



## Energy Sustainability in Artificial Intelligence for Nursing Practice: Addressing the Hidden Cost

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### ABSTRACT

*The adoption of artificial intelligence in nursing practice has accelerated rapidly and offers substantial benefits in terms of efficiency, predictive accuracy, and clinical workflow optimization. Applications such as automated documentation, natural language processing of clinical notes, and decision support systems are increasingly embedded in routine nursing activities. These technologies enhance performance and productivity; however, growing evidence indicates that artificial intelligence systems are associated with significant energy consumption during model training, data storage, and operational deployment. The healthcare sector already contributes a measurable proportion of global greenhouse gas emissions, and energy-intensive digital infrastructures further amplify this burden. Training advanced artificial intelligence models may generate substantial carbon emissions, and repeated inference processes in daily clinical use accumulate additional energy demand. Despite these concerns, current evaluation frameworks for artificial intelligence in nursing remain primarily centered on clinical effectiveness, usability, safety, and organizational readiness. Energy consumption, carbon footprint, and broader ecological implications are rarely incorporated into technology assessment processes. This omission creates a critical gap between digital innovation and environmental responsibility within nursing informatics. This short communication synthesizes available evidence on the hidden energy costs of artificial intelligence in healthcare and nursing contexts, identifies structural gaps in prevailing evaluation paradigms, and proposes the integration of standardized sustainability metrics. The proposed framework emphasizes explicit reporting of energy consumption, carbon emissions, and life-cycle environmental impacts alongside traditional clinical and operational indicators. Reframing artificial intelligence evaluation through a sustainability lens allows nursing to contribute to advancing digital transformation that is not only safe and effective but also environmentally responsible.*

**Keywords:** *Artificial Intelligence; Nursing Informatics; Energy Consumption; Carbon Footprint; Sustainable AI*

### 1. INTRODUCTION

The adoption of artificial intelligence in nursing practice has increased substantially over the past decade. Applications now extend beyond experimental contexts and encompass automated clinical documentation, natural language processing of free text nursing notes, early disease detection, workflow optimization, and clinical decision support systems (von Gerich et al., 2022). Bibliometric analyses further demonstrate exponential growth in publications at the intersection of artificial intelligence and nursing, indicating that nurses are increasingly positioned at the forefront of digital transformation

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within healthcare systems (Balpande et al., 2025). This expansion reflects not only technological progress but also a structural reconfiguration of how clinical data are generated, processed, and operationalized in nursing workflows. Artificial intelligence has therefore become embedded in core nursing functions, influencing assessment, documentation, coordination of care, and clinical decision making.

The performance of artificial intelligence systems in nursing research is commonly evaluated using predictive metrics such as accuracy, sensitivity, specificity, area under the curve, and F1 score. These indicators are essential for assessing clinical validity and safety. Contemporary evaluation metrics such as accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve are widely used to assess the effectiveness of artificial intelligence systems in healthcare. These metrics primarily capture algorithmic performance outcomes and do not account for the computational resources required to achieve such performance. Contemporary artificial intelligence models, particularly deep learning architectures, depend on large-scale data processing, high-performance computing infrastructures, and cloud-based deployment environments. These technical requirements translate into substantial electricity consumption and associated environmental impacts.

Concerns regarding the environmental footprint of artificial intelligence have gained increasing attention in other health related disciplines. Studies in radiology and medical imaging report that training deep learning models requires significant electricity consumption and considerable water usage for cooling large scale data centers (Champendal et al., 2026). Additional evidence indicates that training a single advanced model may generate a carbon footprint comparable to that of five passenger vehicles over their lifetime (Mikhailova & Sharova, 2023). Repeated inference processes embedded in routine healthcare delivery further contribute to cumulative energy demand, particularly when models are deployed continuously across institutions (Rehman et al., 2025). These findings demonstrate that artificial intelligence systems rely on energy intensive infrastructures and cannot be considered environmentally neutral technologies.

Discussions in nursing scholarship surrounding artificial intelligence predominantly focus on ethical considerations, data governance, workforce readiness, professional roles, and implementation challenges (Mohammed et al., 2025; Arcadi, 2025; Ramadan et al., 2024). These analyses provide valuable insights into organizational and professional implications. Nevertheless, they do not explicitly address carbon emissions, energy consumption, or the broader ecological consequences associated with artificial intelligence deployment in nursing practice. The absence of sustainability metrics in prevailing evaluation frameworks indicates a methodological blind spot in contemporary nursing informatics research. As artificial intelligence becomes increasingly integrated into routine nursing workflows, ignoring its energy footprint risks overlooking an important dimension of responsible innovation.

Healthcare systems represent one of the largest consumers of energy within the public sector, and digital transformation initiatives are often promoted under the banner of efficiency and modernization. Integrating artificial intelligence without considering its energy implications may inadvertently shift environmental burdens from physical to digital infrastructures. A comprehensive evaluation paradigm for artificial intelligence in nursing must therefore extend beyond predictive accuracy and operational efficiency to include resource utilization and environmental sustainability.

This article argues that current evaluation standards for artificial intelligence in nursing practice require reframing. It calls for the integration of energy sustainability into the assessment of artificial intelligence systems within clinical informatics. By highlighting the hidden energy cost of artificial intelligence in nursing practice, this paper seeks to stimulate scholarly dialogue and to propose the foundation for sustainable evaluation metrics that align clinical innovation with environmental responsibility.

## 2. METHODS

This article employed a structured narrative synthesis to integrate and critically analyze the body of literature previously identified in the preceding discussion. The aim was not to conduct a systematic

review with formal database searching or quantitative aggregation, but to develop a coherent conceptual analysis focused on the energy implications of artificial intelligence in nursing practice. The methodological orientation was interpretive and integrative, designed to identify thematic convergence and evaluation gaps across the selected sources.

This study employed a structured narrative synthesis approach to examine the emerging literature related to the energy implications of artificial intelligence in healthcare and nursing practice. The literature was identified through exploratory searches conducted in major academic databases including Scopus. The search process was performed between January and February 2026 using combinations of keywords such as “artificial intelligence”, “energy consumption”, “carbon footprint”, “healthcare AI”, and “nursing informatics”.

Articles were included if they discussed (1) artificial intelligence applications in healthcare or nursing, (2) energy consumption or environmental impacts of AI systems, or (3) sustainability related evaluation frameworks for digital health technologies. Studies focusing solely on algorithmic development without discussion of healthcare applications or environmental aspects were excluded.

The identified literature was then screened for relevance through title and abstract review, followed by conceptual analysis of selected publications. The analysis was limited to a predefined corpus of literature encompassing five domains: sustainability and energy consumption of artificial intelligence systems, environmental emissions within healthcare sectors, artificial intelligence applications in nursing practice, established evaluation frameworks for health related artificial intelligence, and energy efficient technological strategies such as federated learning and edge computing. No additional sources were introduced beyond this predefined set.

An iterative thematic analysis was conducted. Key concepts were extracted from each source, including energy consumption, carbon emissions, computational requirements, evaluation metrics, and implementation considerations. These concepts were coded and organized into higher order thematic categories through conceptual clustering. The objective was to synthesize patterns across domains rather than to quantify effect sizes or perform statistical comparisons.

The synthesis resulted in four principal thematic domains: energy consumption and emissions associated with healthcare artificial intelligence systems; implications for nursing practice; gaps in prevailing artificial intelligence evaluation standards; and proposed sustainability oriented metrics for nursing informatics. This structured narrative approach provided the analytical foundation for articulating the hidden energy costs of artificial intelligence in nursing practice and for proposing the integration of sustainability considerations into evaluation frameworks.

### 3. RESULTS

#### 3.1 Energy Consumption of Artificial Intelligence in Healthcare Systems

Available evidence indicates that the healthcare sector carries a substantial ecological footprint. Global health systems account for approximately 4–5% of total worldwide greenhouse gas emissions, with a significant proportion attributable to infrastructure, digital systems, and technology dependent services (Richie et al., 2025). Within this sector, hospitals represent the largest contributors to carbon emissions among healthcare facilities due to their energy intensive operations and continuous service delivery (Keil et al., 2024).

Artificial intelligence systems contribute additional energy demand across multiple stages of their computational lifecycle. Training large-scale models, including large language models and deep neural networks such as convolutional neural networks and artificial neural networks, requires extensive computational resources and prolonged processing time (Champendal et al., 2026; Ueda et al., 2024). Additional energy consumption results from large scale data storage and high volume data processing activities (Rojek et al., 2025). Daily inference operations embedded in routine healthcare services further increase cumulative energy use, particularly when models are deployed continuously and at scale

(Rehman et al., 2025). Data centers and server cooling infrastructures add indirect energy burdens, including electricity and water consumption for thermal regulation (Ueda et al., 2024).

Quantitative estimates illustrate the magnitude of this burden. Training a single advanced artificial intelligence model has been associated with carbon emissions comparable to those produced by five passenger vehicles over their lifetime (Mikhailova & Sharova, 2023). Inference level applications also generate measurable energy demand. The use of large language model systems such as ChatGPT has been estimated to require approximately 50 Wh for 50 prompts under certain operational assumptions (Duane et al., 2026). Comparative analyses indicate that lightweight architectures, such as MobileNet, demonstrate greater energy efficiency relative to more computationally intensive architectures such as ResNet during inference tasks (Rehman et al., 2025).

These findings demonstrate that artificial intelligence systems deployed within healthcare environments rely on energy intensive infrastructures. The environmental impact extends beyond isolated model training events and includes cumulative effects from storage, inference processes, and data center operations.

**Table 1. Evidence of Energy Consumption of Artificial Intelligence in Healthcare Systems**

Aspect	Key Findings	Implication for Healthcare AI	Source
Healthcare sector emissions	Healthcare accounts for approximately 4–5% of global greenhouse gas emissions	Digital health technologies may further increase sectoral energy demand if sustainability considerations are not integrated	(Richie et al., 2025; Keil et al., 2024)
Hospital carbon burden	Hospitals represent the largest contributors to healthcare carbon footprint	AI deployment in hospital infrastructures must consider energy-efficient computing strategies	(Keil et al., 2024)
AI model training	Training deep learning models requires significant electricity and water consumption	Model development stages contribute substantially to the environmental footprint of AI systems	(Champendal et al., 2026; Ueda et al., 2024)
Model level emissions	Training a single advanced AI model may generate emissions comparable to five passenger vehicles over their lifetime	Large-scale model development should be balanced with sustainability considerations	(Mikhailova & Sharova, 2023)
Inference energy	Lightweight architectures such as MobileNet demonstrate higher energy efficiency compared with ResNet	Model selection influences operational energy consumption in clinical AI systems	(Rehman et al., 2025)
Large language model usage	Approximately 50 Wh may be required for 50 prompts in large language model systems	Frequent AI interactions in clinical workflows may accumulate significant energy demand	(Duane et al., 2026)

The evidence summarized in Table 1 indicates that artificial intelligence systems contribute to healthcare energy consumption across multiple stages, including model development, infrastructure operation, and routine inference processes. These findings highlight the need to incorporate sustainability metrics when evaluating artificial intelligence technologies in healthcare settings.

### 3.2 Implications of Energy Consumption for Nursing Practice

Artificial intelligence has been implemented across multiple domains of nursing practice. Applications include natural language processing based documentation automation (Dave et al., 2026), interpretation of unstructured clinical notes (Chen et al., 2026), and clinical decision support systems designed to enhance diagnostic and treatment accuracy (von Gerich et al., 2022) (Ruksakulpiwat et al., 2024). Artificial intelligence has also been explored as a strategy to reduce healthcare worker burnout through workload prediction and task optimization (Dave et al., 2026), as well as to support artificial intelligence education and digital literacy among nurses (Bozkurt et al., 2025; Tomlinson et al., 2026; Reading Turchioe et al., 2025). These developments indicate that artificial intelligence is increasingly embedded in routine nursing workflows, influencing documentation, decision-making, professional development, and organizational efficiency.

Although artificial intelligence has demonstrated benefits in improving efficiency and supporting quality of care, each deployment of such systems entails computational processes that require energy. Model inference conducted repeatedly throughout daily clinical activities accumulates energy demand over time. Applications that process large volumes of nursing documentation, provide continuous decision support, or operate through mobile and cloud based platforms rely on persistent server activity and data transmission infrastructures. These technical operations are inherently energy dependent.

Despite this reliance on computational resources, the nursing literature does not explicitly address several critical dimensions of energy impact. There is limited discussion of energy consumption per inference during routine use, carbon footprint associated with artificial intelligence enabled clinical workflows, or the cumulative energy burden placed on local servers and centralized data centers due to widespread adoption of nursing applications. The absence of such considerations suggests that energy externalities remain largely invisible within current nursing informatics discourse.

As artificial intelligence becomes increasingly integrated into everyday nursing activities, the aggregate energy demand associated with its use may contribute to a gradual increase in the overall energy burden of healthcare systems. Without transparent reporting and sustainability oriented evaluation, digital innovation in nursing practice may inadvertently intensify environmental impacts while pursuing efficiency gains.

### 3.3 Gaps in Evaluation: Limited Sustainability Metrics in Nursing Artificial Intelligence

The evaluation of health technologies has been guided by multiple established frameworks that emphasize clinical effectiveness, integration feasibility, safety, and technical risk management. Several assessment models have been developed to support the structured evaluation of artificial intelligence systems in healthcare settings, including the AQuAS AI Assessment Guide (Moltó-Puigmartí et al., 2026), evaluative approaches discussed in BMJ Health & Care Informatics (Reddy et al., 2021), broader reviews of artificial intelligence frameworks (Jacob et al., 2025; Fajkis-Zajączkowska et al., 2025), and implementation guidance documents. These frameworks provide structured criteria for assessing reliability, transparency, validation, governance, and organizational readiness.

Despite their methodological rigor, none of these evaluation frameworks explicitly incorporate metrics related to energy consumption, carbon emissions, or environmental impact associated with artificial intelligence systems. The prevailing evaluation paradigm remains centered on clinical performance, technical robustness, and implementation readiness, while resource utilization and ecological externalities are not systematically addressed.

Emerging sustainability oriented analyses in healthcare artificial intelligence emphasize the importance of incorporating energy use, carbon accounting, and environmental cost indicators into evaluation models (Ramachandran et al., 2025). However, such considerations have not been operationalized within the field of nursing informatics. As artificial intelligence tools are increasingly embedded in nursing workflows, the absence of sustainability metrics represents a structural limitation in current evaluation standards.

This gap is observable across multiple domains of assessment. Clinical evaluations focus on predictive accuracy and safety without examining trade-offs between performance gains and energy intensity (Rehman et al., 2025). Operational assessments emphasize workflow efficiency but do not quantify energy consumption associated with artificial intelligence enabled processes (Dave et al., 2026). Environmental dimensions are largely absent, although life cycle assessment and carbon metrics have been recommended in broader sustainability discourse (Bratan et al., 2024; Ramachandran et al., 2025). Organizational readiness frameworks assess staff preparedness and governance structures; yet the potential energy implications of large-scale artificial intelligence deployment are not integrated into managerial decision-making (Almagharbeh, Alharrasi, et al., 2025). An overview of these gaps in artificial intelligence evaluation in nursing is presented in Table 2.

**Table 2. Gaps in Artificial Intelligence Evaluation in Nursing**

Domain	Existing Focus	Identified Gap	Source
Clinical	Accuracy and safety	Trade-off between accuracy and energy not considered	(Rehman et al., 2025)
Operational	Workflow efficiency	Energy per workflow not quantified	(Dave et al., 2026)
Environmental	Minimal integration	Need for life cycle assessment and carbon metrics	(Bratan et al., 2024; Ramachandran et al., 2025)
Organizational	Staff readiness and governance	Energy impact not included in managerial decisions	(Almagharbeh, Alharrasi, et al., 2025)

### 3.4 Sustainable Artificial Intelligence Strategies for Nursing Practice

Several technological approaches have been proposed to reduce the energy intensity of artificial intelligence systems. One approach involves the development of lightweight models through techniques such as pruning and quantization, which decrease the number of parameters and computational operations required during inference (Champendal et al., 2026; Rehman et al., 2025). By reducing model complexity, these methods can lower energy consumption while maintaining acceptable levels of predictive performance.

Distributed learning paradigms have also been advanced as energy-aware strategies. Federated learning enables model training across decentralized data sources without transferring raw data to a central server, thereby reducing large-scale data movement and potentially lowering the load on centralized infrastructure (Alahmari & Alghamdi, 2025; J. et al., 2025; Kommusaar et al., 2026). Edge computing further supports this approach by processing data locally at or near the point of care, which can decrease reliance on energy-intensive central data centers and reduce network-related energy demand (Rojek et al., 2025). Such strategies aim to balance computational efficiency with data privacy and system scalability (Thakur et al., 2024). An overview of these energy-efficient artificial intelligence strategies is summarized in Table 3.

**Table 3. Energy Efficient Artificial Intelligence Strategies**

Strategy	Description	Source
Lightweight models	Reduce energy consumption during inference through pruning and quantization	(Champendal et al., 2026; Rehman et al., 2025).
Federated learning	Reduce data transfer and improve distributed efficiency	(Alahmari & Alghamdi, 2025; J. et al., 2025; Kommusaar et al., 2026)
Edge computing	Enable local processing to decrease central data center load	(Rojek et al., 2025)
AI based life cycle assessment	Monitor energy use and emissions across the system lifecycle	(Bratan et al., 2024; Aggarwal et al., 2025; Ramachandran et al., 2025)
Green data centers	Reduce carbon intensity through infrastructure optimization	(Aggarwal et al., 2025)

At the infrastructure level, green data center initiatives seek to reduce carbon intensity through renewable energy integration, improved cooling efficiency, and optimized hardware utilization (Aggarwal et al., 2025). In addition, decision frameworks that incorporate energy, emission, and cost considerations into artificial intelligence deployment have been proposed to support more sustainable governance models (Ramachandran et al., 2025). Life cycle assessment-based approaches have also been recommended to evaluate environmental impacts across the entire operational lifespan of artificial intelligence systems, from model development to deployment and maintenance (Bratan et al., 2024; Ramachandran et al., 2025).

For nursing practice, the adoption of such strategies provides a pathway toward aligning digital innovation with environmental responsibility. Integrating energy efficient architectures, distributed learning models, and sustainability oriented evaluation frameworks may help ensure that artificial intelligence supports both clinical excellence and ecological stewardship.

### 3.5 Proposed Framework: Sustainable Nursing Artificial Intelligence Evaluation Metrics

The synthesis of evidence indicates the need for an expanded evaluation framework that integrates sustainability dimensions into the assessment of artificial intelligence systems in nursing practice. Current evaluation approaches emphasize clinical validity and operational performance but do not systematically incorporate energy, emission, and environmental considerations. A comprehensive framework should therefore encompass multiple interrelated domains to ensure balanced and responsible implementation.

The proposed Sustainable Nursing Artificial Intelligence Evaluation Metrics framework includes seven core domains. Clinical metrics remain essential to ensure safety, effectiveness, and patient outcomes. Operational metrics assess workflow efficiency and productivity gains associated with artificial intelligence integration. Energy metrics quantify computational consumption, particularly during training and inference stages. Emission metrics capture carbon intensity and environmental impact associated with system deployment. Social and organizational metrics evaluate workforce implications, including workload redistribution and burnout reduction. Economic metrics consider cost effectiveness and resource allocation efficiency. Environmental metrics extend the analysis to life cycle impacts, including water usage and electronic waste generation. The conceptual structure of the proposed framework is illustrated in Figure 1, while the detailed domains, indicators, and example metrics are summarized in Table 4.

Integrating these domains allows for a multidimensional assessment that aligns technological innovation with principles of sustainability and responsible governance. Rather than evaluating artificial intelligence systems solely on predictive accuracy or efficiency gains, this framework encourages a balanced appraisal of clinical benefit, resource utilization, and ecological responsibility.

**Table 4. Proposed Sustainable Artificial Intelligence Evaluation Framework for Nursing Practice**

Domain	Indicator	Example Metric
Clinical	Safety and effectiveness	Sensitivity, specificity
Operational	Efficiency	Time saved per shift
Energy	Artificial intelligence energy consumption	Wh per 100 inferences
Emission	Carbon impact	gCO <sub>2</sub> e per use
Social	Workforce impact	Burnout reduction indicators
Economic	Cost effectiveness	Cost per deployment
Environmental	Life cycle assessment	Water use, electronic waste

As shown in Table 4, the proposed framework translates sustainability concepts into measurable indicators that can support practical evaluation of artificial intelligence systems in nursing environments.

This proposed framework provides a conceptual foundation for integrating sustainability considerations into artificial intelligence evaluation within nursing informatics. It supports a shift from performance centered assessment toward a more holistic and environmentally conscious evaluation paradigm.

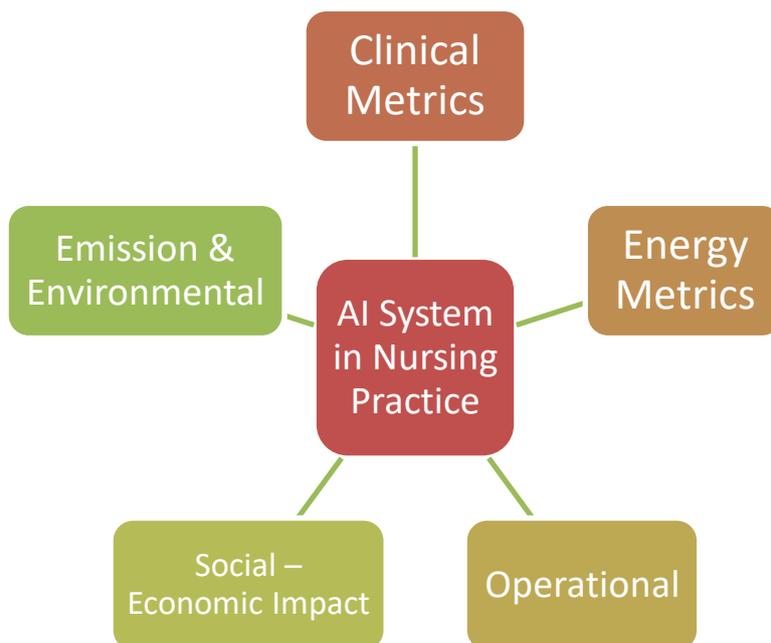


Fig. 1. Sustainable Nursing Artificial Intelligence Evaluation Framework

#### 4. DISCUSSION

The evidence synthesized in this study indicates that artificial intelligence contributes meaningfully to energy consumption and carbon emissions within healthcare systems. At the same time, nursing represents one of the primary domains of clinical artificial intelligence deployment, particularly in documentation systems, decision support tools, and workflow optimization platforms. Despite this central role, sustainability and energy considerations remain largely absent from nursing oriented evaluation frameworks. This disconnect suggests a structural imbalance between technological adoption and environmental accountability.

Several factors may explain this gap. Nursing scholarship has predominantly concentrated on ethical considerations, professional acceptance, governance structures, and organizational culture in relation to artificial intelligence implementation (Mohammed et al., 2025; Almagharbeh, Alfanash, et al., 2025; Almagharbeh, Alharrasi, et al., 2025; Arcadi, 2025). These areas are critical for safe and equitable adoption. Environmental externalities, nevertheless, have not been conceptualized as part of the evaluative discourse. As a result, energy consumption and carbon impact remain outside the dominant research agenda.

Limited awareness of digital carbon footprints among nursing professionals may further contribute to this omission. Current educational efforts emphasize digital literacy and artificial intelligence competencies, yet they rarely address sustainability dimensions or the environmental costs associated with computational infrastructures (Bozkurt et al., 2025; Tomlinson et al., 2026; Reading Turchioe et

al., 2025). Without foundational knowledge regarding the energy intensity and carbon emissions of digital technologies, sustainability is unlikely to become embedded in routine evaluation practices.

Organizational governance structures also play a role. In many healthcare institutions, there are no explicit policies establishing energy thresholds or sustainability criteria for the procurement and deployment of clinical technologies (Ramachandran et al., 2025). Decision making processes often prioritize functionality, cost, and compliance, while energy efficiency and environmental impact remain peripheral considerations. This policy vacuum limits institutional incentives to integrate sustainability metrics into artificial intelligence adoption strategies.

Future directions require a multidimensional response. Nursing professionals should strengthen competencies in sustainable artificial intelligence and develop awareness of environmental implications associated with digital systems. Life cycle assessment approaches should be incorporated into health technology appraisal processes to evaluate energy use, carbon emissions, water consumption, and electronic waste across the full operational lifespan of artificial intelligence tools. The adoption of lightweight model architectures and distributed computing strategies should be encouraged to reduce computational burden. Collaboration between nursing leaders, informatics specialists, and information technology teams is essential to optimize workflow design and minimize unnecessary energy consumption in artificial intelligence enabled systems.

Reframing artificial intelligence evaluation in nursing practice through a sustainability lens supports alignment between digital innovation and environmental responsibility. Integrating energy aware metrics into evaluation standards represents a necessary step toward responsible and future oriented nursing informatics.

## CONCLUSION

Artificial intelligence offers substantial benefits for nursing practice, ranging from automated documentation to enhanced clinical decision support and workflow optimization. These innovations have the potential to improve efficiency, reduce administrative burden, and strengthen the quality of patient care. Nevertheless, accumulating evidence demonstrates that artificial intelligence systems are associated with significant energy consumption and measurable ecological impact across their lifecycle.

Current evaluation frameworks for artificial intelligence in healthcare prioritize clinical effectiveness, safety, integration feasibility, and organizational readiness. None of the prevailing frameworks explicitly incorporate metrics related to energy consumption or carbon emissions. This omission creates a critical gap in health technology assessment, particularly as artificial intelligence becomes increasingly embedded in routine nursing workflows. Without sustainability metrics, evaluation processes remain incomplete and risk overlooking environmental externalities linked to digital transformation.

A revised approach is therefore required. The proposed Sustainable Nursing Artificial Intelligence Evaluation Metrics framework calls for the explicit integration of energy consumption measured in watt hours, carbon emissions quantified in grams of carbon dioxide equivalent, and life cycle assessment methodologies that account for environmental impact across development, deployment, and maintenance phases. Incorporating these dimensions alongside clinical and operational indicators would enable a more comprehensive and responsible appraisal of artificial intelligence systems.

Adopting a holistic evaluation paradigm that integrates performance, governance, and sustainability enables nursing to contribute to shaping artificial intelligence that is not only safe and effective but also environmentally responsible. Such a shift aligns digital innovation with broader commitments to sustainable healthcare systems and long-term ecological stewardship.

## DECLARATION OF GENERATIVE AI

The authors declare that generative artificial intelligence tools were used solely to support the preparation of this manuscript. Specifically, ChatGPT was utilized to assist in improving the clarity,

grammar, and readability of the English language in the manuscript. In addition, Scopus AI was used to help validate and verify the relevance of cited references.

These tools were employed only to enhance language quality and assist in reference validation. All intellectual content, interpretation of results, and scientific conclusions presented in this manuscript are the sole responsibility of the authors. The authors have carefully reviewed and edited the outputs generated by these tools to ensure accuracy, originality, and compliance with academic integrity standards.

## REFERENCES

- Aggarwal, T., Kumar, S., Singh, S. K., Subba, C. K., Upadhyaya, B., Arya, V., Ratnaparkhi, A., & Sharma, S. K. (2025). *Reducing the Carbon Footprint in Machine Learning With Eco-Friendly AI Training* (pp. 201–214). <https://doi.org/10.4018/979-8-3693-8034-5.ch010>
- Alahmari, S., & Alghamdi, I. (2025). A comprehensive survey on energy-efficient and privacy-preserving federated learning for edge intelligence and IoT. *Results in Engineering*, 28, 107849. <https://doi.org/10.1016/j.rineng.2025.107849>
- Almagharbeh, W. T., Alfanash, H. A., Alnawafleh, K. A., Alasmari, A. A., Alsaraireh, F. A., Dreidi, M. M., & Nashwan, A. J. (2025). Application of artificial intelligence in nursing practice: a qualitative study of Jordanian nurses' perspectives. *BMC Nursing*, 24(1), 92. <https://doi.org/10.1186/s12912-024-02658-6>
- Almagharbeh, W. T., Alharrasi, M., Rony, M. K. K., Kabir, S., Ahmed, S. K., & Alrazeeni, D. M. (2025). Ethical and Institutional Readiness for Artificial Intelligence in Nursing: An Umbrella Review. *International Nursing Review*, 72(4). <https://doi.org/10.1111/inr.70111>
- Arcadi, P. (2025). Nursing leadership and artificial intelligence ethics: Safeguarding relationships and values. *Nursing Ethics*, 32(8), 2468–2476. <https://doi.org/10.1177/09697330251366599>
- Balpande, V., Rewatkar, P., Dhole, P., Alwadkar, I., & Gomase, K. (2025). Artificial intelligence transforming healthcare and nursing: A comprehensive bibliometric analysis. *Multidisciplinary Reviews*, 8(9), 2025267. <https://doi.org/10.31893/multirev.2025267>
- Bozkurt, S. A., Aydoğan, S., Dursun Ergezen, F., & Türkoğlu, A. (2025). A systematic review and sequential explanatory synthesis: Artificial intelligence in healthcare education, a case of nursing. *International Nursing Review*, 72(2). <https://doi.org/10.1111/inr.70018>
- Bratan, T., Heyen, N. B., Hüsing, B., Marscheider-Weidemann, F., & Thomann, J. (2024). Hypotheses on environmental impacts of AI use in healthcare. *The Journal of Climate Change and Health*, 16, 100299. <https://doi.org/10.1016/j.joclim.2024.100299>
- Champendal, M., Lokaj, B., de Gevigney, V. D., Brulé, G., Zaghir, J., Boiko, P., Lovis, C., Müller, H., Schmid, J., & Ribeiro, R. T. (2026). Exploring environmental sustainability of artificial intelligence in radiology: A scoping review. *European Journal of Radiology*, 194, 112558. <https://doi.org/10.1016/j.ejrad.2025.112558>
- Chen, L.-Y. A., Yeh, E.-H., Lin, P., Hsieh, M.-Y., Lin, C.-P., & Liao, Z.-Y. (2026). Interpreting free-text cardiac catheterisation reports: A machine learning approach informed by focused ethnography. *Nurse Education in Practice*, 91, 104715. <https://doi.org/10.1016/j.nepr.2026.104715>
- Dave, B., Martin, P., David, S. S., Kumar, S., & Chakraborty, T. (2026). Enhancing healthcare worker mental health via artificial intelligence-driven work process improvements: a scoping review. *International Journal of Medical Informatics*, 205, 106122. <https://doi.org/10.1016/j.ijmedinf.2025.106122>
- Duane, B., Ashley, P., & Larkin, J. (2026). Prompt-Driven ChatGPT Carbon Calculator for Dental Practices: Estimation and Tailored Improvement Strategies. *International Dental Journal*, 76(1), 103979. <https://doi.org/10.1016/j.identj.2025.103979>
- Fajkis-Zajączkowska, N., Zawada, A., Bojko, M., & Kolasa, K. (2025). Comprehensive analysis of frameworks for evaluating artificial intelligence solutions in Healthcare: A descriptive review. *Computers in Biology and Medicine*, 196, 110750. <https://doi.org/10.1016/j.combiomed.2025.110750>
- J., J., Mahalingam, N., Wang, B., & Yeo, K. S. (2025). Federated learning for sustainable intrusion detection systems: A review of green computing strategies and future directions. *Internet of Things*, 34, 101730. <https://doi.org/10.1016/j.iot.2025.101730>
- Jacob, C., Brasier, N., Laurenzi, E., Heuss, S., Mouggiakakou, S.-G., Cöltekin, A., & Peter, M. K. (2025). AI for IMPACTS Framework for Evaluating the Long-Term Real-World Impacts of AI-Powered Clinician Tools: Systematic Review and Narrative Synthesis. *Journal of Medical Internet Research*, 27, e67485. <https://doi.org/10.2196/67485>

- Keil, M., Frehse, L., Hagemester, M., Knieß, M., Lange, O., Kronenberg, T., & Rogowski, W. (2024). Carbon footprint of healthcare systems: a systematic review of evidence and methods. *BMJ Open*, 14(4), e078464. <https://doi.org/10.1136/bmjopen-2023-078464>
- Kommusaar, J., Elunurm, S., Chomutare, T., Kangasniemi, M., Salanterä, S., & Peltonen, L.-M. (2026). A roadmap for federated learning projects using health data to guide sustainable artificial intelligence development in the European Union. *International Journal of Medical Informatics*, 208, 106242. <https://doi.org/10.1016/j.ijmedinf.2025.106242>
- Mikhailova, A. A., & Sharova, D. E. (2023). Artificial intelligence ethics code in healthcare. Sustainability of artificial intelligence systems: Why do we talk about their impact on the environment? *Digital Diagnostics*, 4(1S), 93–95. <https://doi.org/10.17816/DD430356>
- Mohammed, S. A. A. Q., Osman, Y. M. M., Ibrahim, A. M., & Shaban, M. (2025). Ethical and regulatory considerations in the use of AI and machine learning in nursing: A systematic review. *International Nursing Review*, 72(1). <https://doi.org/10.1111/inr.70010>
- Moltó-Puigmartí, C., Trias, S. A., Vallejo, M. B., Domínguez Herrera, D., & Vivanco-Hidalgo, R. M. (2026). *The Assessment of AI-Based Digital Health Technologies from the Perspective of HTA Bodies. The Case of AQuAS' AI Assessment Guide* (pp. 90–96). [https://doi.org/10.1007/978-3-032-10661-2\\_7](https://doi.org/10.1007/978-3-032-10661-2_7)
- Ramachandran, A., Sarabu, C., Gupta, U., Ghose, S., & Lee, V. S. (2025b). Sustainably Advancing Health AI: A Decision Framework to Mitigate the Energy, Emissions, and Cost of AI Implementation. *NEJM Catalyst*, 6(10). <https://doi.org/10.1056/CAT.25.0125>
- Ramadan, O. M. E., Alruwaili, M. M., Alruwaili, A. N., Elsehrawy, M. G., & Alanazi, S. (2024). Facilitators and barriers to AI adoption in nursing practice: a qualitative study of registered nurses' perspectives. *BMC Nursing*, 23(1), 891. <https://doi.org/10.1186/s12912-024-02571-y>
- Reading Turchioe, M., Pepingco, C., Ronquillo, C., Ferrara, S. A., Topaz, M., Austin, R., & Lytle, K. (2025). Education, empowerment, and elevating nursing voices: Nursing informatics leaders' perspectives on the path forward with artificial intelligence in nursing. *Nursing Outlook*, 73(5), 102484. <https://doi.org/10.1016/j.outlook.2025.102484>
- Reddy, S., Rogers, W., Makinen, V.-P., Coiera, E., Brown, P., Wenzel, M., Weicken, E., Ansari, S., Mathur, P., Casey, A., & Kelly, B. (2021). Evaluation framework to guide implementation of AI systems into healthcare settings. *BMJ Health & Care Informatics*, 28(1), e100444. <https://doi.org/10.1136/bmjhci-2021-100444>
- Rehman, Z. U., Hassan, U., Islam, S. U., Gallos, P., & Boudjadar, J. (2025). *Energy-Efficient AI for Medical Diagnostics: Performance and Sustainability Analysis of ResNet and MobileNet*. <https://doi.org/10.3233/SHTI250585>
- Richie, C., Hinrichs-Krapels, S., Dobbe, R., French, P., Wei, J. C. J., Diehl, J. C., & Kong, R. (2025). Environmental impacts of artificial intelligence in health care: considerations and recommendations. *Health and Technology*, 15(6), 1087–1093. <https://doi.org/10.1007/s12553-025-01003-4>
- Rojek, I., Prokopowicz, P., Piechowiak, M., Kotlarz, P., Náprstková, N., & Mikołajewski, D. (2025). The Impact of Data Analytics Based on Internet of Things, Edge Computing, and Artificial Intelligence on Energy Efficiency in Smart Environment. *Applied Sciences*, 16(1), 225. <https://doi.org/10.3390/app16010225>
- Ruksakulpiwat, S., Thorngthip, S., Niyomyart, A., Benjasirisan, C., Phianhasin, L., Aldossary, H., Ahmed, B., & Samai, T. (2024). A Systematic Review of the Application of Artificial Intelligence in Nursing Care: Where are We, and What's Next? *Journal of Multidisciplinary Healthcare, Volume 17*, 1603–1616. <https://doi.org/10.2147/JMDH.S459946>
- Thakur, D., Guzzo, A., & Fortino, G. (2024). Hardware-algorithm co-design of Energy Efficient Federated Learning in Quantized Neural Network. *Internet of Things*, 26, 101223. <https://doi.org/10.1016/j.iot.2024.101223>
- Tomlinson, E., Schoch, M., & McDonall, J. (2026). A curriculum framework for embedding artificial intelligence literacies in pre-registration nursing education. *Nurse Education Today*, 158, 106928. <https://doi.org/10.1016/j.nedt.2025.106928>
- Ueda, D., Walston, S. L., Fujita, S., Fushimi, Y., Tsuboyama, T., Kamagata, K., Yamada, A., Yanagawa, M., Ito, R., Fujima, N., Kawamura, M., Nakaura, T., Matsui, Y., Tatsugami, F., Fujioka, T., Nozaki, T., Hirata, K., & Naganawa, S. (2024). Climate change and artificial intelligence in healthcare: Review and recommendations towards a sustainable future. *Diagnostic and Interventional Imaging*, 105(11), 453–459. <https://doi.org/10.1016/j.diii.2024.06.002>
- von Gerich, H., Moen, H., Block, L. J., Chu, C. H., DeForest, H., Hobensack, M., Michalowski, M., Mitchell, J., Nibber, R., Olalia, M. A., Pruinelli, L., Ronquillo, C. E., Topaz, M., & Peltonen, L.-M. (2022a). Artificial Intelligence -based technologies in nursing: A scoping literature review of the evidence. *International Journal of Nursing Studies*, 127, 104153. <https://doi.org/10.1016/j.ijnurstu.2021.104153>