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A Narrative Integrative Review of Federated Learning as a Privacy-Preserving Artificial Intelligence Framework in Nursing Informatics

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ABSTRACT

The rapid integration of artificial intelligence in nursing practice has enhanced predictive analytics, clinical decision support, and workforce management. However, concerns regarding data privacy, data silo fragmentation, and limited model generalizability remain significant challenges. Federated learning has emerged as a privacy preserving distributed machine learning approach that enables collaborative model development without transferring raw patient data across institutions. This narrative review aims to examine the conceptual foundation of federated learning and analyze its relevance for nursing practice and research. A literature search was conducted using Scopus and ScienceDirect databases covering publications from 2015 to 2025. Articles were analyzed through thematic synthesis focusing on technical architecture, clinical applications, ethical implications, and implementation challenges. The review indicates that federated learning has substantial potential to support predictive risk modeling, multicenter nursing outcome research, and integration within clinical decision support systems while maintaining patient confidentiality. Nevertheless, challenges related to non identical data distribution, governance accountability, interoperability, and digital literacy among nurses must be addressed to ensure safe and equitable implementation. Federated learning may represent a potentially viable approach for developing collaborative and privacy conscious artificial intelligence in nursing, provided that ethical safeguards, standardized data frameworks, and institutional readiness are systematically strengthened.

Keywords: federated learning; nursing informatics; data privacy; clinical decision support systems; distributed artificial intelligence.

1. INTRODUCTION

The use of artificial intelligence and predictive analytics in nursing has increased rapidly, particularly for early detection, clinical decision support, and workload management (Park et al., 2025). However, its effectiveness is often constrained by data silos caused by fragmented information systems and the limited integration of nursing data into predictive models (Ramirez & Jenkins, 2024). Another major challenge is limited model generalizability, as many algorithms perform suboptimally in real-world settings due to data bias and inadequate external validation (Gerich et al., 2022). Therefore, the implementation of artificial intelligence in nursing requires improved data quality and cross-context evaluation to ensure broader applicability across healthcare settings (Sacca et al., 2024).

Nursing data privacy constitutes a primary concern because the clinical information collected by nurses is highly sensitive and may generate emotional, social, and financial consequences in the event

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of a breach (Nikbakht Nasrabadi et al., 2024). This level of sensitivity requires that patient data confidentiality and security be maintained in accordance with professional ethical principles and personal data protection regulations (Weston et al., 2023). Evidence indicates that unauthorized access and insufficient training may impede ethical practice in the use of health information systems (Kamalzadeh et al., 2025). Therefore, continuous education and strict adherence to professional codes of ethics must be ensured to enable nurses to protect patient data consistently and responsibly (Abuhammad, 2025).

Federated learning has become increasingly relevant in nursing because cross-institutional collaboration can be achieved without centralizing data, thereby preserving patient privacy (Mamun, 2025). This approach addresses the common problem of data silos in healthcare by allowing data to remain at the source location while still contributing to global model training (Xu et al., 2021). In addition, model generalizability can be improved through federated learning because heterogeneous data from multiple institutions are incorporated without violating privacy regulations (Jiang et al., 2026).

This narrative review was developed to explore the conceptual foundations of federated learning and to examine its relevance in contemporary nursing practice and research. A synthesis of recent literature was conducted to identify how federated learning can be utilized in the development of artificial intelligence systems that preserve patient data privacy while enabling cross-institutional analytical collaboration in healthcare settings. The potential clinical applications of federated learning in nursing, including predictive modeling, clinical decision support systems, and quality improvement initiatives, were analyzed from a conceptual perspective. In addition, the ethical, regulatory, and governance implications associated with the implementation of distributed artificial intelligence in nursing were critically examined.

In recent years, several reviews have examined federated learning in healthcare broadly and artificial intelligence applications in nursing separately (Gerich et al., 2022; Upreti et al., 2024; Eden et al., 2025). However, these studies primarily focus either on technical architectures across medical domains or on general AI adoption in nursing without systematically integrating federated learning into a nursing-specific governance and workforce framework. To date, limited literature has synthesized federated learning from a nursing informatics perspective that simultaneously addresses clinical application, professional ethics, data governance accountability, and workforce digital readiness within a unified conceptual model. Therefore, this review aims to bridge that gap by positioning federated learning not merely as a distributed algorithmic technique but as a nursing-oriented socio-technical framework.

2. METHODS

2.1 Design

This article was prepared using a narrative review approach and was analyzed through thematic synthesis of relevant literature. The identified studies were critically examined to categorize the findings into major conceptual themes related to the implementation of federated learning in nursing. This approach was selected to provide a comprehensive understanding of conceptual developments, clinical implications, and implementation challenges within the context of nursing practice and research.

A narrative review design was selected because the objective of this study was conceptual integration rather than quantitative aggregation of effect sizes. Federated learning in nursing remains an emerging interdisciplinary domain characterized by heterogeneous methodologies, including technical modeling studies, governance analyses, and informatics conceptual papers. A systematic review approach would restrict inclusion to narrowly defined empirical study types, whereas this review aims to synthesize theoretical, technical, ethical, and professional dimensions into a unified conceptual framework specific to nursing informatics.

2.2 Literature Search Strategy

The literature search was conducted in a structured manner and was limited to the Scopus and ScienceDirect databases for publications issued between 2015 and 2025. The search strategy included the keywords federated learning, nursing, healthcare data privacy, distributed artificial intelligence, and clinical decision support, which were combined using appropriate Boolean operators. The identified articles were screened based on title and abstract relevance, after which full-text assessment was performed for studies that met the predefined inclusion criteria.

2.3 Inclusion and Exclusion Criteria

Articles included in this review were restricted to peer-reviewed publications written in English that examined federated learning within healthcare or nursing contexts. Studies describing conceptual frameworks, methodological approaches, or clinical applications of federated learning were considered for further analysis.

In contrast, brief editorials lacking sufficient technical discussion, opinion pieces, and non-scientific publications were excluded from the selection process. Documents that were not directly related to the application of federated learning in healthcare were also excluded from this review

2.4 Data Extraction and Thematic Synthesis

Data from articles that met the inclusion criteria were systematically extracted by identifying the research objectives, study design, application context, and principal findings relevant to federated learning in healthcare and nursing. The extracted information was organized descriptively to facilitate comparative analysis across studies.

Subsequently, the articles were analyzed narratively and classified into major themes, including the technical architecture of federated learning, potential clinical applications in nursing, ethical and data governance implications, and institutional-level implementation challenges. This thematic synthesis approach was employed to construct a structured conceptual framework regarding the relevance and future prospects of federated learning in nursing practice and research.

Thematic coding was conducted through iterative reading and categorization of extracted data. Initial open coding identified recurring domains, including architecture, privacy mechanisms, governance structures, clinical implementation, and workforce implications. These categories were then refined through axial coding to construct four principal analytical themes: technical architecture, clinical integration, governance and accountability, and professional readiness. This structured thematic process strengthened conceptual coherence across heterogeneous study types

2.5 Screening Process and Study Selection

The initial database search yielded 412 records from Scopus and 286 records from ScienceDirect. After duplicate removal, 538 unique records remained. Title and abstract screening excluded 412 articles that were not directly related to federated learning in healthcare or nursing contexts. Full-text assessment was conducted on 126 articles, of which 68 met the inclusion criteria. The final synthesis included 68 publications.

The Boolean search string applied in Scopus was: (“federated learning” OR “distributed machine learning”) AND (“nursing” OR “healthcare” OR “clinical decision support”) AND (“data privacy” OR “governance” OR “electronic health record”). A comparable structure was adapted for ScienceDirect. The screening process followed structured stages of identification, screening, eligibility, and inclusion, although a formal PRISMA design was not applied due to the narrative review framework.

3. CONCEPTUAL FOUNDATION OF FEDERATED LEARNING

3.1 Architecture and Workflow

The federated learning architecture operates under a client–server model, in which the server coordinates the model update process while clients transmit training results without sharing their local data (Rehman et al., 2022). Local training is independently performed by each client using its respective dataset, thereby preserving data confidentiality and reducing the risk of information leakage (Dharmaji et al., 2024).

After the completion of local training, model parameters or gradients are transmitted to the server for parameter aggregation to construct an improved global model (Kaur & Grewal, 2024). The aggregation process may apply averaging techniques or adaptive methods to enhance learning stability in heterogeneous data environments (Wang et al., 2022). Therefore, collaborative model development can be achieved without centralizing data in a single repository, which supports efficiency and security (Rehman et al., 2022).

3.2 Comparison With Centralized Machine Learning

Federated learning differs from centralized machine learning because data are not consolidated in a single repository, thereby providing stronger privacy protection and reducing the risk of information leakage (Mohamed & El-Gayar, 2022). Compared with centralized approaches, federated learning is considered more appropriate for sensitive data environments and cross-institutional collaboration in which direct data sharing is not feasible (Joynab et al., 2024).

Federated learning also demonstrates advantages in addressing scalability issues that frequently arise in centralized learning when data volume and the number of participating devices increase (Shiri et al., 2025). However, centralized learning often achieves higher accuracy because the entire dataset is directly accessed and optimized on a single server (Chai et al., 2020).

Federated learning may experience performance degradation due to non-independent and identically distributed data and the constraints of distributed model updates (Grataloup & Kurpicz-Briki, 2024). Repeated communication and distributed computation further introduce additional overhead that is not present in centralized approaches (Tuli et al., 2023). Nevertheless, empirical evidence indicates that federated learning can approach or even match the performance of centralized learning in various real-world applications while maintaining data privacy (Garst et al., 2025). Table 1 presents a comparison between federated learning and centralized machine learning.

Tabel 1. Comparison between Federated Learning and Centralized Machine Learning

Aspect	Federated Learning	Centralized Machine Learning
Data privacy	Data remain on local devices, thereby ensuring stronger privacy protection	Data are transferred to a central server, which increases vulnerability to data breaches
Cross-source collaboration	Collaboration is enabled without sharing raw data	Data centralization is required, which restricts collaborative flexibility
Scalability	Distributed devices and datasets can be managed more effectively	Scalability decreases as the number of devices and data volume increase
Model accuracy	Accuracy may decline due to non-IID data and distributed updates	Higher accuracy is typically achieved because all data are trained centrally
Communication requirements	High communication overhead occurs due to repeated transmission of model updates	Repeated communication among multiple nodes is not required
Real-world performance	Performance can approach or rival centralized learning under certain conditions	Strong and consistent performance is achieved through full access to the entire dataset
Suitability of use	Suitable for applications requiring strict data privacy protection	Suitable for applications supported by robust centralized server infrastructure

3.3 Security Enhancements

Security enhancement in federated learning largely depends on secure aggregation, which enables the server to aggregate model updates without accessing the individual contributions of clients (Yurdem et al., 2024). This technique typically applies secure multi-party computation or homomorphic encryption to ensure that model parameters remain protected during the aggregation process (Li et al., 2023).

In addition, differential privacy provides an additional layer of protection by injecting noise into gradients or parameters, thereby reducing the likelihood that individual data can be reconstructed (Michalakopoulos et al., 2024). This mechanism mitigates risks associated with attacks such as gradient inversion and membership inference, which attempt to extract sensitive information from trained models (Kanada et al., 2025).

Secure aggregation and differential privacy are frequently combined to balance privacy preservation and model performance in sensitive federated learning scenarios, including healthcare and edge computing environments (S N et al., 2025). Nevertheless, the application of differential privacy may reduce model accuracy due to excessive noise injection, particularly in small or heterogeneous datasets (Xin et al., 2025).

Tabel 2. Summary of Federated Learning Applications in Healthcare Relevant to Nursing

Author and Year	Clinical Context	Model Objective	Federated Approach	Key Findings	Relevance to Nursing
(Xu et al., 2021)	Healthcare informatics	Develop collaborative predictive models without centralizing data	Cross-silo federated learning with parameter aggregation	Demonstrated feasibility of distributed model training with preserved privacy	Supports cross-hospital collaboration in nursing data analytics
(Sarma et al., 2021)	Multicenter clinical imaging	Improve model performance across institutions	Federated deep learning	Improved site performance without sharing raw data	Relevant for multicenter nursing outcomes research
(Yordanov et al., 2024)	Cardiovascular population study	Compare federated vs centralized strategies	Federated learning with local model updates	Comparable performance to centralized models	Supports generalization of patient risk predictive models
(Obakhena et al., 2024)	Electronic Health Records integration	Integrate federated learning into EHR systems	Federated model embedded in EHR infrastructure	Enhanced privacy while maintaining analytic capability	Relevant for nursing data-based CDSS integration
(Upreti et al., 2024)	Healthcare AI systems review	Survey healthcare applications of federated learning	Horizontal federated learning across institutions	Identified privacy and scalability advantages	Provides a conceptual basis for the development of AI in nursing practice
(Eden et al., 2025)	Governance in healthcare federated systems	Examine governance and accountability mechanisms	Federated governance frameworks	Highlighted need for accountability and metadata governance	Important for data governance and nurses' professional responsibilities

To clarify the position of federated learning within the healthcare research landscape, empirical studies that implemented this approach across diverse clinical contexts were systematically mapped. A literature synthesis indicates that federated learning has been applied in the development of predictive models, the integration of electronic health record systems, and multi-center collaboration without transferring raw patient data. A comparative summary of study characteristics, model objectives, federated approaches employed, and their relevance to nursing practice is presented in Table 2.

4. POTENTIAL APPLICATIONS IN NURSING PRACTICE

4.1 Predictive Risk Modeling

Predictive risk modeling has been increasingly applied for the early detection of patient deterioration, particularly through the analysis of vital signs and machine learning–based early warning algorithms (Romero-Brufau et al., 2025). In the prevention of pressure injuries, several studies have demonstrated that machine learning models, including random forest and XGBoost, identify high-risk patients with greater accuracy than conventional risk assessment scales (J. Song et al., 2021). This evidence is further supported by research indicating that the integration of nursing data into predictive models enhances the early detection of pressure injury risk during hospitalization (W. Song et al., 2021).

Predictive modeling also plays a critical role in readmission risk prediction. Various models, including logistic regression, decision trees, and large language model–based approaches, have demonstrated improved accuracy in identifying patients at risk of rehospitalization. The incorporation of nursing data into readmission prediction models has been shown to support more targeted early interventions (Oh et al., 2025).

In addition, machine learning techniques have been applied to personalize discharge planning for older patients at high risk of 30-day readmission (Lee et al., 2025). The inclusion of clinical indicators such as vital signs, comorbidities, and historical health data further strengthens the precision of risk prediction across both acute and chronic conditions (Adamuz et al., 2020).

4.2 Multicenter Nursing Outcome Research

Multicenter nursing outcome research has increasingly shifted toward cross-hospital collaboration without the transfer of raw data through approaches such as federated learning (Sarma et al., 2021). This approach allows each hospital to retain patient data locally while contributing to the development of a global model, thereby preserving privacy and ensuring regulatory compliance (Soni et al., 2025).

Such collaboration is essential because multicenter research provides stronger generalizability and larger sample sizes compared with single-center studies (Kane & Chung, 2020). Furthermore, collaborative methods that avoid raw data transfer have been shown to achieve accuracy and analytical performance comparable to centralized approaches (Yordanov et al., 2024). Evidence also indicates that analyses based on summary statistics or model updates can yield results equivalent to those obtained from pooled individual-level data in cross-institutional clinical research (Yordanov et al., 2024).

Collaborative modeling frameworks can address legal and technical barriers that frequently limit data-driven research across hospitals (Oh & Nadkarni, 2023). By maintaining data within each participating institution, this approach reduces privacy breach risks and strengthens trust among research partners (Zhu et al., 2025).

4.3 Clinical Decision Support Systems

The integration of federated models into Clinical Decision Support Systems facilitates collaborative training of electronic health record–based models without transferring raw data, thereby preserving patient privacy during clinical analytics (Obakhena et al., 2024). Federated models connected to electronic health record systems can generate clinical recommendations derived from multi-institutional data, which enriches decision-making contexts without compromising information security (Dodevski et al., 2024).

This approach enhances the quality of Clinical Decision Support Systems because the resulting global model reflects heterogeneous patient populations across multiple hospitals. Continuous updates can also be supported as local data increase, without requiring centralized model reconstruction (Ankolekar et al., 2024).

Federated learning enables Clinical Decision Support Systems to comply with privacy regulations such as HIPAA and GDPR because data remain at their original locations (Kovačević, 2025). From an operational perspective, federated models facilitate interoperability across electronic health record systems, which supports the extraction of clinical patterns from diverse data sources (El-Yafouri & Klieb, 2025). Furthermore, data breach risks are reduced because only model parameters are transmitted rather than patient records (Upreti et al., 2024).

4.4 Workforce and Nursing Management Analytics

Workforce and nursing management analytics utilize predictive models to estimate nursing workload, thereby enabling scheduling decisions to be aligned more accurately with variations in clinical service demand (Hasselgård et al., 2024). Machine learning approaches are also applied to dynamically predict workload requirements based on patient characteristics and historical trends, which supports more precise resource allocation by nurse managers (McMahon et al., 2025).

In staffing optimization contexts, algorithms such as random forest and regression models have been shown to assist in determining optimal staffing levels according to unit-level workload variability (Aslan & Toros, 2025). Shift-to-shift predictions provide an evidence base for nurse assignment planning to maintain balance between service demand and workforce availability (Song et al., 2024). Time series forecasting further contributes to staff allocation optimization, particularly in high-fluctuation settings such as outpatient services (Xing et al., 2025).

Predictive models derived from routine hospital data enable automated estimation of staffing needs without increasing nurses' administrative burden (Meredith et al., 2025). Empirical evidence indicates that indicators such as patient turnover and nurse-to-patient ratios serve as significant predictors for developing schedules that align with clinical demands (Ostberg et al., 2021).

To integrate technical, clinical, governance, and workforce readiness dimensions into a comprehensive structure, a conceptual model is required to illustrate the relationships among these components. Federated learning should be understood not only as a technical architecture but also as a system that interacts with clinical practice, regulatory frameworks, and professional nursing competencies.

5. ETHICAL AND REGULATORY IMPLICATIONS

5.1 Patient Confidentiality and Professional Ethics

Patient confidentiality constitutes a foundational ethical pillar that sustains patient trust in healthcare professionals throughout the care process (Verma et al., 2023). This principle is closely aligned with beneficence, because the protection of confidential information represents an action that safeguards patient welfare and best interests (Cheraghi et al., 2023). In clinical practice, breaches of confidentiality may damage the therapeutic relationship and impede the attainment of optimal patient benefit as mandated by the principle of beneficence (Varkey, 2021).

Nurses are therefore required to prioritize the protection of personal patient information as an inherent moral and professional obligation within nursing ethics (Salles & Castelo, 2023). This obligation also entails a legal dimension that requires an understanding of the limits and exceptions governing the protection of health information confidentiality (Wasser & Sun, 2024). In contemporary clinical environments, maintaining confidentiality has become increasingly challenging due to data breach risks and the growing complexity of health information technologies (Elgujja, 2022).

5.2 Data Governance and Accountability

Data governance in federated learning emphasizes the importance of procedural, structural, and relational mechanisms to regulate how data and global models are utilized and supervised (Eden et al., 2025). Responsibility for the global model is typically assigned to a coordinating entity that distributes tasks, aggregates updates, and validates the resulting model (H. Zhang et al., 2024).

In certain architectures, metadata governance is required to ensure auditability and accountability for each client's contribution to the global model (Peregrina et al., 2022). Decentralized systems, including blockchain-based frameworks, may redistribute responsibility from a single central server to a multi-party mechanism that enhances transparency (Wang et al., 2025).

The performance of the global model is influenced by the quality of local data; therefore, governance structures must ensure that each participating node provides valid and trustworthy contributions (Xu et al., 2024). Security mechanisms such as anomaly detection and contribution analysis are implemented to preserve model integrity and prevent malicious manipulation (Wang et al., 2026). Governance responsibilities also include compliance with privacy and data protection regulations, which require that model use be controlled in accordance with applicable legal frameworks (Chik & Gamper, 2024).

5.3 Bias and Fairness in Distributed AI

Data imbalance across institutions in distributed artificial intelligence may generate bias due to substantial differences in data quality, quantity, and distribution among participating clients (Karami & Karami, 2025). When data are non-independent and identically distributed, the global model tends to prioritize institutions with dominant data contributions, thereby disadvantaging institutions with smaller or less balanced representations (Wang et al., 2024).

Such disparities may lead to variations in model accuracy across institutions and reduce overall distributional fairness (Pathak & Rajput, 2024). Spurious correlations and differences in local population characteristics may further reinforce structural bias within federated models (F. Zhang et al., 2024). Bias risk also increases when participation frequency varies, as the model disproportionately learns from more active clients (Fittipaldi et al., 2025).

Heterogeneity in data quality, including noise and label variability, may exacerbate performance disparities among federated participants. Consequently, the model may become less equitable for institutions with minority data or significantly different domain conditions (Alharbi et al., 2025). Bias and fairness issues in distributed artificial intelligence must therefore be explicitly addressed through fair aggregation mechanisms and non-IID mitigation strategies to ensure equitable benefit distribution across institutions (Mukhtiar et al., 2025).

6. IMPLEMENTATION CHALLENGES

6.1 Infrastructure and Interoperability

The standardization of nursing terminology constitutes a critical foundation for infrastructure development and interoperability because consistent and meaningful data exchange across health systems can be achieved (Ghimire, 2026). The adoption of terminologies such as ICNP, SNOMED CT, and NANDA International ensures that nursing documentation can be interpreted across platforms and clinical contexts (Fennelly et al., 2021).

Standardization also supports semantic interoperability because alignment of meaning is preserved, which enables nursing data to be integrated with electronic health records and other systems without loss of clinical context (Silva et al., 2020). Cross-terminology mapping practices further facilitate the harmonization of diverse nursing language systems and enhance information exchange across levels of care (Oliveira et al., 2024).

Evidence indicates that standardization improves the quality of nursing documentation and produces structured data that can be leveraged for analytics and quality improvement initiatives (De Groot et al., 2020). The integration of nursing terminologies into interoperability standards such as HL7 FHIR supports the development of cohesive and future-oriented health data architectures (Monsen et al., 2023).

However, adoption remains challenged by practice variation, terminology heterogeneity, and the need for workforce training (Jedwab et al., 2024). Therefore, strong national strategies and robust information governance frameworks are required to accelerate the implementation of standardized terminologies and to achieve sustainable nursing interoperability (Tumulak et al., 2024).

6.2 Digital Literacy and Workforce Readiness

Nurses' readiness to understand and apply artificial intelligence is strongly influenced by their level of digital literacy, and evidence indicates that digital competencies among nurses vary considerably, often remaining at basic to intermediate levels (Comparcini et al., 2025). Several studies report that although positive attitudes toward artificial intelligence in clinical practice are expressed, knowledge of artificial intelligence concepts remains limited among many nurses (Namdar Areshtanab et al., 2025).

Workforce readiness is further shaped by educational background, professional role, and prior experience with technology, which contribute to differences in adaptability to artificial intelligence–based systems (Hariyati et al., 2024). To enable effective utilization of artificial intelligence, structured training programs and the integration of digital competencies into nursing curricula have been emphasized as essential strategies to prepare nurses for technological transformation in healthcare services (Galatzan et al., 2025).

6.3 Institutional Collaboration Barriers

Barriers to cross-institutional collaboration frequently arise from low levels of interorganizational trust, particularly when institutional decisions or actions are perceived as contradictory by stakeholders (Long & Sitkin, 2023). These challenges intensify when actors from multiple institutions are required to establish shared commitments while remaining constrained by individual organizational interests that generate tension between institutional priorities and collective responsibility (Hulme, 2025).

Cross-institutional regulations also constitute significant obstacles because differences in procedures, requirements, and administrative standards may hinder collaboration at national and international levels (Lopez-Baron et al., 2024). In healthcare and other public sectors, misaligned regulatory mechanisms may reduce collaborative effectiveness and diminish institutional motivation for sustained engagement (Aunger et al., 2022).

Institutional power structures and governance complexity may further influence decision-making processes and trust dynamics among collaborating parties (McIlwain et al., 2024). When collaboration requires information exchange, regulatory barriers related to data governance and legal compliance frequently complicate interorganizational relationships (D'Hauwers & Walravens, 2022). Evidence indicates that strong political support and robust organizational structures are necessary to reduce regulatory uncertainty and strengthen mutual trust (Zhou et al., 2025). Overall, trust deficits and regulatory fragmentation necessitate more adaptive governance designs to ensure effective interinstitutional collaboration (Sanz et al., 2025).

7. FUTURE DIRECTIONS FOR NURSING RESEARCH

The future nursing research agenda should be directed toward the development and empirical evaluation of federated learning within real-world clinical contexts. Multicenter experimental studies can be designed to assess the performance of federated models in predicting clinical risks, including patient deterioration and readmission, with outcomes compared against centralized approaches as previously evaluated in healthcare studies (Garst et al., 2025), (Sarma et al., 2021), (Yordanov et al., 2024). Cross-hospital external validation should be conducted to ensure model generalizability and to reduce bias arising from uneven data distributions (Karami & Karami, 2025), (Mukhtiar et al., 2025).

Methodological research is also required to develop aggregation strategies that adapt to non-independent and identically distributed data and to implement fair bias mitigation mechanisms for institutions with heterogeneous population characteristics (Wang et al., 2024), (F. Zhang et al., 2024). Further evaluation of federated learning integration with electronic health record systems and Clinical Decision Support Systems should be undertaken to ensure interoperability and data security in nursing practice (Obakhena et al., 2024), (El-Yafouri & Klieb, 2025). In addition, research on the application of secure aggregation and differential privacy within nursing data contexts should be expanded to examine the balance between privacy protection and model accuracy (Li et al., 2023), (Xin et al., 2025).

Governance and ethical dimensions require comprehensive exploration, particularly in relation to model governance, accountability, and compliance with data protection regulations (Eden et al., 2025), (Chik & Gamper, 2024). Qualitative studies that investigate nurses' perceptions of federated artificial intelligence should be conducted to understand organizational readiness and digital literacy challenges (Comparcini et al., 2025), (Namdar Areshtanab et al., 2025). The development of a distributed collaboration–oriented nursing informatics competency framework may constitute a significant contribution to strengthening workforce readiness for privacy-centered technological transformation.

8. INTEGRATED CONCEPTUAL FRAMEWORK FOR NURSING-ORIENTED FEDERATED LEARNING

This review synthesizes the literature into a nursing-oriented federated learning framework consisting of four interdependent dimensions: (1) distributed technical architecture, (2) clinical application layer, (3) governance and regulatory oversight, and (4) nursing workforce competency readiness. Unlike general healthcare federated learning models, this framework emphasizes the professional accountability of nurses as data stewards and clinical decision facilitators. The interaction among these dimensions determines sustainable implementation. Technical robustness without governance clarity may increase accountability risks, whereas governance without workforce readiness may reduce adoption feasibility.

CONCLUSION

Federated learning has been identified as a strategic approach for developing privacy-oriented artificial intelligence in nursing practice and research. Through distributed model training without transferring raw patient data, data fragmentation and confidentiality breach risks can be substantially reduced. The literature synthesis indicates that this approach has potential applications in predictive clinical risk modeling, multicenter nursing outcome research, integration of Clinical Decision Support Systems, and nursing workforce management analytics.

The implementation of federated learning is influenced by infrastructure readiness, interoperability standardization, data quality, and the clarity of global model governance and accountability mechanisms. Uneven data distribution across institutions may generate bias; therefore, mitigation strategies and systematic fairness evaluation must be designed and applied. Strengthening nurses' digital literacy and integrating nursing informatics competencies are essential to support the safe and responsible use of this technology.

Federated learning can be positioned as a conceptual framework that facilitates cross-institutional collaboration while upholding the principles of confidentiality and beneficence. Structured integration of technical, ethical, and regulatory dimensions is required to ensure that artificial intelligence innovation in nursing delivers optimal and sustainable clinical benefits.

This review presents several methodological limitations that should be acknowledged. The narrative design does not incorporate a formal risk-of-bias assessment, which may introduce selection bias and limit the reproducibility of the synthesis process. The inclusion of heterogeneous study designs, ranging from technical modeling studies to governance analyses, reduces comparability across findings and may affect analytical consistency. The restriction to English-language publications may have excluded relevant regional or non-indexed studies. In addition, federated learning in nursing remains an emerging domain, and the limited availability of nursing-specific empirical implementations constrains the extent to which conclusions can be drawn exclusively from nursing-centered evidence.

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