VIVA MEDIKA
Jurnal Kesehatan, Kebidanan, dan Keperawatan
Homepage: http://ejournal.uhb.ac.id/index.php/vm
P-ISSN: 1979-2026 E-ISSN: 2656-1034
DOI: 10.35960/vm.v18i3.2222

A Scoping Review of Machine Learning Applications in Nursing Practice: Clinical Decision Support, Risk Prediction, and Workflow Optimization

Anton Suhendro[1], Wahyu Caesarendra[2] , Purwono Purwono[3,*]
[1] Department of Anesthesiology Nursing Universitas Harapan Bangsa, Purwokerto, 53182, Indonesia
[2]Department of Mechanical and Mechatronics Engineering, Curtin University, Malaysia
[3]Peneliti Teknologi Teknik Indonesia, Yogyakarta, Indonesia
[1]antonsuhendro@uhb.ac.id, [2]w.caesarendra@curtin.edu.my, [3,*]purwono@ieee.org

ABSTRACT

Machine learning (ML) is rapidly transforming nursing practice by enabling advancements in clinical decision support, risk prediction, and workflow optimization. This scoping review synthesizes evidence from empirical studies, reviews, and implementation reports published between 2018 and 2025, identified through Scopus and ScienceDirect. The findings indicate that supervised learning algorithms, deep learning, and natural language processing are widely utilized for risk assessment, early detection of patient deterioration, and enhancement of administrative efficiency. Natural language processing (NLP) also supports automation of nursing documentation and improved data quality. Despite favorable performance metrics, including AUROC values above 0.85 in many applications, most studies are limited by single-institution data, insufficient external validation, and heterogeneous reporting standards. Major barriers include ethical and legal concerns, data quality issues, algorithmic bias, infrastructural limitations, and limited nurse involvement in model development. Enhancing AI literacy and fostering nurse engagement in system design are highlighted as critical for successful clinical integration. Future research priorities include multicenter validation, development of explainable AI, adoption of standardized reporting guidelines, and interdisciplinary collaboration to address ethical, technical, and regulatory challenges. Overall, this scoping review demonstrates that machine learning offers substantial potential to improve patient outcomes and nursing operations, but responsible adoption requires rigorous validation, transparent governance, and active participation of nursing professionals throughout the technology lifecycle..

Keywords: Machine learning; Nursing practice; Clinical decision support; Risk prediction; Artificial intelligence governance

1. INTRODUCTION

Digital transformation in nursing practice has substantially reshaped the ways in which care is delivered, utilizing technologies such as telehealth, electronic health records, and artificial intelligence to improve efficiency, accessibility, and overall care quality (Rigamonti, 2023; Abou Hashish, 2025; Ebo et al., 2025). At the same time, the incorporation of these technologies has contributed to greater complexity in clinical services, as it requires multidisciplinary coordination, system interoperability, and poses challenges in preserving empathetic and patient-centered communication (Meyer et al., 2024; Babar et al., 2024). Consequently, successful digital transformation depends on the active participation

* **Anton Suhendro**
Tel.: -
Email: antonsuhendro@uhb.ac.id

of healthcare professionals, structured digital competency training, and robust change management approaches to ensure that technological innovations effectively translate into improved clinical outcomes (Jobst et al., 2022).

The rapid development of machine learning (ML), deep learning (DL), and natural language processing (NLP) has significantly transformed healthcare systems by enabling the processing and interpretation of complex medical data, including electronic health records and medical imaging, which enhances diagnostic precision and supports clinical decision-making (Katta et al., 2025). The incorporation of DL techniques within NLP frameworks further allows for the extraction of meaningful information from unstructured data, thereby facilitating disease forecasting, individualized treatment strategies, and more efficient allocation of healthcare resources (Huang et al., 2024; Rahim et al., 2024). Nevertheless, key challenges remain, particularly in relation to data protection, model transparency, and interdisciplinary collaboration, which must be addressed to ensure the responsible and effective use of these technologies in healthcare practice (Khalate et al., 2024).

Discrepancies between technological innovation and practical implementation in nursing often emerge because system development is commonly driven by top-down approaches that insufficiently engage nurses as primary users, resulting in tools that do not fully correspond to clinical requirements (Siebeck & Hoving, 2024). Further obstacles include limited training opportunities, resistance to organizational change, infrastructural constraints, and ethical as well as regulatory issues that hinder the widespread adoption of artificial intelligence and health information technologies (Qutishat & Shakman, 2025; Kleib et al., 2024). Bridging these gaps necessitates bottom-up co-design strategies, stronger partnerships between researchers and practitioners, and continuous investment in education and institutional support to ensure that technological advancements meaningfully improve the quality of nursing care.

This review seeks to systematically integrate current evidence concerning the use of machine learning in nursing practice. Specifically, it aims to identify and categorize machine learning approaches applied in nursing settings, including supervised learning, deep learning, natural language processing, and hybrid models. In addition, the review assesses the documented clinical and operational effects of these technologies within three key areas: clinical decision support, risk prediction, and workflow optimization. Particular emphasis is placed on quantifiable outcomes, such as enhanced diagnostic accuracy, lower mortality rates, reduced hospital readmissions, earlier recognition of patient deterioration, and improved administrative performance.

Recent reviews published between 2023 and 2025 have examined machine learning applications in nursing contexts, particularly focusing on algorithm classification, intensive care prediction models, or bibliometric trends. However, most prior syntheses emphasize descriptive mapping of techniques rather than integrated evaluation of validation rigor, comparative effectiveness, and implementation feasibility. Limited attention has been given to how predictive performance, interpretability, governance considerations, and nurse engagement collectively shape real-world integration. This review addresses that gap by synthesizing technical robustness with socio-technical and workforce dimensions to assess the maturity of machine learning adoption in nursing practice.

2. METHODS

This study adopted a scoping review design to systematically map existing research on the use of machine learning in nursing practice. This scoping review was conducted in accordance with the methodological framework proposed by Arksey and O'Malley (2005) and reported following the PRISMA-ScR guidelines (Tricco et al., 2018). A structured literature search was performed using the Scopus and ScienceDirect databases, employing key terms such as "machine learning," "artificial intelligence," "nursing practice," "clinical decision support," "risk prediction," and "workflow optimization." Eligible studies consisted of peer-reviewed articles published in English between 2018 and 2025 that reported clinical or operational outcomes associated with machine learning applications in nursing. The year 2018 was selected as the starting point to capture the rapid expansion of deep learning and advanced machine learning applications following widespread electronic health record digitization and increased integration of predictive analytics in clinical nursing environments.

The full Boolean search string applied in Scopus was as follows:

("machine learning" OR "artificial intelligence" OR "deep learning" OR "natural language processing") AND ("nursing" OR "nursing practice" OR "nursing care") AND ("clinical decision support" OR "risk prediction" OR "workflow optimization"). Equivalent syntax was adapted for ScienceDirect. The search yielded 156 records in Scopus and 45 records in ScienceDirect. After removal of duplicates, 54 records remained for title and abstract screening.

The selection process was carried out through several stages, starting with screening of titles and abstracts, followed by full-text assessment to confirm relevance and adequacy of reporting. Data extracted from each study comprised author information, year of publication, clinical context, algorithm type, application area, evaluation measures, and reported outcomes. The findings were synthesized using narrative and thematic analysis by organizing the results into key domains, namely clinical decision support, risk prediction, workflow optimization, and documentation or education. This analytical approach enabled a comprehensive understanding of current developments, existing challenges, and future potential for the integration of machine learning within nursing practice.

Although formal risk-of-bias assessment is not mandatory in scoping reviews, a structured methodological appraisal was conducted to contextualize evidentiary strength. Each included study was descriptively evaluated based on study design, validation approach (internal versus external validation), dataset source (single-center versus multicenter), and reporting transparency of preprocessing and performance metrics. This appraisal was used to inform interpretive synthesis rather than to exclude studies.

3. RESULT

The results are presented according to three functional domains identified in the analytical framework, namely clinical decision support, risk prediction, and workflow optimization. These domains reflect the primary functional roles of machine learning systems in nursing environments and represent interconnected layers of clinical and operational integration. In addition, the general characteristics of the included studies are first summarized to provide contextual insight into study distribution and methodological variation.

3.1 Characteristics of Included Studies

The studies included in this review exhibit substantial variation with respect to clinical contexts, geographical distribution, and areas of machine learning utilization. The reviewed literature reports implementations across multiple nursing settings, including hospitals, intensive care units, community-based nursing services, and home care environments. From a geographical perspective, the majority of investigations originate from regions with well-established healthcare infrastructures, such as the United States, Canada, Western Europe, and East Asia, although several studies also emerge from developing countries. The application areas involve clinical decision support, risk prediction, workflow optimization, and documentation and educational functions, using diverse machine learning methods, including random forest algorithms, support vector machines, deep learning models, and natural language processing techniques. The data sources commonly comprise electronic health records (EHRs), nursing documentation, and real-time patient monitoring information. Furthermore, variations in sample size, study duration, and outcome measures reflect the differing objectives and methodological designs adopted across the included studies.

3.2 Machine Learning Techniques in Nursing Practice

Machine learning methods have increasingly become integral to contemporary nursing practice, with their use extending across clinical decision support, patient surveillance, and workflow optimization through predictive modeling, deep learning, and natural language processing (Wangpitipanit et al., 2024; Kim & Kim, 2025; Yip et al., 2025; Ajibade et al., 2024). Techniques such as random forest, support vector machines (SVM), and convolutional neural networks (CNN) are applied to estimate the risk of patient falls and pressure injuries, as well as to facilitate the early identification of sepsis, thereby contributing to enhanced patient safety and improved compliance with established clinical guidelines (Kim & Kim, 2025; Yip et al., 2025). Notwithstanding their considerable promise, the implementation of machine learning in nursing practice continues to encounter several limitations, including insufficient external validation, the presence of algorithmic bias, and challenges related to system integration within existing nursing workflows. These issues underscore the importance of human-centered system design and the establishment of rigorous ethical governance frameworks to ensure responsible deployment (Kim & Kim, 2025; Abi Khalil et al., 2025). A summary of various machine learning techniques, their application areas, and types of datasets used in nursing practice is presented in Table 1. The conceptual map of machine learning application domains in nursing practice (see Figure 1) provides a visual summary of the key areas identified in this review. These areas include clinical decision support, risk prediction, workflow optimization, and documentation and education, each accompanied by the primary machine learning techniques commonly applied in practice. This figure offers an integrated overview of how diverse ML methods are utilized across various aspects of nursing practice.

The distribution presented in Table 1 indicates that supervised learning models dominate risk prediction tasks, whereas reinforcement learning and hybrid systems remain comparatively underexplored in nursing contexts. This imbalance suggests that current research prioritizes predictive surveillance over adaptive care optimization.

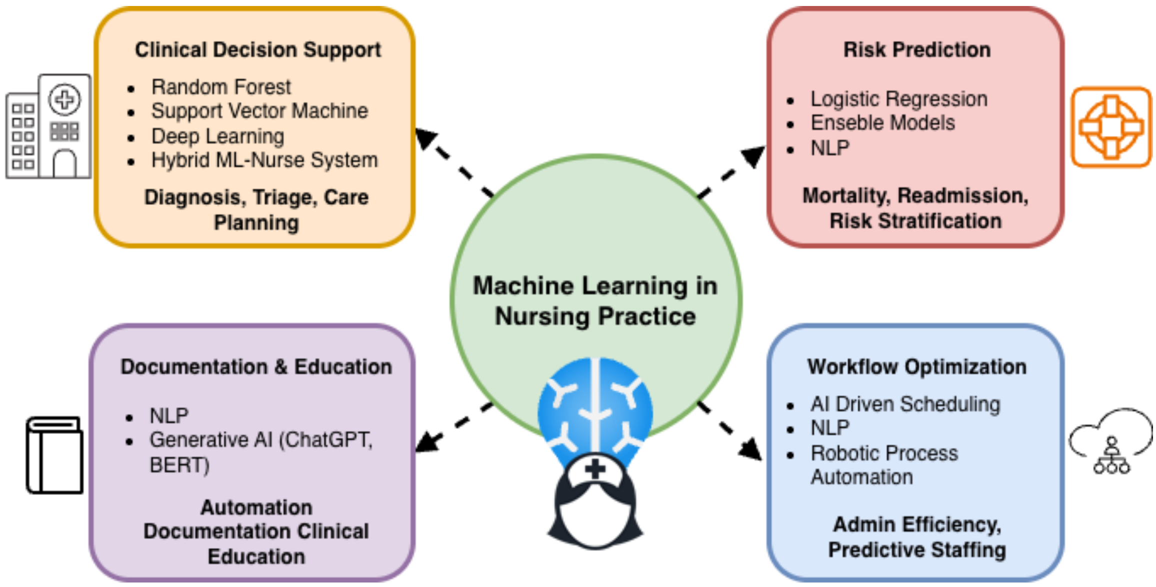

Figure 1. Conceptual map of machine learning application domains in nursing practice, illustrating main domains, key techniques, and practical examples identified in this scoping review.

Table 1. Machine Learning Techniques and Their Applications in Nursing Practice

ML Technique	Main Application Area	Example/Benefit	Source
Random Forest, Logistic Regression, SVM	Risk prediction (pressure ulcers, falls, readmission)	High predictive accuracy, supports preventive interventions	Kim & Kim, 2025
Deep Learning (CNN, ANN)	Early sepsis detection, medical image analysis	COMPOSER model reduces sepsis mortality by 1.9% and increases protocol adherence by 5%	Yip et al., 2025
Natural Language Processing	Clinical data extraction, documentation automation	Reduces administrative burden, increases time for direct patient care	Ajibade et al., 2024; Abi Khalil et al., 2025
Reinforcement Learning	Care strategy optimization	Adaptive therapy recommendations based on patient responses	Ajibade et al., 2024
Automated Machine Learning (AutoML) + Explainable AI (XAI)	Diagnosis and prognosis prediction	Accelerates model development, enhances interpretability	Castro et al., 2026
Hybrid AI Systems (NLP + Generative AI)	Data-driven nursing process support	Automates patient problem identification and care plan creation	Abi Khalil et al., 2025

3.3 Clinical Outcomes and Effectiveness

The use of machine learning within nursing practice has been associated with favorable effects on clinical outcomes and the effectiveness of interventions, particularly in areas such as early risk detection, continuous patient surveillance, and the enhancement of adherence to clinical protocols (Yip et al., 2025; Kim et al., 2025; Thomas et al., 2025). For example, the deep learning-based COMPOSER model for early sepsis detection resulted in a 1.9% absolute (17% relative) reduction in mortality and a 5% absolute (10% relative) increase in sepsis bundle compliance (Yip et al., 2025). Despite these encouraging findings, the practical impact of machine learning in routine clinical settings remains constrained by several factors, including limited external validation, the risk of algorithmic bias, and low levels of adoption in clinical practice. These limitations emphasize the necessity for nurse-centered system integration and continuous evaluation of real-world outcomes to ensure sustained effectiveness (Kim & Kim, 2025; D’Amico et al., 2023). A summary of the effectiveness of machine learning applications in nursing, along with the clinical outcomes achieved by various models, is provided in Table 2.

The pattern of optimization effects across the principal machine learning domains and major clinical outcomes is depicted in Figure 2. This heatmap matrix demonstrates the extent to which various application areasn amely clinical decision support, risk prediction, workflow optimization, and documentation and education are associated with outcomes such as reduced mortality, lower readmission rates, enhanced patient safety, and improved operational performance.

Measurable statistical improvements associated with the adoption of machine learning in nursing practice are accompanied by observable benefits for both patient care and clinical workflows. From the patient perspective, the use of machine learning–based early warning systems and predictive risk models enables more timely and individualized interventions, thereby reducing the likelihood of adverse events, including falls, pressure injuries, and sepsis. Early and reliable recognition of sepsis allows for the prompt initiation of evidence-based treatment bundles, contributing to reduced mortality and more favorable recovery trajectories. These advancements enhance patient safety and strengthen patient confidence in the quality of care delivered.

Table 2. Summary of Clinical Outcomes and Intervention Effectiveness of Machine Learning Applications in Nursing Practice

ML Application / Model	Clinical Outcome / Effectiveness	Example / Measured Benefit	Source
Pain prediction after knee surgery (Random Forest, SVM, KNN)	Higher predictive accuracy than logistic regression	Supports preventive interventions for high-risk patients	Yan et al., 2023
COMPOSER model (Deep Learning) for early sepsis detection	1.9% absolute (17% relative) reduction in mortality; 5% absolute (10% relative) increase in bundle compliance	Enhances sepsis management and clinical outcomes	Yip et al., 2025
Pressure ulcer, fall, and readmission risk prediction	High AUC and accuracy (>0.85)	Enables early data-driven interventions	Kim & Kim, 2025
ML-based speech recognition for documentation	Accuracy improved from 87.06% to 95.07%	Reduces nurses' documentation burden	Lee et al., 2023
AI/ML-based lung cancer survival prediction	Predictive model with high discrimination	Supports personalized care planning	Yuan et al., 2025
ICU data analysis with ML	Identification of factors affecting nursing-sensitive outcomes	Improves ICU care quality	Kim et al., 2025

Clinical workflow efficiency is enhanced through the automation of routine evaluations and documentation tasks by machine learning algorithms, thereby reducing the administrative workload of nursing personnel. Consequently, more time can be allocated by nurses to direct patient care, comprehensive assessment, and personalized health education, which strengthens the therapeutic nurse–patient relationship. Optimal resource utilization and effective team coordination are also facilitated through the integration of machine learning into care planning and task distribution, particularly in high-acuity environments or resource-limited settings.

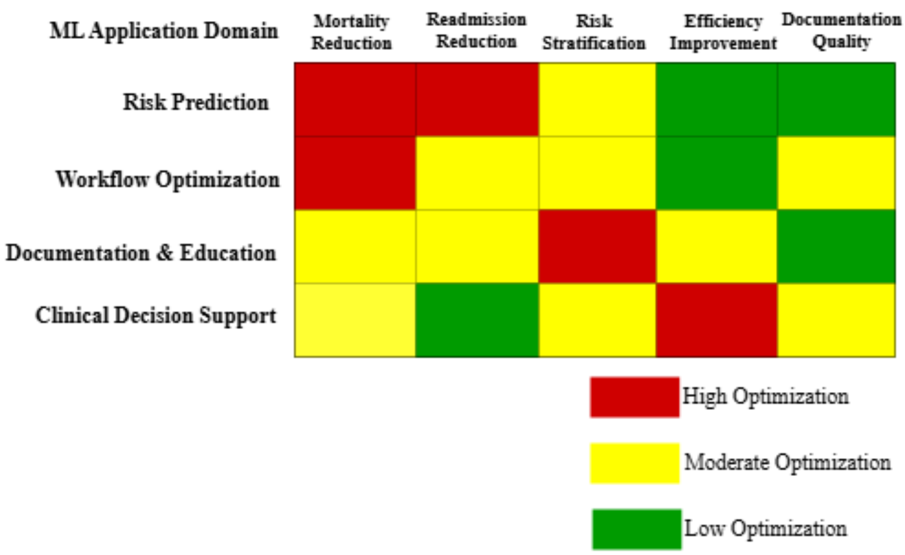

Figure 2. Heatmap matrix illustrating the degree of clinical outcome optimization achieved by different machine learning domains in nursing practice. Red indicates high optimization, yellow moderate, and green low optimization.

3.4 Performance Metrics and Validation

Assessing the performance of machine learning models in nursing practice necessitates the application of multiple evaluation indicators, including accuracy, sensitivity (recall), specificity, precision, F1-score, and the Area Under the Receiver Operating Characteristic Curve (AUC-ROC), in order to determine a model's capacity to correctly classify clinical states (Wu et al., 2023; Li et al., 2025). Model validation is conducted using methods such as k-fold cross-validation (for example, 10-fold) to test generalizability on unseen data, as well as external validation to ensure consistent performance beyond the training dataset (Zolnoori et al., 2023; Adami et al., 2023). This combined strategy plays a critical role in minimizing overfitting and in confirming that machine learning algorithms can be applied with confidence in real clinical environments, thereby supporting nurses' clinical judgments in a precise and safe manner (Tsanakas et al., 2025). The spectrum of performance measures and validation procedures employed in the development of machine learning models for nursing applications is summarized in Table 3. This table outlines the definitions of each metric, the validation approaches implemented, and their practical relevance for assessing model discrimination, predictive accuracy, and generalizability. In doing so, it provides a clear basis for evaluating the effectiveness and dependability of models reported across different nursing studies.

An evaluation approach that combines technical metrics with clinical validation ensures that ML models are not only statistically robust but also relevant and safe for use in nursing decision-making. This integration is crucial for building healthcare professionals' trust in technology and for maximizing its positive impact on patient outcomes.

Table 3. Summary of Performance Metrics and Validation Methods Used in Evaluating Machine Learning Models in Nursing

Performance Metric	Brief Definition	Clinical Purpose	Validation Method	Source
Accuracy	Proportion of correct predictions out of all cases	Assesses overall model correctness	10-fold cross-validation, external validation	Nkemdirim Okere et al., 2025
Sensitivity (Recall)	Proportion of positive cases correctly detected	Reduces false negatives in disease detection	Stratified cross-validation	Kalayou et al., 2024
Specificity	Proportion of negative cases correctly detected	Reduces false positives in screening	External validation	Tsanakas et al., 2025
Precision	Proportion of predicted positives that are correct	Ensures clinical intervention relevance	F1-score optimization	Zolnoori et al., 2023
F1-score	Harmonic mean of precision and recall	Balances sensitivity and precision	Cross-validation	Nkemdirim Okere et al., 2025
AUC-ROC	Model's ability to distinguish positive and negative	Evaluates diagnostic discrimination	ROC curve analysis, external validation	Li et al., 2025
Matthews Correlation Coefficient (MCC)	Correlation between predictions and actual labels	Evaluates performance on imbalanced data	Cross-validation	Wu et al., 2023
Cohen's Kappa	Agreement between predictions and labels, chance-corrected	Assesses model reliability	Cross-validation	Hossain & Roy, 2025

As summarized in Table 3, although accuracy and AUC-ROC are frequently reported, fewer studies provide calibration metrics or real-world validation data. This pattern reinforces the need for more comprehensive evaluation frameworks in future nursing AI research.

Beyond reporting predictive accuracy, the synthesis of validation approaches highlights substantial variability in methodological rigor across studies. While internal cross-validation is commonly applied, external validation and multicenter testing remain limited. The structured comparison of performance metrics and validation strategies presented in this review enables a more critical assessment of evidentiary strength, distinguishing algorithmic performance claims from implementation readiness.

3.5 Comparative Effectiveness

Based on previous findings, machine learning models generally outperform conventional risk scores across various nursing clinical contexts, such as infection risk prediction, postoperative pain, and intensive care unit (ICU) outcomes (Kim et al., 2023; Arjmand et al., 2025). Methods such as random forest, support vector machines, and deep learning architectures frequently achieve superior predictive performance when compared with conventional techniques, including logistic regression and rule-based scoring systems (Yan et al., 2023; Arjmand et al., 2025). This performance advantage largely stems from the capacity of machine learning algorithms to process and integrate complex, high-dimensional data that are challenging for traditional statistical models to accommodate.

Restricted model interpretability continues to represent a significant obstacle to their widespread clinical use. Although machine learning approaches can yield more precise predictions, many models particularly those based on deep learning operate as “black-box” systems, limiting clinicians’ ability to comprehend the reasoning underlying their predictions (Alijoyo et al., 2024; B. et al., 2025). Within nursing practice, professional trust and the capability to communicate and justify results to patients and multidisciplinary teams are essential. Consequently, despite their methodological advantages, low-transparency models often face substantial barriers to clinical implementation. A comprehensive comparison between machine learning models and conventional risk scoring systems in predicting nursing outcomes is provided in Table 4.

Table 4. Comparison of Advantages and Limitations of Machine Learning Models Versus Conventional Risk Scores in Nursing Practice

Aspect	Machine Learning Models	Conventional Risk Scores
Predictive Accuracy	Often higher, especially with complex, multivariate data	Generally moderate; may miss subtle or non-linear relationships
Data Handling	Can process large-scale, high-dimensional, and unstructured data	Typically limited to predefined variables and structured data
Adaptability	Continuously improvable with new data and retraining	Static rarely updated after validation
Interpretability	Often low, especially in deep learning models; considered a “black box”	Usually high; scoring rules are explicit and transparent
Clinical Trust & Adoption	Limited by lack of explainability and transparency; requires user education and trust-building	Generally trusted and widely used in clinical practice
Implementation Barriers	Needs technical infrastructure, external validation, and nurse-centered integration	Simple to implement; requires minimal technical resources
Bias & Overfitting Risk	Susceptible if not properly validated; bias from unbalanced datasets	Lower risk if developed with representative samples
Regulatory and Ethical Issues	Complex, often under ongoing regulatory review	Well-established in terms of regulatory acceptance

3.5 Cross-Domain Analytical Integration

Across the reviewed literature, a consistent pattern emerges in which high internal predictive performance is frequently reported, yet external validation remains limited. Many studies achieve strong AUROC or accuracy values within single-institution datasets, but relatively few demonstrate robustness across multicenter settings. This disparity indicates that algorithmic development has progressed more rapidly than implementation maturity. In parallel, risk prediction applications substantially outnumber workflow optimization initiatives, suggesting that research attention remains concentrated on clinical surveillance rather than system-level operational redesign. Interpretability challenges are reported across domains, regardless of model type, reinforcing that explainability represents a structural barrier to adoption rather than a model-specific limitation. Collectively, these findings indicate that machine learning integration in nursing is technically promising but remains uneven in governance readiness, validation rigor, and socio-technical alignment.

4. CHALLENGES AND LIMITATIONS

4.1 Ethical and Legal Considerations

The implementation of machine learning in nursing is accompanied by substantial ethical and legal concerns, particularly related to patient data confidentiality, information security, and the presence of algorithmic bias (Nasir et al., 2024). The reliance on extensive clinical datasets requires transparent informed consent procedures, rigorous data anonymization, and strict adherence to regulatory frameworks such as HIPAA and the EU AI Act (Geng et al., 2024; Mohammed & Malhotra, 2025). In addition, the “black box” characteristics of advanced models, including deep learning systems, complicate the explanation of outputs to patients and healthcare professionals, thereby undermining trust and limiting clinical uptake (Nasir et al., 2024). Accordingly, the advancement of machine learning in nursing should be guided by explainable AI principles, supported by clearly defined accountability mechanisms, and positioned as an aid to rather than a substitute for professional clinical judgment (Levin et al., 2025).

4.2 Data Quality and Generalizability

The quality of data and the generalizability of machine learning models represent key factors influencing their successful deployment in nursing practice. Issues such as dataset shift, population-related bias, and inadequate external validation may compromise both predictive accuracy and fairness (Silva et al., 2025). Models developed using data from a single institution or geographic area frequently demonstrate reduced performance when applied in alternative clinical contexts, underscoring the importance of strategies such as domain adaptation and ongoing performance surveillance (Silva et al., 2025). Moreover, ensuring adequate representation of diverse patient populations is crucial to avoid discriminatory outcomes and to promote equity in care delivery (Ayus & Jena, 2025). The integration of fairness-oriented assessment methods, data shift detection approaches, and periodic model updating is therefore essential to strengthen the robustness and practical applicability of machine learning in nursing.

4.3 Nurse Involvement and AI Literacy

Active nurse participation and adequate levels of AI literacy are fundamental requirements for the effective integration of machine learning into nursing practice (Abuejheisheh et al., 2025). Empirical evidence indicates that limited digital and AI-related competencies among nurses can restrict the use of such technologies in clinical settings (Yuan et al., 2025). AI literacy extends beyond technical proficiency to include comprehension of algorithmic mechanisms, potential sources of bias, ethical considerations, and inherent technological constraints (Ghimire & Qiu, 2025). The provision of structured educational initiatives, AI-supported simulation exercises, and interdisciplinary cooperation can increase nurses’ confidence in employing machine learning tools, while also enhancing their capacity to critically interpret and incorporate algorithmic outputs into clinical decision-making processes (El Arab et al., 2025).

5. RESEARCH GAPS AND FUTURE DIRECTIONS

Although scholarly output on machine learning in nursing has grown substantially since 2018, notable gaps persist with respect to clinical deployment and external validation. The majority of existing studies emphasize the construction of highly accurate predictive models, while only a limited number describe their implementation in real clinical environments. Such implementation is frequently constrained by ethical concerns, workflow incompatibilities, and minimal nurse participation in system development. Furthermore, the overall quality of reporting remains suboptimal, particularly in relation to data preprocessing procedures and the handling of class imbalance, thereby limiting transparency and reproducibility. Future investigations should follow standardized reporting frameworks, such as TRIPOD+AI, and provide detailed documentation of each stage of model development to facilitate safe and effective clinical integration.

A further critical limitation relates to data quality and the generalizability of predictive models. Numerous machine learning systems are trained on datasets derived from a single institution or geographic region, resulting in reduced performance when applied to alternative clinical settings. Problems including dataset shift, population-related bias, and insufficient representation of diverse patient populations may compromise predictive equity. Subsequent research should therefore focus on developing domain adaptation methods, incorporating continuous model updating, and conducting fairness-oriented evaluations to support the widespread and unbiased application of machine learning. In addition, international and interdisciplinary collaboration is essential to broaden data sources and strengthen model generalizability.

Beyond technical considerations, insufficient attention has been given to AI literacy and the active involvement of nurses in the development of machine learning systems. Limited understanding among nurses regarding algorithmic functioning, potential biases, and technological constraints represents a major obstacle to clinical uptake. Future work should investigate structured educational initiatives, AI-supported simulation training, and participatory co-design approaches that engage nurses from the earliest design phases. These strategies are expected not only to enhance user confidence but also to ensure that machine learning solutions are aligned with nursing needs and routine workflows.

Infrastructural and regulatory challenges continue to restrict the implementation of machine learning in nursing practice. Inadequate interoperability with existing health information systems, high costs of deployment, and variability in legal frameworks across different jurisdictions hinder widespread adoption. Future research should address innovative financing mechanisms, cost-efficient integration models, and the harmonization of regulatory standards governing artificial intelligence in healthcare. Moreover, the establishment of accountability frameworks for adaptive AI systems and the development of explainable clinical decision-support tools will be essential for fostering trust and safeguarding patient safety.

6. IMPLICATIONS FOR NURSING PRACTICE

The results of this scoping review highlight the substantial transformative capacity of machine learning within contemporary nursing practice. The incorporation of ML-driven tools for clinical decision support, risk prediction, and workflow optimization has the potential to markedly improve patient safety, increase the precision of clinical interventions, and enhance administrative performance. To ensure successful implementation, active participation of nursing professionals in the design, deployment, and ongoing evaluation of ML systems is crucial, so that these technologies are appropriately aligned with practical clinical processes and patient-centered care requirements.

Strengthening AI literacy among nurses through structured educational programs, simulation-based learning, and interdisciplinary cooperation will enable nursing personnel to critically interpret ML-generated outputs and effectively integrate them into routine clinical decision-making. Furthermore, the use of explainable AI approaches and transparent reporting standards can promote trust and accountability, thereby supporting ethical and responsible utilization of technology. As nursing practice continues to evolve toward a data-driven paradigm, the profession’s proactive role in guiding and regulating ML applications will be essential for achieving sustained advancements in care quality and patient outcomes.

7. DISUSSION

The synthesis of the reviewed studies indicates that machine learning applications in nursing practice demonstrate strong technical performance, particularly in predictive tasks such as fall detection, pressure injury risk estimation, infection surveillance, and early sepsis identification. Several models report high discriminative metrics, and specific systems such as COMPOSER show measurable improvements in mortality reduction and protocol adherence (Yip et al., 2025). However, predictive superiority alone does not equate to implementation maturity. When examined collectively, the literature reveals a persistent gap between algorithmic robustness and real-world integration.

A recurring limitation across studies is restricted external validation. Many models are developed and internally validated within single-institution datasets, which constrains generalizability and increases vulnerability to dataset shift (Silva et al., 2025). This pattern suggests that current research priorities remain concentrated on performance optimization rather than scalability and cross-context reliability. Without multicenter validation and domain adaptation strategies, predictive gains may not translate into consistent improvements across diverse nursing environments (Ayus & Jena, 2025).

Ethical and regulatory considerations further complicate implementation readiness. Data privacy, algorithmic bias, and accountability mechanisms are frequently acknowledged yet inconsistently operationalized (Nasir et al., 2024; Geng et al., 2024; Mohammed & Malhotra, 2025). The interpretability limitations of deep learning architectures pose additional challenges, particularly in nursing contexts where professional accountability and patient communication are central to care delivery. The requirement for explainable AI is therefore not merely a technical refinement but a prerequisite for trust formation and clinical legitimacy.

From a socio-technical perspective, workforce readiness represents a structural determinant of successful integration. Limited AI literacy among nurses restricts meaningful engagement with predictive systems and may contribute to resistance or superficial adoption (Yuan et al., 2025; Abuejheisheh et al., 2025). Educational interventions, simulation-based training, and participatory co-design approaches are consistently identified as mechanisms to align algorithmic outputs with clinical reasoning processes (Ghimire & Qiu, 2025; El Arab et al., 2025). The literature therefore indicates that sustainable implementation requires simultaneous advancement of technical validation, governance safeguards, and professional competency development.

Substantial heterogeneity in study design, outcome definitions, and reporting standards further limits cumulative knowledge building. The predominance of retrospective designs restricts insight into longitudinal effectiveness and real-world workflow adaptation. Variability in reporting of preprocessing procedures, class imbalance handling, and validation protocols also constrains reproducibility. These methodological inconsistencies highlight the need for standardized reporting frameworks and structured implementation studies to advance the field beyond experimental validation toward system-level integration.

CONCLUSION

Machine learning has shown a lot of promise in helping make nursing better, especially by supporting doctors in making decisions, predicting risks, and making work processes and record-keeping more efficient. Different methods like supervised learning, deep learning, and natural language processing have been shown to help improve predictions, lower the risk of death, and make administrative tasks more efficient in various nursing environments. However, many challenges remain in widely using and applying machine learning, including issues with testing outside of original settings, poor data quality, difficulty in applying results to different situations, ethical and legal concerns, and a lack of understanding of AI among nurses. To use machine learning in a responsible and sustainable way, it's important for everyone to work together. This means improving how we report on machine learning projects, checking the models in different places to make sure they work well everywhere, creating AI that can explain its decisions, and making sure nurses are involved at every step of developing and using new technology. In short, machine learning can help improve the quality of nursing care and patient results, but this happens only if it is properly managed with clear rules, proper training, and based on proven evidence.

Declaration of Use of Generative AI

In the preparation of this manuscript, the authors utilized generative AI tools to assist with idea brainstorming, accelerate literature summarization, and enhance language clarity and academic phrasing. AI was employed strictly as a supportive tool; all content, analysis, and interpretation have been fully verified and remain the responsibility of the authors to ensure the scientific integrity and validity of the manuscript.

REFERENCES

Abi Khalil, C., Saab, A., Rahme, J., Bouaud, J., & Seroussi, B. (2025). Capabilities of computerized decision support systems supporting the nursing process in hospital settings: a scoping review. *BMC Nursing*, *24*(1), 677. https://doi.org/10.1186/s12912-025-03272-w

Abou Hashish, E. A. (2025). Compassion through technology: Digital empathy concept analysis and implications in nursing. *DIGITAL HEALTH*, *11*. https://doi.org/10.1177/20552076251326221

Abuejheisheh, A. J., Haddad, R. H., Alafaghani, S., Thawabteh, A., Khanafseh, M., Sheebat, B., Horaini, L., Hawareen, B., Abughannam, Y., Dugan, C., & Zuraikat, N. (2025). A national survey on navigating new era in healthcare services in hospitals through artificial intelligence: Awareness and attitudinal trends among nurses. *DIGITAL HEALTH*, *11*. https://doi.org/10.1177/20552076251393284

Adami, G., Fassio, A., Rossini, M., Benini, C., Bixio, R., Rotta, D., Viapiana, O., & Gatti, D. (2023). Machine learning to characterize bone biomarkers profile in rheumatoid arthritis. *Frontiers in Immunology*, *14*. https://doi.org/10.3389/fimmu.2023.1291727

Ajibade, S.-S. M., Alhassan, G. N., Zaidi, A., Oki, O. A., Awotunde, J. B., Ogbuju, E., & Akintoye, K. A. (2024). Evolution of machine learning applications in medical and healthcare analytics research: A bibliometric analysis. *Intelligent Systems with Applications*, *24*, 200441. https://doi.org/10.1016/j.iswa.2024.200441

Alijoyo, F. A., Janani, S., Santosh, K., Shweihat, S. N., Alshammry, N., Ramesh, J. V. N., & Baker El-Ebiary, Y. A. (2024). Enhancing AI interpretation and decision-making: Integrating cognitive computational models with deep learning for advanced uncertain reasoning systems. *Alexandria Engineering Journal*, *99*, 17–30. https://doi.org/10.1016/j.aej.2024.04.073

Arjmand, A., Bani-Yaghoub, M., Sutkin, G., Corkran, K., & Paschal, S. (2025). Comparative analysis of machine learning models for predicting hospital- and community-associated urinary tract infections using demographic, hospital, and socioeconomic predictors. *Journal of Hospital Infection*, *162*, 263–271. https://doi.org/10.1016/j.jhin.2025.04.024

Arksey, H., & O'Malley, L. (2005). Scoping studies: towards a methodological framework. International Journal of Social Research Methodology, 8(1), 19–32.

Ayus, I., & Jena, B. (2025). Machine learning approaches for epilepsy analysis in current clinical trials. In *Signal Processing Strategies* (pp. 175–193). Elsevier. https://doi.org/10.1016/B978-0-323-95437-2.00008-2

B., H., D.K., M., T.M., R., W., B., R., W., V., V., J., D., J., R.-M., F.J., D., P., G., & A.H., H. (2025). Advances in diagnosis and prognosis of bacteraemia, bloodstream infection, and sepsis using machine learning: A comprehensive living literature review. *Artificial Intelligence in Medicine*, *160*, 103008. https://doi.org/10.1016/j.artmed.2024.103008

Babar, M., Qureshi, B., & Koubaa, A. (2024). Review on Federated Learning for digital transformation in healthcare through big data analytics. *Future Generation Computer Systems*, *160*, 14–28. https://doi.org/10.1016/j.future.2024.05.046

Castro, G. A., Barioto, L. G., Cao, Y. H., Silva, R. M., Caseli, H. M., Machado-Neto, J. A., Cerri, R., Villavicencio, A., & Almeida, T. A. (2026). Automated Machine Learning in medical research: A systematic literature mapping study. *Artificial Intelligence in Medicine*, *171*, 103302. https://doi.org/10.1016/j.artmed.2025.103302

D'Amico, G., Colli, A., Malizia, G., & Casazza, G. (2023). The potential role of machine learning in modelling advanced chronic liver disease. *Digestive and Liver Disease*, *55*(6), 704–713. https://doi.org/10.1016/j.dld.2022.12.002

Ebo, T. O., Clement David-Olawade, A., Ebo, D. M., Egbon, E., & Olawade, D. B. (2025). Transforming healthcare delivery: A comprehensive review of digital integration, challenges, and best practices in integrated care systems. *Digital Engineering*, *6*, 100056. https://doi.org/10.1016/j.dte.2025.100056

El Arab, R. A., Al Moosa, O. A., Sagbakken, M., Ghannam, A., Abuadas, F. H., Somerville, J., & Al Mutair, A. (2025). Integrative review of artificial intelligence applications in nursing: education, clinical practice, workload management, and professional perceptions. *Frontiers in Public Health*, *13*. https://doi.org/10.3389/fpubh.2025.1619378

Geng, C., Wang, Z., & Tang, Y. (2024). Machine learning in Alzheimer's disease drug discovery and target identification. *Ageing Research Reviews*, *93*, 102172. https://doi.org/10.1016/j.arr.2023.102172

Ghimire, A., & Qiu, Y. (2025). Redefining pedagogy with artificial intelligence: How nursing students are shaping the future of learning. *Nurse Education in Practice*, *84*, 104330. https://doi.org/10.1016/j.nepr.2025.104330

Hossain, M. M., & Roy, K. (2025). The development of classification-based machine-learning models for the toxicity assessment of chemicals associated with plastic packaging. *Journal of Hazardous Materials*, *484*, 136702. https://doi.org/10.1016/j.jhazmat.2024.136702

Huang, G., Li, Y., Jameel, S., Long, Y., & Papanastasiou, G. (2024). From explainable to interpretable deep learning for natural language processing in healthcare: How far from reality? *Computational and Structural Biotechnology Journal*, *24*, 362–373. https://doi.org/10.1016/j.csbj.2024.05.004

Jobst, S., Lindwedel, U., Marx, H., Pazouki, R., Ziegler, S., König, P., Kugler, C., & Feuchtinger, J. (2022). Competencies and needs of nurse educators and clinical mentors for teaching in the digital age – a multi-institutional, cross-sectional study. *BMC Nursing*, *21*(1), 240. https://doi.org/10.1186/s12912-022-01018-6

Kalayou, M. H., Kassaw, A.-A. K., & Shiferaw, K. B. (2024). Empowering child health: Harnessing machine learning to predict acute respiratory infections in Ethiopian under-fives using demographic and health survey insights. *BMC Infectious Diseases*, *24*(1), 338. https://doi.org/10.1186/s12879-024-09195-2

Katta, S., Singh, P., Garg, D., & Diwakar, M. (2025). *Fundamentals of Machine Learning and Deep Learning for Healthcare Applications* (pp. 267–279). https://doi.org/10.1007/978-3-031-98728-1_13

Khalate, P., Gite, S., Pradhan, B., & Lee, C.-W. (2024). Advancements and gaps in natural language processing and machine learning applications in healthcare: a comprehensive review of electronic medical records and medical imaging. *Frontiers in Physics*, *12*. https://doi.org/10.3389/fphy.2024.1445204

Kim, E. J., & Kim, S. K. (2025). Machine Learning Applications in Nursing-Affiliated Research: A Systematic Review. *Korean Journal of Adult Nursing*, *37*(3), 189–214. https://doi.org/10.7475/kjan.2025.0327

Kim, M., Park, S., Kim, C., & Choi, M. (2023). Diagnostic accuracy of clinical outcome prediction using nursing data in intensive care patients: A systematic review. *International Journal of Nursing Studies*, *138*, 104411. https://doi.org/10.1016/j.ijnurstu.2022.104411

Kim, Yesol, Kim, M., Kim, Yeonju, & Choi, M. (2025). Using nursing data for machine learning-based prediction modeling in intensive care units: A scoping review. *International Journal of Nursing Studies*, *169*, 105133. https://doi.org/10.1016/j.ijnurstu.2025.105133

Kleib, M., Darko, E. M., Akingbade, O., Kennedy, M., Majekodunmi, P., Nickel, E., & Vogelsang, L. (2024). Current trends and future implications in the utilization of ChatGPT in nursing: A rapid review. *International Journal of Nursing Studies Advances*, *7*, 100252. https://doi.org/10.1016/j.ijnsa.2024.100252

Lee, T.-Y., Li, C.-C., Chou, K.-R., Chung, M.-H., Hsiao, S.-T., Guo, S.-L., Hung, L.-Y., & Wu, H.-T. (2023). Machine learning-based speech recognition system for nursing documentation – A pilot study. *International Journal of Medical Informatics*, *178*, 105213. https://doi.org/10.1016/j.ijmedinf.2023.105213

Levin, C., Zaboli, A., Turcato, G., & Saban, M. (2025). Nursing judgment in the age of generative artificial intelligence: A cross-national study on clinical decision-making performance among emergency nurses. *International Journal of Nursing Studies*, *172*, 105216. https://doi.org/10.1016/j.ijnurstu.2025.105216

Li, Z., Xu, X., & Zhang, K. (2025). Exploring the relationship between per- and polyfluoroalkyl substances exposure and rheumatoid arthritis risk using interpretable machine learning. *Frontiers in Public Health*, *13*. https://doi.org/10.3389/fpubh.2025.1581717

Meyer, L. M., Stead, S., Salge, T. O., & Antons, D. (2024). Artificial intelligence in acute care: A systematic review, conceptual synthesis, and research agenda. *Technological Forecasting and Social Change*, *206*, 123568. https://doi.org/10.1016/j.techfore.2024.123568

Mohammed, S., & Malhotra, N. (2025). Ethical and regulatory challenges in machine learning-based healthcare systems: A review of implementation barriers and future directions. *BenchCouncil Transactions on Benchmarks, Standards and Evaluations*, *5*(1), 100215. https://doi.org/10.1016/j.tbench.2025.100215

Nasir, Y., Kadian, K., Sharma, A., & Dwivedi, V. (2024). Interpretable machine learning for dermatological disease detection: Bridging the gap between accuracy and explainability. *Computers in Biology and Medicine*, *179*, 108919. https://doi.org/10.1016/j.compbiomed.2024.108919

Nkemdirim Okere, A., Li, T., Theran, C., Nyasani, E., & Ali, A. A. (2025). Evaluation of factors predicting transition from prediabetes to diabetes among patients residing in underserved communities in the United States – A machine learning approach. *Computers in Biology and Medicine*, *187*, 109824. https://doi.org/10.1016/j.compbiomed.2025.109824

Qutishat, M., & Shakman, L. (2025). Navigating Challenges in the Integration of Artificial Intelligence in Nursing Practice: An Integrative Literature Review. *International Nursing Review*, *72*(3). https://doi.org/10.1111/inr.70077

Rahim, F., Abdulkareem Hameed, N., Abdulfattah Salih, S., Mahmood Jawad, A., Mahmood Salman, H., & Chornomordenko, D. (2024). Natural language processing for healthcare: Applications, progress, and future directions. *Edelweiss Applied Science and Technology*, *8*(4), 2027–2041. https://doi.org/10.55214/25768484.v8i4.1579

Rigamonti, K. (2023). Injecting Humanity Into Health Care Enhances the Culture and Quality of an Organization. *Journal of Radiology Nursing*, *42*(2), 214–216. https://doi.org/10.1016/j.jradnu.2023.01.002

Siebeck, O. S., & Hoving, C. (2024). Characteristics of a Successful Nurse Peer Champion in the Implementation of Innovative Digital Technologies in Hospitals: A Qualitative Study. *PEC Innovation*, *5*, 100339. https://doi.org/10.1016/j.pecinn.2024.100339

Silva, G. F. dos S., Barcellos Filho, F. N., Wichmann, R. M., da Silva Junior, F. C., & Chiavegatto Filho, A. D. P. (2025). Strategies for detecting and mitigating dataset shift in machine learning for health predictions: A systematic review. *Journal of Biomedical Informatics*, *170*, 104902. https://doi.org/10.1016/j.jbi.2025.104902

Thomas, E., Kumar, S. N., Venu, A., & Nicole, R. (2025). Analysis of genetic and clinical features in neuro disorders using deep learning models. In *Deep Learning in Genetics and Genomics* (pp. 411–431). Elsevier. https://doi.org/10.1016/B978-0-443-27574-6.00012-6

Tsanakas, A. T., Mueller, Y. M., van de Werken, H. JG., Pujol Borrell, R., Ouzounis, C. A., & Katsikis, P. D. (2025). An explainable machine learning model for COVID-19 severity prognosis at hospital admission. *Informatics in Medicine Unlocked*, *52*, 101602. https://doi.org/10.1016/j.imu.2024.101602

Tricco, A. C., et al. (2018). PRISMA Extension for Scoping Reviews (PRISMA-ScR): Checklist and Explanation. Annals of Internal Medicine, 169(7), 467–473.

Wangpitipanit, S., Lininger, J., & Anderson, N. (2024). Exploring the deep learning of artificial intelligence in nursing: a concept analysis with Walker and Avant's approach. *BMC Nursing*, *23*(1), 529. https://doi.org/10.1186/s12912-024-02170-x

Wu, W., Wang, Y., Tang, J., Yu, M., Yuan, J., & Zhang, G. (2023). Developing and evaluating a machine-learning-based algorithm to predict the incidence and severity of ARDS with continuous non-invasive parameters from ordinary monitors and ventilators. *Computer Methods and Programs in Biomedicine*, *230*, 107328. https://doi.org/10.1016/j.cmpb.2022.107328

Yan, Z., Liu, M., Wang, X., Wang, J., Wang, Z., Liu, J., Wu, S., & Luan, X. (2023). Construction and Validation of Machine Learning Algorithms to Predict Chronic Post-Surgical Pain Among Patients Undergoing Total Knee Arthroplasty. *Pain Management Nursing*, *24*(6), 627–633. https://doi.org/10.1016/j.pmn.2023.04.008

Yip, S. S. W., Ning, S., Wong, N. Y. K., Chan, J., Ng, K. S., Kwok, B. O. T., Anders, R. L., & Lam, S. C. (2025). Leveraging machine learning in nursing: innovations, challenges, and ethical insights. *Frontiers in Digital Health*, *7*. https://doi.org/10.3389/fdgth.2025.1514133

Yuan, Y., Zhang, G., Gu, Y., Hao, S., Huang, C., Xie, H., Mi, W., & Zeng, Y. (2025). Artificial intelligence-assisted machine learning models for predicting lung cancer survival. *Asia-Pacific Journal of Oncology Nursing*, *12*, 100680. https://doi.org/10.1016/j.apjon.2025.100680

Zolnoori, M., Barrón, Y., Song, J., Noble, J., Burgdorf, J., Ryvicker, M., & Topaz, M. (2023). HomeADScreen: Developing Alzheimer's disease and related dementia risk identification model in home healthcare. *International Journal of Medical Informatics*, *177*, 105146. https://doi.org/10.1016/j.ijmedinf.2023.105146

Zolnour, A., Eldredge, C. E., Faiola, A., Yaghoobzadeh, Y., Khani, M., Foy, D., Topaz, M., Kharrazi, H., Fung, K. W., Fontelo, P., Davoudi, A., Tabaie, A., Breitinger, S. A., Oesterle, T. S., Rouhizadeh, M., Zonnor, Z., Moen, H., Patrick, T. B., & Zolnoori, M. (2023). A risk identification model for detection of patients at risk of antidepressant discontinuation. *Frontiers in Artificial Intelligence*, *6*. https://doi.org/10.3389/frai.2023.122960.