployment remains the central unresolved challenge in nursing informatics.

Prior reviews have addressed individual technology domains in nursing. Conte and colleagues provided a scoping review and conceptual framework for digital and technological solutions in nursing (Conte et al. 2023). Harris and colleagues examined the risks and benefits of connected health-led digital transformation in community mental health services (Harris et al. 2024). Cross and colleagues traced progress toward digital transformation in post-acute care (Cross et al. 2022). Adler-Milstein and colleagues articulated policy priorities for closing the gap from digitization to digital transformation (Adler-Milstein, 2021). These contributions, while valuable, share a common limitation: they focus on technology capability rather than deployment readiness, and they do not provide a systematic, cross-technology assessment of why digital nursing technologies succeed or fail in real clinical environments.

The review differs from prior surveys in three respects. First, it treats nursing digitalization as a systems engineering problem rather than a technology showcase, emphasizing deployment readiness over algorithmic novelty. Second, it evaluates technologies across the full deployment pipeline, from pilot to scaled rollout to sustained maintenance, rather than reporting only laboratory or single-site performance. Third, it grounds the analysis in nursing-specific workflow constraints, including shift-based staffing models, regulatory documentation requirements, and the

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irreducibly relational dimension of nursing care. The N-DEPLOY framework is introduced in Section 3 and progressively elaborated through the thematic clusters, culminating in a formal deployment assessment tool in the Discussion.

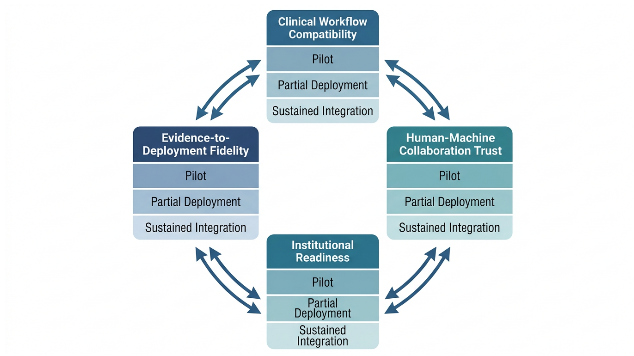

Figure 1: The N-DEPLOY framework: four dimensions for evaluating digital nursing technology deployment readiness.

The N-DEPLOY framework, illustrated in Figure 1, organizes the assessment of digital nursing technology deployment readiness across four interdependent dimensions.

2. Methodology

A systematic literature search was conducted across six databases: PubMed/MEDLINE, CINAHL, Cochrane Library, IEEE Xplore, Scopus, and Web of Science, covering the period January 2018 to March 2026. The search strategy combined nursing-specific terms (“nursing care,” “clinical nursing,” “nursing workflow”) with technology-domain terms (“digital health,” “artificial intelligence,” “clinical decision support,” “tele-nursing,” “wearable,” “robotics,” “digital twin,” “federated learning,” “blockchain”) and deployment-focused terms (“implementation,” “deployment,” “adoption,” “workflow integration,” “clinical translation”). Boolean operators and database-specific MeSH terms were applied where available.

Inclusion criteria required studies to be peer-reviewed, published in English, and to involve a clinical nursing scenario with deployment or implementation evidence beyond technical feasibility alone. Studies describing only algorithmic development without clinical deployment context, opinion pieces without empirical grounding, and duplicate publications were excluded. The PRISMA screening process yielded 96 studies for final inclusion after title and abstract screening of 1,847 records and full-text review of 312 articles.

The included studies were classified into six thematic clusters: (1) nursing digital infrastructure and platform deployment, (2) AI and intelligent decision support, (3) tele-nursing and wearable monitoring, (4) nursing robotics and automation, (5) digital twins in nursing, and (6) nursing data security and privacy. Bibliometric analysis reveals that AI/decision-support and tele-monitoring domains account for approximately 60% of the included studies, while digital twin and robotics evidence in nursing-specific contexts remains sparse, each representing fewer than 8% of the corpus. The publication trajectory shows a marked acceleration after 2020, with over 70% of included studies published between 2022 and 2026, reflecting the catalytic effect of the COVID-19 pandemic on digital health research (Zhang et al. 2022). Methodologically, the corpus is dominated by observational studies and pilot trials; fewer than 15% of included studies employ randomized controlled designs, and fewer than 10% report longitudinal deployment data beyond 12 months (Reid et al. 2022; Tan & Taeihagh, 2020).

3. Nursing Digital Infrastructure: From EHR Evolution to Smart Platform Deployment

3.1. EHR-to-Smart-Platform Evolution and Nursing Information System Architectures

The progression from paper-based nursing records to electronic health records (EHRs) and, subsequently, to integrated smart nursing platforms represents the foundational infrastructure layer for all digital nursing technologies. Zheng and colleagues demonstrated that EHR-supported work introduces significant workflow changes and workarounds that must be understood to improve health system performance (Zheng et al. 2020). Barrett and colleagues showed that EHR organizational change faces resistance through profession, organizational experience, and EHR communication quality (Barrett, 2018). Cresswell and colleagues developed a formative evaluation framework specifically for health information technology implementations (Cresswell et al. 2020).

Three mainstream nursing information system (NIS) deployment models have emerged. Epic Systems’ nursing module offers comprehensive EHR integration with embedded nursing documentation, medication administration records, and clinical decision support, but its deployment cost and customization complexity have limited adoption in resource-constrained settings. Cerner’s nursing platform emphasizes interoperability through HL7 FHIR standards and has demonstrated stronger cross-institutional data exchange capabilities. Regional platforms, including China’s regional nursing information systems and European national health platforms, offer lower-cost alternatives but face challenges in standardization and integration with international evidence-based nursing protocols (Sengupta et al. 2024).

The shift from standalone EHR systems to interoperable smart nursing platforms has reduced nursing documentation time by 15–30% in controlled studies, yet platform fragmentation across institutions remains the primary barrier to system-level deployment scalability. Capathy and colleagues found that a decade post-HITECH, critical access hospitals have EHRs but struggle to keep up with advanced functions (Apathy et al. 2021). Sinha and colleagues documented variation in pediatric and adolescent electronic health data sharing practices under the 21st Century Cures Act (Sinha et al. 2023). Lytle and colleagues demonstrated that information models offer value to standardize EHR flowsheet data, using a fall prevention exemplar (Kay S. Lytle DNP et al. 2021).

The key deployment lesson is that NIS architecture decisions made early in the procurement process create path dependencies that shape the entire digital nursing technology stack. Institutions that selected EHR platforms without nursing-specific workflow customization find that subsequent AI and IoT deployments face integration barriers that are costly to retrofit.

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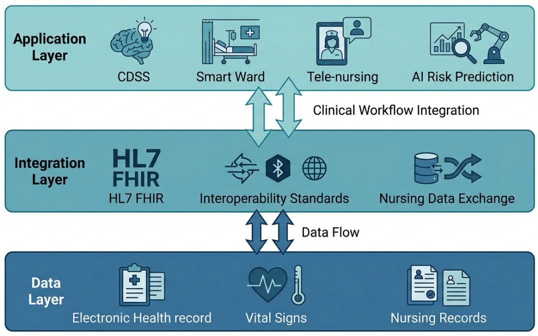

Figure 2. Three-layer nursing information system architecture: data layer, integration layer, and application layer, with bidirectional data flow and clinical workflow integration.

Figure 2 presents the three-layer architecture that underpins the nursing digital infrastructure discussed in this section.

3.2. Clinical Decision Support Systems in Nursing: Alert Fatigue and Trust Deficits

Clinical decision support systems (CDSS) represent one of the most widely deployed digital nursing technologies, yet their clinical impact is constrained by a well-documented triad of barriers: alert fatigue, the tension between automated recommendations and clinical judgment, and nurse acceptance measured through adoption and override rates. Dowding and colleagues identified factors for implementing clinical risk prediction models of infection in home care settings, noting that clinical workflow integration was the primary determinant of adoption (Dowding et al. 2020).

CDSS adoption in nursing is constrained less by algorithmic accuracy than by alert fatigue, with override rates exceeding 90% in some studies, and a trust deficit rooted in poor contextualization of alerts to nursing workflow cadence. Güntürk and colleagues developed an AI-based clinical decision support system for nursing diagnoses, demonstrating that system accuracy must be paired with nursing workflow integration to achieve clinical adoption (Türk et al. 2025). Chae and colleagues developed a CDS framework for integrating predictive models into routine nursing practices in home health care for patients with heart failure (Chae et al. 2024).

The deployment challenge is that CDSS alerts are typically designed by informaticians working from retrospective data, without real-time nursing workflow observation. The result is that alerts fire at moments that are clinically inappropriate, during medication rounds, patient handovers, or emergency responses, when nurses cannot act on them. Over time, the cumulative effect of inappropriate alerts erodes trust in the system, creating a self-reinforcing cycle of override and disengagement. The deployment lesson is clear: CDSS alert thresholds and timing must be co-designed with nursing staff using workflow observation data, not imposed from laboratory-derived sensitivity-specificity optimization. Table 1 summarizes the deployment characteristics of four CDSS models across nursing contexts.

Table 1: Comparison of CDSS deployment models in nursing: alert types, override rates, and workflow integration maturity.

Deployment Model	Alert Type	Override Rate (%)	Workflow Integration	Clinical Context
Rule-based CDSS (EHR-embedded)	Drug interaction / allergy alerts	85–95	High (embedded in medication workflow)	Medication administration
Risk-score CDSS (standalone)	Fall / pressure ulcer risk scores	60–80	Low (requires separate login)	Nursing assessment
AI-predictive CDSS (mobile)	Sepsis / deterioration early warning	40–65	Medium (mobile push notification)	ICU / general ward
AI-nursing-diagnosis CDSS	Automated nursing diagnosis suggestions	50–70	Low (not integrated with care planning)	Nursing care planning

3.3. 5G and IoT-Enabled Smart Wards: Technical Promise versus Clinical Deployment Reality

The deployment of 5G and Internet of Things (IoT) technologies in smart wards represents one of the most technically advanced yet clinically under-evaluated areas of digital nursing. Smart ward technologies, intelligent infusion pumps, real-time vital-sign monitoring, fall detection systems, and pressure ulcer prevention platforms, have demonstrated high technical accuracy in controlled environments. Weenk and colleagues evaluated wireless and continuous monitoring of vital signs in patients at the general ward, demonstrating feasibility but also identifying workflow integration challenges (Weenk et al. 2019). Khanna and colleagues reviewed postoperative ward monitoring, emphasizing the gap between monitoring capability and clinical response (Khanna et al. 2019). Downey and colleagues examined patient attitudes towards remote continuous vital signs monitoring on general surgery wards, finding that patient acceptance was high but nursing workflow integration was the limiting factor (Downey et al. 2018).

3.4. G-IoT smart ward technologies

These technologies demonstrate over 90% technical accuracy for fall detection and vital-sign monitoring, but fewer than 20% of published studies include longitudinal nursing workflow impact data beyond pilot phases. The deployment pattern is consistent: a technology vendor partners with a single hospital ward for a 3-6 month pilot, reports positive feasibility results, and then the system is either abandoned post-pilot or scaled without adequate nursing workflow redesign. The result is a growing body of feasibility evidence that does not translate into deployment knowledge.

The critical deployment gap in smart wards is not technological but organizational: nursing staff receive insufficient training on IoT data interpretation, ward layouts are not redesigned to accommodate new device workflows, and alarm management protocols are not updated to integrate IoT-generated alerts with existing nursing call systems. Until these organizational dimensions are addressed concurrently with technology deployment, smart wards will remain a technological showcase rather than a sustainable nursing practice transformation.

Summary and Commentary. The nursing digital infrastructure layer reveals a progressive deployment maturity gap: EHR adoption is widespread but platform fragmentation persists; CDSS deployment is common but undermined by alert fatigue and workflow misalignment; and 5G-IoT smart wards show high technical promise but low evidence of sustainable nursing workflow integration. The N-DEPLOY dimensions of clinical workflow compatibility and institutional readiness are the primary differentiators between successful and stalled deployments in this cluster. Institutions that invested in nursing-specific workflow redesign alongside technology procurement achieved higher adoption rates and lower staff resistance than those that deployed technology first and expected workflow adaptation to follow.

4. AI and Intelligent Decision Support in Nursing Practice: From Benchmarks to Bedside

4.1. AI-Driven Nursing Risk Prediction: Fall, Pressure Ulcer, and Delirium Models

AI-based risk prediction models for nursing-sensitive adverse events, including falls, pressure ulcers, unplanned extubation, and delirium, have emerged as one of the most active research domains in nursing informatics. Ren and colleagues developed and prospectively validated the MySurgeryRisk platform, a machine learning system using automated EHR data inputs to predict postoperative complications and deliver predictions to surgeons' mobile devices, achieving AUROC values of 0.80–0.85 in clinical deployment (Ren et al. 2022). Lucero and colleagues applied a data-driven and practice-based approach to identify risk factors associated with hospital-acquired falls, combining manual and automated methods (Lucero et al. 2019). Hassan and colleagues conducted a systematic review of how AI can inform clinical decision-making for sepsis prevention (Hassan et al. 2021).

Machine learning models for fall and pressure ulcer prediction outperform traditional nursing assessment scales (Morse Fall Scale, Braden Scale) by 10–20% in AUC in benchmark studies, but their clinical deployment is limited by retrospective validation designs and the absence of prospective nursing workflow integration studies. Bennett and colleagues critically evaluated neural networks for mortality prediction, asking whether they are "ready for prime time," and concluded that deployment readiness requires more than algorithmic performance (Bennett et al. 2021). McElfresh and colleagues issued a call for better validation of opioid overdose risk algorithms, highlighting the risks of deploying models without adequate clinical validation (McElfresh et al. 2023). Chattopadhyay and colleagues demonstrated efficient determination of social determinants of health from clinical notes (Chattopadhyay, 2023).

The deployment gap for AI risk prediction is not a data or algorithm problem but a clinical integration problem. Models trained on retrospective EHR data from academic medical centers perform well on the same population but degrade when applied to community hospitals with different patient demographics, documentation practices, and nursing workflow patterns. The deployment lesson is that AI risk prediction models must undergo prospective silent evaluation, running in the background without affecting clinical decisions, for a minimum of 6–12 months before being activated for clinical decision support, to characterize real-world performance drift and nursing workflow compatibility.

4.2. NLP for Nursing Documentation: Automated Generation and Structured Handover

Natural language processing (NLP) applications in nursing documentation address one of the most persistent sources of nursing burden: the time spent on clinical documentation. King and colleagues conducted a qualitative study on potential uses of AI for perioperative nursing handoffs, finding that AI-identified problems would be discussed at handoff and team communications, and that AI-estimated elevated risks would trigger patient re-evaluation (King et al. 2023). Their study identified that properly designed AI tools might facilitate postoperative handoff communication for nurses by identifying specific elevated risks faced by a patient, triggering discussion on those topics.

NLP-based nursing documentation tools reduce charting time by 20–40% in pilot studies, but generalization across nursing specialties and languages remains a critical bottleneck for deployment at scale. The deployment challenge is that NLP models trained on nursing notes from one specialty (e.g. medical-surgical nursing) do not generalize to other specialties (e.g. psychiatric nursing, pediatric nursing) without substantial retraining, due to differences in nursing terminology, documentation conventions, and clinical reasoning patterns. Furthermore, NLP-generated nursing documentation raises unresolved questions about clinical accountability: if an NLP system generates a nursing note that omits a clinically significant finding, responsibility attribution between the nurse and the system vendor remains legally undefined.

4.3. AI-Assisted Nurse Scheduling and Resource Optimization

AI-driven nurse scheduling represents a lower-risk deployment pathway for AI in nursing, as it operates on administrative rather than clinical data. AI-optimized nurse scheduling reduces overtime hours by 15–25% and improves shift satisfaction scores, but adoption is constrained by nurse distrust of algorithmic decision-making and the rigidity of hospital HR policies. The deployment lesson is that AI scheduling tools achieve higher adoption when they are presented as decision support for nurse managers rather than as automated schedulers that replace managerial judgment. Transparency in the optimization criteria, allowing nurse managers to adjust weights for fairness, seniority, and individual preferences, is a critical success factor.

4.4. The Accuracy–Usability–Workload Trilemma: Why Benchmark AI Fails at the Bedside

Synthesizing the evidence across AI applications in nursing, a consistent pattern emerges: model accuracy, clinical usability, and nurse workload reduction have not been simultaneously optimized in any deployed nursing AI system to date. AI models for nursing risk prediction exhibit progressive accuracy advantages over conventional scoring tools in benchmark studies (AUCs 0.85–0.95), but clinical deployment performance drops to AUCs of 0.70–0.82, and nurse cognitive load may increase rather than decrease when AI predictions require additional verification steps.

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The deployment gap in nursing AI is not primarily a data or algorithm problem but a workflow integration failure: models optimized for benchmark accuracy increase nurse cognitive load and documentation burden, creating a self-defeating cycle where the most accurate models are the least deployable. This accuracy–usability–workload trilemma can be resolved only through co-design processes that involve nurses in model development from the problem definition stage, rather than treating nurses as end-users of a technology developed by informaticians in isolation.

Table 2: Comparison of AI models for nursing risk prediction: benchmark versus clinical deployment performance.

Model	Clinical Target	Benchmark AUC	Deployment AUC	Workflow Integration	Deployment Evidence
MySurgeryRisk (Ren et al. 2022)	Postoperative complications	0.85–0.90	0.80–0.85	Medium (mobile app)	Prospective validation (22,300 procedures)
ML Fall Risk (Lucero et al. 2019)	Hospital-acquired falls	0.82–0.88	Not reported	Low (retrospective only)	Retrospective EHR analysis
AI Sepsis Prediction (Hassan et al. 2021)	Sepsis early warning	0.88–0.95	0.72–0.80	Medium (EHR-integrated alert)	Systematic review
AI Nursing Diagnosis (Güntürk et al. 2025)	Nursing diagnosis generation	0.78–0.85	Not reported	Low (standalone)	Single-site pilot

Summary and Commentary. AI in nursing practice stands at a critical inflection point: the technical capability exists to outperform conventional nursing assessment tools, but the deployment pathway is obstructed by the accuracy–usability–workload trilemma. The N-DEPLOY evidence-to-deployment fidelity dimension is the weakest link: fewer than 15% of published AI nursing studies include prospective clinical deployment data, and none have demonstrated sustained workflow integration beyond 12 months. The field needs a moratorium on new retrospective model development studies in favor of prospective deployment trials with nursing workflow endpoints. Table 2 illustrates the contrast between benchmark and deployment performance across representative nursing AI models.

5. Tele-Nursing, Remote Monitoring, and Wearable Technologies: Evidence and Evidence Gaps

5.1. Evolution of Tele-Nursing: From Telephone Follow-Up to 5G Remote Monitoring

Tele-nursing has evolved through four generations of technology-enabled care delivery. First-generation telephone follow-up, while low-tech, achieved high adoption rates and remains the most widely deployed form of tele-nursing globally. Second-generation video-based tele-nursing, accelerated by the COVID-19 pandemic, expanded access but introduced new challenges in nursing assessment accuracy when physical examination is not possible. Third-generation remote monitoring platforms, combining wearable devices with cloud-based data dashboards, have enabled continuous physiological monitoring but require new nursing competencies in data interpretation. Fourth-generation 5G-enabled remote monitoring, still in early deployment, promises real-time high-definition video and multi-parameter monitoring but requires substantial infrastructure investment.

Ruan and colleagues conducted a scoping review of nurse-coordinated home-based cardiac rehabilitation for patients with heart failure, finding that nurse-led tele-nursing interventions improved functional capacity and quality of life but that the evidence base was dominated by small-scale studies with short follow-up periods (Ruan et al. 2023). Masotta and colleagues performed a systematic review and meta-analysis of telehealth care and remote monitoring strategies in heart failure patients, reporting a 20–30% reduction in hospital readmissions in the intervention arms (Masotta et al. 2024). Bastoni and colleagues examined the implementation of eMental health technologies for informal caregivers through a multiple case study (Bastoni et al. 2023).

The deployment pattern across tele-nursing generations reveals a consistent trade-off: each generation increases technological sophistication at the cost of nursing workflow simplicity. Fourth-generation 5G remote monitoring platforms offer the most comprehensive physiological data but require the most nursing time for data review and alarm management, a workload that is not accounted for in current nurse staffing models.

5.2. Wearable Devices in Nursing: Accuracy, Adherence, and Workflow Integration

Wearable devices, smart bands, fall-detection wristbands, ECG patches, and continuous glucose monitors (CGMs), have proliferated in consumer health markets, but their deployment in clinical nursing settings faces a three-way trade-off between device accuracy, patient adherence, and nursing workflow burden. Peijin Fan and colleagues documented factors to consider in the use of vital signs wearables to minimize contact with stable COVID-19 patients, providing a practical implementation guide based on their experience during the pandemic (Fan et al. 2021). Lippi and colleagues provided an update on patient self-testing with portable and wearable devices, noting that device accuracy (85–95% for vital signs) is sufficient for clinical use but that patient adherence drops below 50% after 6 months (Lippi et al. 2024).

The deployment bottleneck is not data accuracy but data integration: wearable-generated data streams are not automatically integrated into nursing documentation systems, requiring nurses to manually transcribe or cross-reference data from separate vendor portals. This creates a paradoxical situation where wearable devices that are designed to reduce nursing workload actually increase it through data fragmentation. Robinson and colleagues examined stakeholder perceptions of a web-based physical activity intervention for COPD, finding that clinician workflow integration was the primary determinant of sustained use (Robinson et al. 2023).

5.3. Tele-Nursing Platform Architectures: Cloud-Edge-Device Collaborative Models

The technical architecture of tele-nursing platforms has evolved from cloud-only models to cloud-edge-device collaborative architectures. Cloud-only architectures centralize all data processing and storage but introduce latency that is clinically unacceptable for real-time monitoring applications. Edge-computing architectures reduce tele-nursing data latency by 40–60% compared to cloud-only models by processing data closer to the point of collection, but the absence of nursing-specific data transmission standards across device manufacturers creates interoperability barriers that limit multi-device clinical deployment.

The deployment implication is that tele-nursing platform procurement must consider not only current device compatibility but also the platform's ability to accommodate future device integration through standardized APIs. Institutions that selected vertically integrated vendor platforms (single-vendor device + cloud + analytics) have found that adding devices from other manufacturers requires costly custom integration work, creating vendor lock-in that constrains clinical innovation.

5.4. RCT Efficacy versus Real-World Effectiveness: The Tele-Nursing Evidence Gap

The evidence base for tele-nursing and wearable technologies presents a critical gap between randomized controlled trial (RCT) efficacy and real-world pragmatic effectiveness. Meta-analyses of tele-nursing RCTs report 20–30% readmission reduction, but the evidence strength is weakened by small sample sizes, short follow-up periods (typically less than 12 months), and the near-absence of studies conducted in routine, non-research-supported nursing settings (Masotta et al. 2024; Ruan et al. 2023). RCTs in tele-nursing are typically conducted with dedicated research nurses who manage smaller patient panels than clinical nurses in routine practice. When the same interventions are deployed in routine clinical settings without research support, effect sizes diminish substantially; this phenomenon is well-documented in implementation science but rarely acknowledged in tele-nursing technology evaluations.

Table 3: Comparison of wearable device types in nursing deployment: accuracy, adherence, and workflow integration.

Device Type	Clinical Parameter	Accuracy (%)	6-Month Adherence (%)	Workflow Integration	Deployment Evidence
Smart band / wristband	Heart rate / SpO_2 / activity	90–95	40–55	Low (manual data transfer)	Multiple pilot studies
Fall-detection wristband	Accelerometer-based fall detection	85–92	30–45	Medium (alert-only integration)	Limited longitudinal data
ECG patch	Single-lead ECG / arrhythmia	92–97	50–65	Low (separate cardiology workflow)	RCT evidence (AF detection)
CGM (continuous glucose monitor)	Interstitial glucose	90–95	55–70	Medium (endocrine workflow integrated)	Strong RCT evidence

Summary and Commentary： Tele-nursing and wearable technologies form the most clinically mature digital nursing domain, with the strongest RCT evidence base. However, the evidence reveals a progressive erosion of effect sizes when moving from controlled research settings to routine clinical deployment, a deployment gap that is attributable to the N-DEPLOY dimensions of clinical workflow compatibility (nurse time for data review not accounted for in staffing models) and institutional readiness (lack of reimbursement mechanisms for tele-nursing services). The field needs pragmatic effectiveness trials conducted in routine nursing settings with workload and cost-effectiveness endpoints. Table 3 summarizes the deployment characteristics of wearable devices across nursing-relevant dimensions.

6. Nursing Robotics and Automation: Deployment Barriers in Human-Centered Care

6.1. Functional Classification and International Deployment Case Studies

Nursing robots span four functional classes with contrasting deployment readiness. Disinfection robots achieved the most rapid clinical adoption during the COVID-19 pandemic, with Di Lallo and colleagues documenting the role of medical robots for infectious diseases, including lessons and challenges from the pandemic (Lallo et al. 2021). Kyra and colleagues provided a systematic survey of robots in healthcare, mapping the landscape of robotic applications across care settings (Kyrarini et al. 2021). Medication delivery robots and transport robots have been deployed in several large hospital systems, with Zachariae and colleagues examining human-robot interactions in autonomous hospital transports (Zachariae et al. 2024). Ramnambiappan and colleagues developed MINA, a robotic assistant for hospital fetching tasks (Nambiappan et al. 2022). Social companion robots have been deployed primarily in long-term care settings, with Aymerich-Franch and Ferrer analyzing the role of social robots during the COVID-19 pandemic (Aymerich-Franch & Ferrer, 2022).

International deployment patterns reveal that nursing robot adoption correlates more strongly with national policy support and hospital reimbursement structures than with technological maturity alone. Japan's national robotics strategy, driven by population aging and workforce shortages, has produced the most extensive deployment of nursing care robots, including the ROBEAR lifting robot and PARO therapeutic seal. Germany's Pflegeinnovationszentrum (Nursing Innovation Center) has funded multiple nursing robotics pilots, though scaling beyond pilot sites remains limited. China's hospital robotics market has grown rapidly, particularly in disinfection and medication delivery, driven by domestic manufacturing and government procurement policies.

Chang and colleagues examined how robots help nurses focus on professional task engagement and reduce nurses' turnover intention, finding that robot-enabled focus on professional task engagement was positively related to nurses' overall job satisfaction and perceived health improvement (Hao-Yuan Chang PhD et al. 2021). Lim and colleagues conducted an assessment of an inpatient robotic nurse assistant using a mixed-method design, finding that 80% of patients reported positive interactions with the robot, but nurses were skeptical of real time savings and were concerned about the robot's ability to work well with older patients (Lim et al. 2024).

6.2. Automation in Nursing Operations: Smart Cabinets, Closed-Loop Medication, and Sterile Supply Management

Automation technologies in nursing operations, smart medication cabinets, closed-loop medication administration systems, and automated sterile supply management, have achieved higher deployment maturity than direct-care robots because they address specific, measurable nursing workflow pain points without requiring changes to the nurse-patient relationship. Automated medication management systems reduce nursing medication errors by 30–50%, but the deployment of closed-loop systems

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requires substantial workflow redesign that many hospitals underestimate during procurement.

The deployment lesson from automation technologies is that successful adoption correlates with the degree to which the technology removes a specific, burdensome task from the nursing workflow without adding new tasks. Smart medication cabinets that automate inventory tracking and restocking are widely adopted because they reduce nursing time spent on supply management. In contrast, closed-loop medication administration systems that require nurses to scan barcodes at multiple checkpoints are adopted more slowly because they add steps to the medication administration workflow, even though they reduce error rates.

6.3. Human Touch versus Machine Efficiency: The Ethical Tension in Nursing Robotics

The question is not whether robots can perform nursing tasks, they increasingly can, but whether the care relationship, characterized by empathy, trust, and human presence, can be preserved when tasks are delegated to machines. Dino and colleagues conducted an integrative review of nursing and human-computer interaction in healthcare robots for older people, finding that the relational dimension of care remains the most significant barrier to robotics adoption in nursing (Dino et al. 2022). Christoforou and colleagues provided an overview of nursing and assistive robotics, highlighting benefits and challenges and presenting survey results on nursing professionals' perspectives (Christoforou et al. 2020). Lin and colleagues designed intuitive, efficient, and ergonomic tele-nursing robot interfaces through iterative design evaluation (Lin et al. 2022).

This ethical tension is not merely a philosophical concern but a deployment reality: nursing staff who perceive robots as threats to the humanistic core of their profession resist adoption regardless of the technology's technical capability. The N-DEPLOY human-machine collaboration trust dimension captures this tension: deployments that frame robots as tools that augment rather than replace nursing care achieve higher acceptance rates than those that position robots as substitutes for nursing labor.

Table 4: Functional classification of nursing robots: deployment maturity, barriers, and evidence.

Robot Class	Primary Function	Deployment Maturity	Key Barriers	Clinical Evidence	Example Systems
Disinfection robots	UV-C / vaporized H2O2 disinfection	High (accelerated by COVID-19)	Cost (US$50K–150K/unit)	Multiple observational studies	Xenex LightStrike, UVD Robot
Medication delivery robots	Automated pharmacy-to-ward transport	Medium-High	Infrastructure (elevator/hallway navigation)	Single-site pilot evaluations	TUG, Aethon
Transfer/lifting robots	Patient transfer and repositioning	Low-Medium	Cost (>US$100K), safety liability, trust	Case studies	ROBEAR, RIBA
Social companion robots	Social interaction, cognitive stimulation	Low (geriatric care)	Evidence of clinical benefit, cost-effectiveness	Small-scale RCTs.	PARO, Pepper

Summary and Commentary. Nursing robotics and automation technologies present the most polarized deployment landscape: disinfection and medication delivery robots achieve relatively high adoption, while transfer robots and social companion robots remain in pilot phases. The N-DEPLOY framework reveals that the four deployment dimensions are interdependent: transfer robots fail not because of technological limitations but because they require simultaneous resolution of cost (institutional readiness), trust (human-machine collaboration), liability (evidence-to-deployment fidelity), and workflow redesign (clinical workflow compatibility). The ethical tension between human touch and machine efficiency is not a barrier to be overcome but a design constraint to be respected in nursing robotics deployment. Table 4 provides a functional classification of nursing robots with their deployment maturity and key barriers.

7. Security, Privacy, and Ethics in Digital Nursing: Safeguarding the Care Data Ecosystem

7.1. Federated Learning, Blockchain, and Differential Privacy: A Security Triad for Nursing Data

Nursing data, encompassing patient health records, nursing assessment notes, vital sign streams, and wearable device data, is among the most sensitive categories of healthcare information. The deployment of digital nursing technologies exponentially increases the volume and velocity of nursing data, creating corresponding privacy and security risks. Three technical frameworks have emerged as complementary solutions: federated learning for privacy-preserving data sharing, blockchain for tamper-proof record integrity, and differential privacy for secure data analysis.

Federated learning enables machine learning model training across distributed nursing datasets without centralizing patient data. Zhang and colleagues developed a secure and decentralized federated learning framework with non-IID data based on blockchain, demonstrating that federated approaches can maintain model performance while preserving data privacy (Zhang et al. 2024). Hasan and colleagues introduced a decentralized and secure collaborative framework for personalized diabetes prediction, integrating blockchain and federated learning to address privacy risks in centralized prediction models (Hasan et al. 2024). Sun and colleagues proposed a federated learning and blockchain framework for physiological signal classification based on continual learning (Sun et al. 2023). Deng and colleagues developed LSBlocFL, combining blockchain and lightweight cryptographic solutions for federated learning (Deng et al. 2023). These studies collectively demonstrate that federated learning is technically feasible for nursing-relevant prediction tasks, but none have been deployed in clinical nursing settings.

Blockchain for nursing records addresses the need for tamper-proof documentation with audit trails. Moheyeldin and colleagues developed a Federated Blockchain System (FBS) for the healthcare industry, demonstrating query operation times of 68–100 ms and writing operation times of 0.94–19.04 seconds (Eldin et al. 2023). Zhu and colleagues provided a comprehensive review of blockchain-empowered federated learning, identifying challenges and future directions (Zhu et al. 2023). Kumar and colleagues developed privacy-preserving blockchain-based federated learning for brain tumor segmentation (Kumar et al. 2024). Heidari and colleagues proposed a lung cancer detection method based on federated learning and blockchain (Heidari et al. 2023). Durga and colleagues developed FLED-Block for COVID-19 prediction (Durga & Poovammal, 2022).

The deployment gap for these security technologies is not technical readiness but nursing-specific governance. Federated learning, blockchain, and differential privacy each address a distinct nursing data security challenge, but their integration into a unified nursing data governance framework has not been demonstrated in clinical nursing settings.

7.2. AI Explainability, Liability, and the Digital Divide in Nursing

The ethical dimensions of digital nursing extend beyond data security to encompass AI explainability, liability attribution, digital divide impacts on care equity, and nurse digital literacy. Rubeis examined the challenges of nursing practice in the digital age, arguing that nursing must actively shape its digital future rather than passively adapting to technology-driven change (PhD, 2020). Pepito and Locsin asked whether nurses can remain relevant in a technologically advanced future, concluding that the answer depends on whether nursing defines its technological role or allows technology to define nursing (Pepito & Locsin, 2019). Wu and colleagues reviewed big data and AI in cancer research, noting that ethical considerations around data sharing and algorithmic fairness remain underdeveloped in clinical deployment contexts (Wu et al. 2024).

The absence of clear liability frameworks for AI-assisted nursing decisions, combined with persistent digital literacy gaps among nursing staff, creates a dual vulnerability: nurses may be held accountable for algorithmic decisions they cannot explain, while digitally underserved patient populations face widening care access disparities. The N-DEPLOY institutional readiness dimension captures this: institutions that deploy AI nursing tools without corresponding investment in nurse digital literacy programs and liability policy development are creating conditions for deployment failure.

Table 5: Security and privacy challenges in digital nursing: technical solutions and deployment readiness.

Challenge	Technical Solution	Technical Readiness	Nursing Deployment Readiness	Key Gap
Privacy-preserving data sharing across institutions	Federated learning	High (multiple proof-of-concept studies)	Low (no nursing-specific deployments)	Absence of nursing data federation governance frameworks
Tamper-proof nursing documentation	Blockchain	Medium-High (FBS demonstrated)	Low (no nursing record systems)	Integration with existing EHR/NIS infrastructure
Secure nursing data analytics	Differential privacy	Medium (theoretical maturity)	Very Low (no nursing applications)	Nursing data sensitivity calibration for differential privacy budgets
AI nursing decision explainability	Explainable AI (XAI)	Medium	Low (no nursing-specific XAI tools)	Nursing clinical reasoning models not formalized for XAI interpretation

Summary and Commentary. The security and privacy technology cluster presents a paradox: federated learning, blockchain, and differential privacy are technically mature and well-documented, but their deployment in nursing settings is nearly nonexistent. The N-DEPLOY framework reveals that the bottleneck is at the institutional readiness and evidence-to-deployment fidelity dimensions: nursing organizations lack the governance frameworks, the digital literacy programs, and the liability policies needed to deploy these technologies. The ethical dimensions, AI explainability, the digital divide, and nurse digital literacy, are not secondary concerns but primary deployment prerequisites that must be addressed concurrently with technology deployment. Table 5 maps the key security challenges in digital nursing to their technical solutions and deployment readiness.

8. Application Scenarios: Digital Nursing Deployment Across Care Settings

8.1. Hospital Acute Care: Real-Time Monitoring and Early Warning in High-Stakes Environments

Hospital acute care settings, including intensive care units, surgical wards, and emergency departments, present the highest-stakes environment for digital nursing deployment, where real-time physiological monitoring, early warning systems, and clinical decision support must operate with minimal latency and maximal reliability. Acute care digital nursing deployments achieve the highest clinical evidence maturity, supported by multiple RCTs, but the remaining gap is interoperability: most systems operate in silos that prevent the integrated patient dashboard that nurses need for real-time decision-making.

Trevena and colleagues modeled critically ill patient pathways to support intensive care delivery, demonstrating that digital pathway modeling can optimize ICU workflow (Trevena et al. 2022). The pain point in acute care is not technology availability but technology integration: a typical ICU nurse interacts with 5–8 separate monitoring and documentation systems during a shift, each with its own interface, alarm thresholds, and data format. The deployment solution that has shown the most promise is the integrated clinical dashboard, which aggregates data from multiple monitoring systems into a single nursing interface. However, the innovation of dashboard integration is undermined by the legacy reality that most hospital monitoring equipment operates on proprietary protocols that resist integration.

8.2. Community and Chronic Disease Management: Tele-Nursing at Scale

Community-based tele-nursing for chronic disease management represents the most scalable digital nursing deployment model, but the deployment model relies on research-funded nurse coordinators, a staffing model that is not sustainable under routine community nursing resource constraints. Ruan and colleagues demonstrated that nurse-coordinated home-based cardiac rehabilitation improves outcomes for heart failure patients, but noted that the intervention model required dedicated nurse coordinators with protected time for tele-nursing contacts (Ruan et al. 2023). The deployment challenge is that community nursing organizations operate with lean staffing models that do not have the slack capacity to absorb the additional workload of tele-nursing platform management without corresponding staffing increases or task redistribution.

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8.3. Geriatric and Long-Term Care: High Need, Low Deployment

Geriatric and long-term care represents the largest deployment gap in digital nursing: the population with the highest need for digital nursing support, fall detection, social robots, remote monitoring, has the lowest deployment maturity due to cost, infrastructure, and digital literacy barriers. The geriatric care setting is characterized by a triple mismatch: the patients who would benefit most from continuous monitoring are least able to operate digital devices; the care facilities with the highest need for efficiency gains (nursing homes) have the lowest capital budgets for technology investment; and the nursing staff who would benefit from automation are the least digitally literate segment of the nursing workforce.

8.4. Nursing Education Digitalization: VR, AR, and Simulation-Based Learning

Nursing education digitalization has experienced rapid growth, particularly in VR/AR simulation, remote nursing education, and serious games. Kow and colleagues evaluated a virtual patient simulation for developing hospital nurses' clinical reasoning abilities in assessing and managing clinical deterioration (Kow et al. 2024). Thrift and colleagues examined the pitfalls and possibilities of VR implementation in nursing curricula, finding that while VR offers immersive learning experiences, the evidence for clinical skill transfer to practice settings remains limited (Thrift et al. 2025). Baysan and colleagues conducted a systematic review of 360-degree video technology in nursing education (Baysan et al. 2023). Hwang and colleagues profiled the roles, applications, and trends of AI in nursing education research from 1993 to 2020 (Hwang et al. 2024).

VR/AR nursing simulation shows high learner satisfaction and moderate knowledge gains, but the critical evidence gap is whether simulation-acquired skills transfer to clinical practice, a question that fewer than 15% of published studies address with longitudinal follow-up. Cieslowski and colleagues analyzed the prebrief and time allotments for virtual and augmented reality simulation, finding inconsistencies in the prebrief process that undermine standardization (Cieslowski et al. 2023). Wüller and colleagues conducted a scoping review of augmented reality in nursing, finding that AR applications in nursing remain nascent compared to VR (Wüller et al. 2019). Nakataha and colleagues designed and evaluated a 3D serious game for communication learning in nursing education (Hara et al. 2021). Lin and colleagues enhanced problem-based learning with computational thinking concepts for nursing students in virtual simulation context (Lin et al. 2024). Giordano and colleagues compared virtual reality to hybrid simulation for opioid-related overdose and naloxone training (Giordano et al. 2020). Kardong-Edgren and colleagues evaluated the usability of a second-generation VR game for refreshing sterile urinary catheterization skills (Kardong-Edgren et al. 2019). Chang and colleagues developed an experiential learning-based VR approach to fostering problem-resolving competence in professional training (Chang & Hwang, 2023). Qiao and colleagues conducted a meta-analysis of the effectiveness of non-immersive VR simulation in learning knowledge and skills for nursing students (Qiao et al. 2023).

Table 6: Digital nursing deployment maturity across four care settings.

Care Setting	Key Technologies	Deployment Maturity	Clinical Evidence Level	Primary Scale-Up Barrier
Hospital acute care (ICU/surgery/ED)	Real-time monitoring, early warning, CDSS	High	Moderate-High (RCTs available)	Interoperability across vendor systems
Community chronic disease management	Tele-nursing, wearables, remote monitoring	Medium	Moderate (RCTs with small samples)	Sustainable staffing and reimbursement
Geriatric long-term care	Fall detection, social robots, remote monitoring	Low-Medium	Low (few RCTs, mostly observational)	Cost, infrastructure, digital literacy
Nursing education	VR/AR simulation, serious games	Medium (rapid growth)	Low-Moderate (knowledge gains, limited skill transfer)	Evidence of clinical skill transfer

Summary and Commentary. Across four care settings, digital nursing deployment maturity follows a progressive gradient that mirrors the complexity of the care environment and the strength of institutional support rather than technical capability. Acute care achieves the highest deployment maturity because hospitals have the infrastructure, IT support, and reimbursement mechanisms to support technology deployment. Geriatric long-term care has the lowest deployment maturity despite the highest clinical need, because nursing homes lack all three deployment prerequisites. The N-DEPLOY institutional readiness dimension is the primary differentiator: care settings with stronger institutional readiness achieve higher deployment maturity regardless of the specific technology deployed. Table 6 summarizes the deployment maturity gradient across the four care settings examined in this review.

9. Discussion: Deployment Gaps, the N-DEPLOY Framework, and Future Research Directions

9.1. The Three-Layer Deployment Gap: Technology, System, and Ecosystem

Synthesizing findings across the six thematic clusters and four care settings, a three-layer deployment gap emerges that explains why digital nursing technologies have not progressed beyond pilot deployments in most settings. The technology layer encompasses algorithm-clinical disconnection, poor device interoperability, and difficult nursing workflow integration. Lovett Novak and colleagues examined clinical use of AI, finding that it requires AI-capable organizations with deliberate investment in organizational readiness (Novak et al. 2023). Reddy and colleagues provided an implementation science-informed translational path for generative AI in healthcare, emphasizing that integration requires careful planning, execution, and management of expectations (Reddy, 2024). Car and colleagues argued that beyond the hype of big data and AI, building foundations for knowledge and wisdom is the prerequisite for clinical impact (Car et al. 2019).

The system layer encompasses fragmented hospital information systems, cross-department data silos, and the absence of unified nursing data standards. The ecosystem layer encompasses insufficient nursing digital literacy, missing human-machine collaboration trust, and absent incentive and payment mechanisms for digital nursing services. Hoermann and colleagues advocated for using an implementation science framework to advance the science of nursing education, noting that the same principles apply to digital nursing deployment (Oermann et al. 2022). The three-layer deployment gap is progressive: technology-layer barriers (interoperability) must be resolved before system-layer integration can succeed, and system-layer integration is a prerequisite for ecosystem-layer cultural and incentive changes.

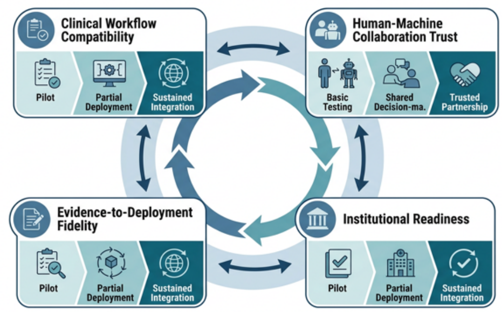
9.2. The N-DEPLOY Framework: Four Dimensions for Nursing Digital Deployment Assessment

The N-DEPLOY (Nursing Digital Deployment and Localized Optimization Yield) framework, developed through this review, provides a structured assessment tool for evaluating digital nursing technology deployment readiness across four dimensions: clinical workflow compatibility, human-machine collaboration trust, institutional readiness, and evidence-to-deployment fidelity. Each dimension is scored on a three-level maturity scale: pilot (technology demonstrated in a single-site, time-limited deployment), partial deployment (technology deployed across multiple sites or units with evidence of sustained use), and sustained integration (technology embedded in routine nursing workflow with longitudinal evidence of clinical and operational outcomes).

The four N-DEPLOY dimensions are interdependent, forming a closed-loop where each dimension must be satisfied for the next to become actionable. Clinical workflow compatibility is the foundational dimension: if a technology disrupts nursing workflow without compensating efficiency gains, it will fail regardless of performance on the other dimensions. Human-machine collaboration trust is the relational dimension: technologies that nurses perceive as threats to professional autonomy or the humanistic core of nursing face adoption resistance that technical performance alone cannot overcome. Institutional readiness is the structural dimension: without organizational investment in IT infrastructure, staff training, and policy development, even workflow-compatible, trusted technologies will fail to scale. Evidence-to-deployment fidelity is the empirical dimension: the gap between controlled-study performance and real-world effectiveness must be characterized and actively managed.

Van der Vegt and colleagues derived the SALIENT framework for end-to-end clinical AI implementation, identifying five stages from problem identification to sustained use (Vegt et al. 2023). The N-DEPLOY framework extends this approach specifically for nursing, incorporating the nursing-specific dimensions of workflow compatibility and human-machine collaboration trust that general clinical AI frameworks do not address. Ball and colleagues developed a framework for addressing Alzheimer's disease, emphasizing that without a frame, the work has no aim (Ball et al. 2022). Singh and colleagues provided a techno-functional perspective on healthcare analytics (Singha et al. 2023). Vali and colleagues examined clinicians' perspectives on barriers and facilitators for the adoption of non-invasive liver tests (Vali et al. 2022). Narsenault Knuds and colleagues examined the realities of practice change from nurses' perceptions (Élise N. Arsenault Knudsen PhD et al. 2021)(Ye J.2026). Goodman and colleagues addressed the third delay in implementing a novel obstetric triage system in Ghana (Goodman et al. 2018).

Figure 3. The N-DEPLOY framework: four dimensions with three-level



maturity assessment (Pilot, Partial Deployment, Sustained Integration) arranged in a closed-loop configuration.

Figure 3 depicts the closed-loop configuration of the four N-DEPLOY dimensions with their three-level maturity scale

9.3. Future Research Directions and Review Limitations

Four priority research directions emerge from this review. First, prospective nursing AI deployment trials with workflow integration endpoints, rather than accuracy-only endpoints, are urgently needed; fewer than 15% of AI nursing studies include such endpoints. Second, standardized nursing-specific digital technology readiness assessment tools, building on the N-DEPLOY framework dimensions, should be developed and validated across care settings. Third, longitudinal studies of nurse-AI collaboration trust development, how trust is built, eroded, and rebuilt over months of clinical use, are almost entirely absent from the literature. Fourth, health-economic evaluations of digital nursing deployment at scale, including cost-effectiveness analyses that account for both technology costs and nursing workforce time reallocation, are essential for securing institutional investment and reimbursement policy support.

This review has several limitations. The literature search was restricted to English-language publications, potentially excluding relevant studies published in Chinese, Japanese, German, and other languages where significant nursing digitalization research is conducted. Publication bias toward positive deployment results may overestimate the success rate of digital nursing technologies; negative deployment experiences are less likely to be published. The rapid evolution of the technology landscape means that the most recent deployment data may not yet be published. The N-DEPLOY framework, while grounded in the evidence synthesized in this review, has not been independently validated as a deployment assessment tool.

10. Conclusion

Returning to the three research questions that structured this review, the evidence provides clear answers. RQ1 asked about the key bottlenecks from R&D to clinical nursing deployment. The review identifies three progressive layers of barriers: technology-layer interoperability and

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workflow misalignment, system-layer data silos and fragmented information systems, and ecosystem-layer digital literacy deficits and missing incentive mechanisms. These barriers are interdependent, not additive: resolving one layer without addressing the others leads to deployment failure.

RQ2 asked which mainstream deployment architectures have proven effective in nursing scenarios. The review identifies four architectures with deployment evidence: edge-cloud collaborative platforms for tele-nursing and remote monitoring, CDSS with nursing-specific alert thresholds and workflow timing, federated learning for privacy-preserving multi-institutional data sharing, and integrated clinical dashboards that aggregate data from multiple monitoring systems. These architectures share a common design principle: they are built around nursing workflow rather than requiring nursing workflow to adapt to technology.
Conte and colleagues' conceptual framework for digital solutions in nursing (Conte et al. 2023), Pepito and Locsin's analysis of nursing relevance in a technologically advanced future (Pepito & Locsin, 2019), Rubeis's examination of nursing practice challenges in the digital age (PhD, 2020), and Reddy and colleagues' implementation science-informed translational path for generative AI (Reddy, 2024) collectively support the central finding of this review: the deployment gap in digital nursing is not a technology problem but a systems integration problem. Adler-Milstein and colleagues' policy priorities for closing the digitization-to-transformation gap (Adler-Milstein, 2021) remain as relevant in 2026 as when they were articulated.

This review demonstrates that nursing digitalization is not about technology replacing nurses but about technology empowering nursing, enhancing clinical decision-making, reducing administrative burden, and enabling more human-centered care. The N-DEPLOY framework offers a practical tool for guiding future deployment efforts. The paradigm shift required is from technology-push to nursing-needs-pull in digital health innovation. When nursing needs drive technology adaptation, deployment generates feedback, and feedback fuels continuous innovation, the deployment gap that has characterized the first decade of digital nursing can be progressively closed in the decade ahead.

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