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SYSTEMATIC REVIEW

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Ethical challenges in the algorithmic era: a systematic rapid review of risk insights and governance pathways for nursing predictive analytics and early warning systems

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Abstract

Background Predictive analytics and early warning systems are now widely used in nursing practice worldwide. While these tools can improve efficiency and patient safety, but at the same time posing ethical challenges related to data privacy, algorithmic fairness, accountability, professional autonomy, and patient rights. Through a systematic rapid review, we identify the major ethical risks in nursing contexts and propose actionable governance pathways to inform clinical practice and policy.

Methods This study used a systematic rapid review, searching eight databases—PubMed, Embase, Web of Science, Scopus, Cochrane Library, Ovid, EBSCOhost, and ProQuest—for English-language articles published from 2015 through May 2025. Two reviewers independently screened records and extracted data, with a third reviewer resolving disagreements, yielding 22 included studies. Using inductive thematic analysis, we summarized the ethical-risk dimensions and governance pathways of predictive analytics and early warning systems in nursing practice, and conducted an overall quality appraisal of the included literature.

Results The included studies came from 11 countries, with publication volume rising markedly in recent years—reflecting growing attention to ethical issues in nursing. Most were reviews or commentaries, with fewer qualitative and mixed-methods studies. Thematic analysis identified five ethical-risk dimensions: (i) Data- and Algorithm-Related Ethical Risks; (ii) Professional Role and Responsibility Attribution Risks; (iii) Patient Rights and Humane-Care Ethical Risks; (iv) Ethical-Governance and Misuse Risks; and (v) Technological Accessibility and Social Acceptance Barriers. In response, the literature proposes four governance pathways—Technical–Data Governance, Clinical Human–Machine Collaboration, Organizational-Capacity Building, and Institutional–Policy Regulation—with concrete measures including privacy protection, algorithmic-bias monitoring and fairness audits, transparency and explainability enhancement, nurse training and digital literacy, interdisciplinary collaboration and co-creation, and policy and regulatory guidelines.

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Conclusions Predictive analytics and early warning systems in nursing practice show substantial promise yet are accompanied by multidimensional ethical risks. For the first time in a nursing context, this study proposes a "five ethical-risk dimensions–four governance pathways" framework, offering actionable ethical-governance guidance for nurses, administrators, and policymakers. Future work should pursue interdisciplinary, multicenter empirical studies to evaluate the framework's feasibility and effectiveness and to align technological benefits with ethical values, thereby improving nursing quality and patient safety.

Keywords Predictive analytics, Early warning systems, Nursing ethics, Governance framework, Rapid review, Ethical guidelines, Nursing decision support

Introduction

With the rapid development of artificial intelligence and machine learning, nursing decision support tools based on predictive analytics and early warning systems have been widely applied in nursing practice worldwide [1]. By leveraging real-time analysis of patient monitoring data, these tools enable the early identification of potential health risks and support nurses in implementing interventions at the early stages of disease. In settings such as intensive care, emergency nursing, and community nursing, they have demonstrated the potential to improve nursing efficiency and patient safety [2]. Systems now widely used include the National Early Warning Score (NEWS), the Modified Early Warning Score (MEWS), the electronic Cardiac Arrest Risk Triage (eCART), and the Epic Deterioration Index (EDI), which integrate vital signs, laboratory indicators, and electronic health record data to generate individualized risk scores and issue real-time alerts [3]. Although such tools accelerate response times, they also raise a series of ethical challenges—for example, false alarms may lead to over-intervention, while the opaque mechanisms of risk scoring may undermine nurses' confidence in their clinical judgment.

However, the ethical and practical challenges accompanying the diffusion of these technologies have become increasingly salient—especially in data-driven clinical environments—where patient privacy, algorithmic bias and fairness, responsibility attribution and legal accountability, and shifts in nurses' professional roles have emerged as key issues in nursing practice [4]. With respect to privacy, the frequent collection and cross-institutional sharing of patient data in nursing practice may blur informed consent, obscure data ownership, and heighten the risk of breaches [5, 6]. Regarding fairness, systems such as the Epic Deterioration Index (EDI) show uneven accuracy among minority groups and patients with chronic diseases, potentially widening health inequities and creating ethical conflicts for nurses [7]. Meanwhile, nurses' roles are expanding from traditional bedside caregivers to data interpreters and algorithm gatekeepers, requiring judgment in alert-threshold setting and results communication, while adding cognitive load and training pressures [8]. When prediction errors or false positives occur, clear standards for delineating responsibility among nurses, developers, and institutions remain lacking; the tension between trust in technology and ethical accountability requires urgent attention [9, 10].

Despite growing attention to these ethical issues, the existing literature still lacks systematic scope and practical applicability [11]. For example, on privacy, most studies remain at the level of legal compliance and rarely address real-world challenges in nursing workflows, such as data acquisition and patient communication. Although algorithmic bias and fairness are recognized, research on how nurses identify and mitigate model bias is limited [12]. Regarding responsibility attribution and legal accountability, there is no operational framework to delineate parties' responsibilities when early-warning misclassifications occur. Discussions of nurses' role transformation tend to emphasize "technological adaptation" or "functional expansion," without probing long-term implications for professional identity, ethical conflicts, and training mechanisms [13]. Overall, current work largely adopts macro perspectives from medical or information ethics, lacks an analytic lens deeply embedded in nursing workflows, and has yet to establish an integrated ethical-governance framework that covers data privacy, algorithmic bias and fairness, responsibility delineation, and role transformation [14, 15].

Therefore, this study adopts a systematic rapid review to balance timeliness with methodological rigor, systematically mapping the ethical challenges arising from the use of predictive analytics and early warning systems in nursing practice and synthesizing the governance pathways proposed in the existing literature, thereby addressing the current fragmentation and lack of integration in nursing ethics research. The study focuses on two core questions: (i) What are the major ethical challenges encountered when implementing predictive analytics and early warning systems in nursing practice? and (ii) What governance pathways and measures have been proposed to address these challenges? By integrating recent findings, identifying gaps, and outlining directions for development, this article aims to provide clear, actionable ethical-governance pathways for clinical nurses, hospital administrators, and policymakers, aligning technological benefits with ethical values and ultimately achieving sustained improvements in nursing quality and patient safety.

Methods

Choice of methods

We positioned this study as a systematic rapid review to address contexts with highly heterogeneous literature, dispersed evidence, and the need for expedited policy- and practice-oriented decisions, aiming to deliver timely evidence synthesis while maintaining traceability and verifiability [16]. Compared with traditional systematic reviews, rapid reviews offer streamlined procedures, timely updating, and efficient harmonization of cross-disciplinary evidence, albeit with trade-offs in the granularity and exhaustiveness of in-depth quality appraisal. To balance timeliness and rigor, we predefined two simplifications: (i) moderately narrowing the search scope; and (ii) replacing item-by-item quantitative quality assessment with a two-level overall rating. While preserving the core steps and traceability of a systematic review, these strategies shortened the study timeline and supported flexible integration of multi-source, multi-type evidence with rapid responsiveness. This review adhered to the PRISMA 2020 guidelines and was registered with PROSPERO (CRD420251079212).

Information sources and search strategy

We developed a systematic search strategy and searched eight databases: PubMed, Embase, Web of Science, Scopus, Cochrane Library, Ovid, EBSCOhost, and ProQuest. Starting with PubMed, we used the MeSH Database (synonyms/entry terms) to build synonym clusters for three conceptual blocks—technology-related, nursing-related, and ethics-related—and constructed the initial search strings using wildcards and Boolean operators. The strategy combined free-text terms with database-specific subject headings (e.g., MeSH) and covered three groups of keywords (complete search strings and optimization records are provided in the Appendix): (1) technology-related terms, including "predictive analytics," "early warning system*," "clinical prediction model*," "risk prediction," "prognostic model*," "machine learning," and "artificial intelligence"; (2) nursing-related terms, including "nursing," "nurse*," "nursing practice," "clinical nursing," and "nurse-led care"; and (3) ethics-related terms, including "ethic*," "ethical issue*," "ethical challenge*," "ethical concern*," "ethical consideration*," and "ethical implication*." The final search strategy was peer reviewed by an information-retrieval specialist using the PRESS checklist and then refined after a pilot search based on hit-structure feedback; the full strings and optimization records are provided in the Appendix.

Table 1 Inclusion and exclusion criteria for literature selection

Criterion Type	Inclusion Criteria	Exclusion Criteria
Publication Year	January 1, 2015 – May 30, 2025	Studies published before January 1, 2015
Language	English	Non-English
Study Type	Qualitative, quantitative, mixed-methods studies, and reviews	Conference abstracts, news/editorials, social media, and other non-academic publications
Thematic Scope	Nursing practice settings addressing ethical issues/challenges	Studies not involving nursing practice or not discussing ethical issues
Technological Scope	Predictive analytics or early warning systems	Non–predictive analytics or non–early warning systems

Inclusion and exclusion criteria

To ensure scientific rigor and consistency in study selection, we established explicit inclusion and exclusion criteria (Table 1): we included published scholarly literature in English from January 1, 2015, through May 30, 2025, whose study contexts were explicitly situated in nursing practice (e.g., patient monitoring, triage, clinical decision support, or nursing intervention guidance) and that explicitly discussed ethical challenges associated with the use of predictive analytics or early warning systems in nursing; study design was unrestricted, allowing qualitative, quantitative, mixed-methods studies, and reviews/commentaries.

We excluded articles not involving nursing practice or not explicitly addressing ethical challenges, articles not involving predictive analytics or early warning systems, non-English publications, and non-scholarly or non-verifiable sources (e.g., news reports, conference abstracts, social media).

Literature screening process

All records retrieved from the databases were imported into EndNote and deduplicated using its automated function. Before formal screening, we conducted calibration training and a pilot run on a randomly selected subsample to harmonize inclusion/exclusion criteria, refine operational definitions, and codify conflict-resolution rules. During formal screening, two independent reviewers—one with a clinical nursing background and the other in health policy research—independently assessed titles/abstracts and full texts. Disagreements were resolved by a third adjudicator with medical ethics expertise through independent review and, when necessary, consensus discussion. An information-retrieval specialist was engaged early to calibrate screening forms and procedures, ensuring consistency in terminology interpretation and mapping of search results, thereby integrating clinical relevance, policy applicability, and ethical sensitivity into the screening process. After title/

abstract screening, full texts were retrieved and reviewed, again by two independent reviewers; persistent disagreements were referred to the third adjudicator. Final inclusion decisions were reached by team consensus, with decision rationales and procedural details documented to support the PRISMA flow diagram and methodological transparency.

Data extraction
Based on the data extraction process and the specific research questions and analytical objectives of this review, information was systematically and uniformly extracted from the included studies. The extracted data encompassed: the basic characteristics of each study (title, authors, year of publication, and country or region); the study type and design (e.g., qualitative, quantitative, mixed-methods, or review); the characteristics of study participants (nursing personnel, patient populations, or other stakeholders); the application scenarios of predictive analytics or early warning systems in nursing practice; the ethical risks and challenges associated with their use; and the ethical-governance recommendations or mitigation measures proposed by the authors. Data extraction was performed independently by two researchers using a standardized template, followed by comparison and cross-checking; discrepancies were resolved through discussion and by revisiting the original texts until a consensus dataset was achieved. Throughout the process, emphasis was placed on consistency of criteria and standardized documentation to ensure the reliability and uniformity of the extracted results.

Critical appraisal
Given that, within the nursing practice context, research on the ethics of predictive analytics and early warning systems consists predominantly of theoretical expositions, opinion pieces, and reviews—with a clear paucity of systematic, rigorous, high-quality empirical studies—and that the included literature shows substantial heterogeneity in study design, methods, and data presentation, we did not apply traditional risk-of-bias tools for item-by-item appraisal. Instead, to differentiate study quality and reduce the influence of lower-quality evidence on the robustness of our synthesis, we adopted a simplified, practical approach and assigned a two-level overall quality rating to each article. Specifically, the team jointly reviewed every study and, based on (1) the clarity of study design and methodological description, (2) the degree of relevance to this review's topic, and (3) the logical coherence of data analysis and discussion, made a holistic judgment: studies meeting higher methodological standards and closely aligned with the review objectives were rated 2, whereas studies with notable methodological limitations or weaker relevance were rated 1 [17]. These ratings were used in the Results and Discussion to aid interpretation of the reliability and applicability of the evidence.

Data synthesis and analysis
During the thematic synthesis, the team repeatedly read each article to become thoroughly familiar with the source material and recorded preliminary impressions and key details in research memos. No a priori theoretical framework was imposed; adopting an open stance, we conducted initial inductive coding of all content related to the ethics of predictive analytics and early warning systems in nursing practice, ensuring analytical flexibility and inclusiveness. We then collated and compared dispersed codes, merged semantically similar entries, and gradually distilled a set of preliminary themes. Afterward, we iteratively examined fit with the source texts, within-theme coherence, and between-theme distinctness, refining and revising themes until the thematic structure was clear and stable. We subsequently delineated dimensions for each theme and assigned names and definitions to clarify their core meanings, boundaries, and links to the overall research objectives, thereby enhancing depth and focus. Finally, during manuscript preparation, we selected representative quotations to illustrate and substantiate each theme and its dimensions. Throughout, we followed Braun and Clarke's (2006) inductive thematic analysis, integrating findings and textual data across the included studies [18].

Results
Search results
Through the initial database search, 1,999 records were identified—244 from PubMed, 244 from Embase, 482 from Web of Science, 42 from Scopus, 86 from Cochrane Library, 225 from Ovid, 476 from EBSCOhost, and 200 from ProQuest. After removing 1,270 duplicates, 729 records remained for preliminary screening. At this stage, 646 records were excluded for topic irrelevance and 32 for inappropriate study design/type, leaving 48 articles for full-text assessment. Rigorous full-text screening then excluded 5 conference abstracts, 2 book chapters, 1 non-academic article, 4 studies with inadequate quality, and 8 studies with mismatched content; ultimately, 22 articles met all inclusion criteria. All included studies were published from January 1, 2015, through May 30, 2025. No inaccessible or additional duplicate records were encountered during selection. The detailed search and selection process is shown in Fig. 1.

Characteristics of included studies
As shown in Fig. 2, among the 22 included articles, most were published in 2024 (50%) and 2025 (41%) [15, 19–37], with a few in 2020 and 2023 [38, 39]. This pronounced recent uptick indicates growing attention in nursing to

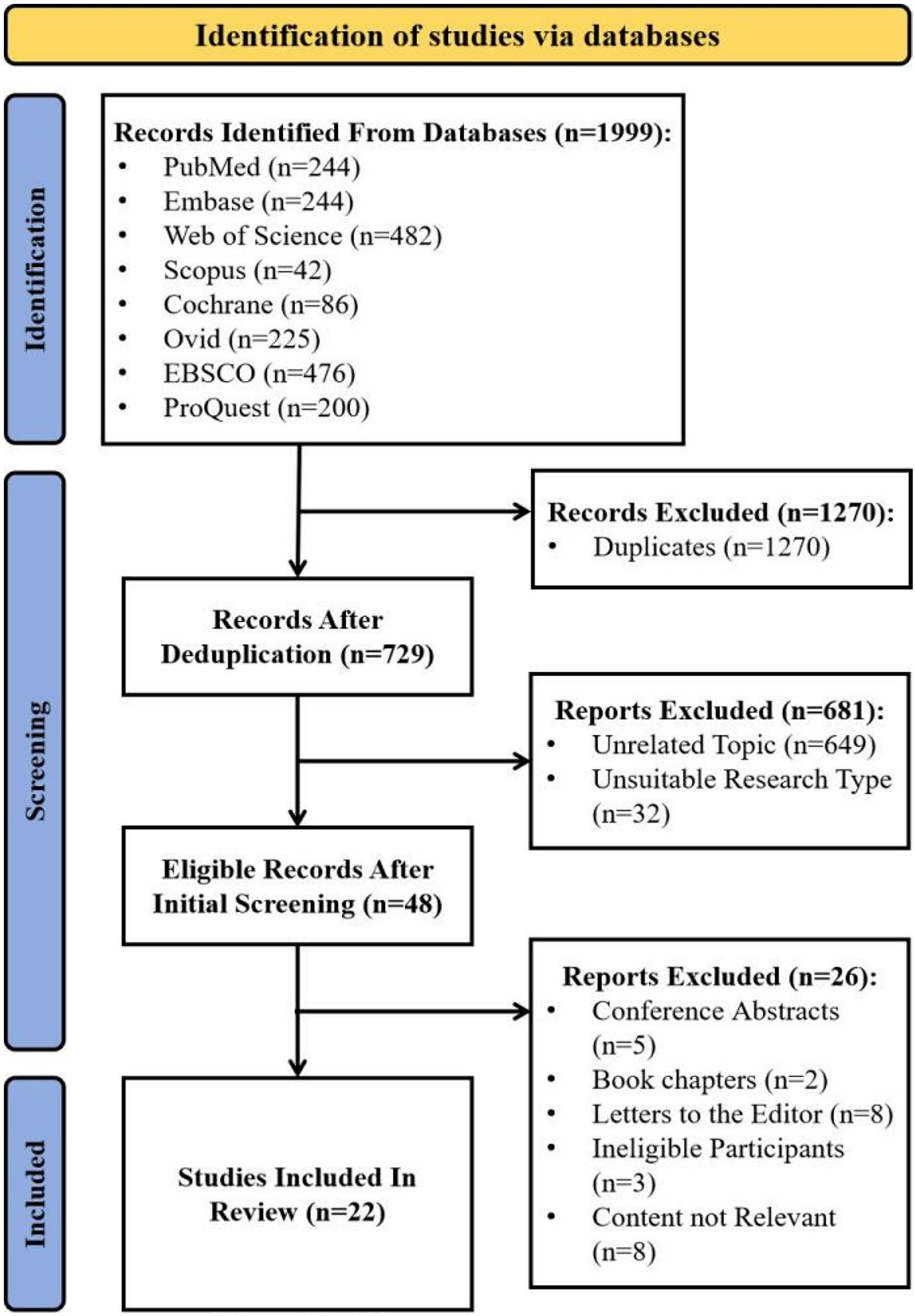

Fig. 1 PRISMA Flow Diagram of Literature Search and Selection for Ethical Studies on Predictive Analytics and Early Warning Systems

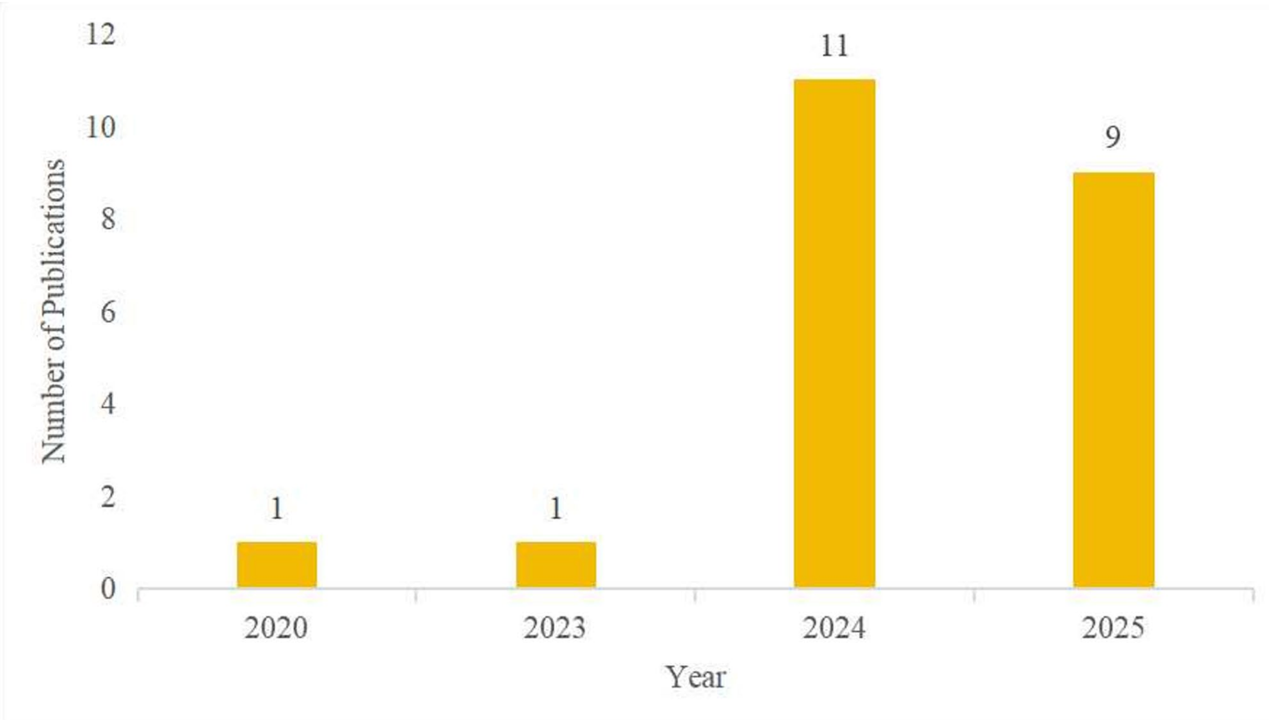

Fig. 2 Annual distribution of publications on ethical studies of predictive analytics and early warning systems, 2015–2025

the ethical issues associated with predictive analytics and early warning systems.

As shown in Fig. 3, the included studies come from multiple countries worldwide, with Saudi Arabia (27.3%) and the United States (22.7%) accounting for the largest shares [15, 19, 22, 23, 27, 29–32, 34, 37], followed by Canada (13.6%) [33, 38, 39]. Each of the following countries contributed one study: the Netherlands, Ecuador, Malaysia, China, Australia, the United Kingdom, Bangladesh, and Portugal [20, 21, 24–26, 28, 35, 36]. This broad geographical distribution indicates an increasingly international perspective on the ethical issues associated with predictive analytics and early warning systems in nursing practice.

Study design and methodological characteristics

The 22 included studies exhibit methodological diversity and are dominated by reviews and commentaries, notably systematic reviews, scoping reviews, integrative literature reviews, and conceptual commentaries [15, 19, 20, 22–27, 30–32, 34, 35, 38]. Qualitative studies employed grounded theory, ethnography combined with interviews and focus groups, interpretative phenomenological studies, and interpretive descriptive designs supplemented by content/thematic analysis, to depict nurses' ethical dilemmas and practice experiences when applying predictive analytics and early warning systems [21, 28, 33, 36, 37]. In addition, two mixed-methods studies were included [29, 39], one of which proposed an innovative mixed-methods design integrating computational ethnography with electronic health record (EHR) machine-learning modeling, reflecting an exploratory direction for interdisciplinary and methodological integration [39]. The characteristics of the included studies, methodological highlights, and two-level overall quality ratings are presented in Table 2.

Ethical risk landscape of predictive analytics and early warning systems in nursing practice

Based on the systematic rapid review and thematic analysis, this study identifies and synthesizes the ethical risks of applying predictive analytics and early warning systems in nursing practice, and proposes five ethical-risk dimensions with twelve themes: Data- and Algorithm-Related Ethical Risks (including Data Privacy and Security Risk, Algorithmic Bias and Fairness Risk, Transparency and Explainability Risk); Professional Role and Responsibility Attribution Risks (including Responsibility Attribution and Legal Accountability Risk, Erosion of Professional Autonomy and Clinical Judgment Risk); Patient Rights and Humane-Care Ethical Risks (including Humanistic Care and Empathy Risk, Complex Informed Consent and Patient Autonomy Risk); Ethical-Governance and Misuse Risks (including Regulatory Policy and Legal-Gap Risk, Systemic Misuse and Risk Issues); and Technological Accessibility and Social Acceptance Barriers (including Technical Infrastructure and Digital Divide Risk, Cultural and Social-Factor Risk). Detailed

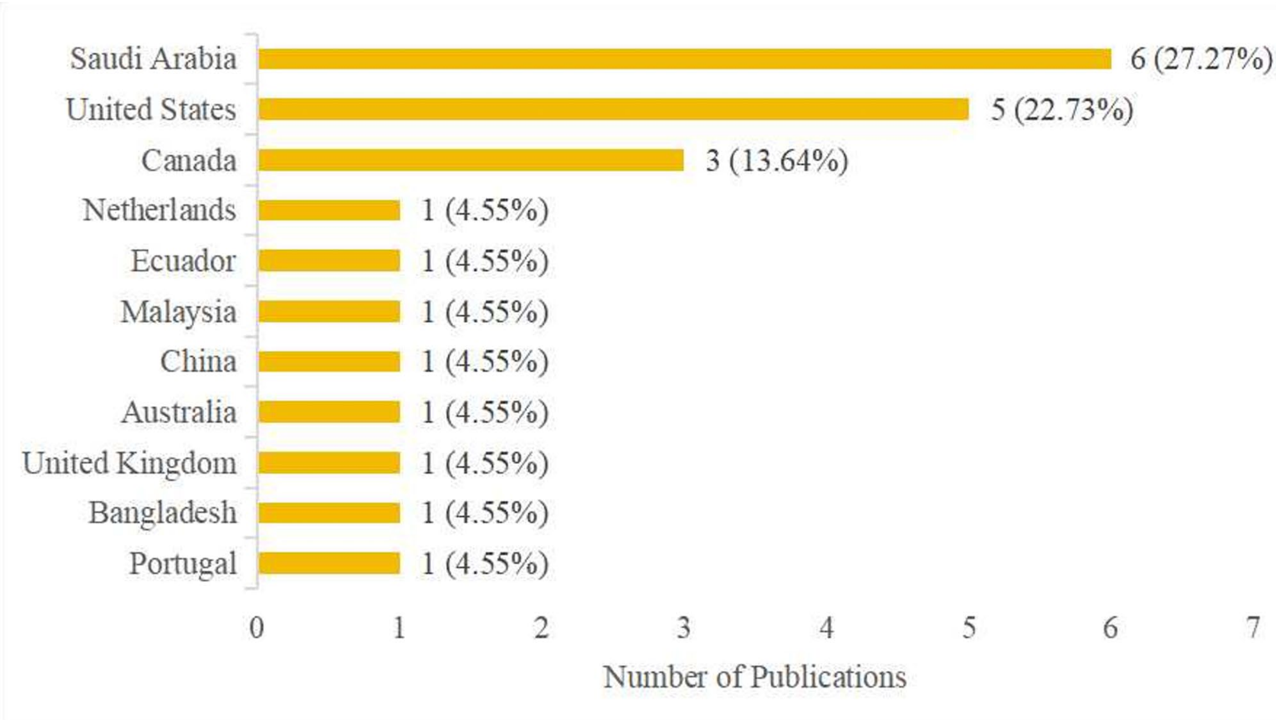

Fig. 3 Global Geographic Distribution of Ethical Research on Predictive Analytics and Early Warning Systems

definitions for each dimension and theme are presented in Table 3.

Data- and Algorithm-Related ethical risks

The data- and algorithm-related ethical risks include privacy and security risks in data collection, storage, and cross-institutional transfer; bias and fairness risks in algorithm training and application; and the erosion of clinical trust and effective use stemming from insufficient transparency and explainability.

From the perspective of data privacy and security, 15 studies reported that AI-enabled predictive systems in nursing may expose sensitive information during cross-border data transfers and cloud storage, owing to insufficient anonymization, unclear data-sharing policies, and weak enforcement of GDPR and HIPAA [15, 19, 22–27, 29, 30, 32, 34–36, 38]. Mohammed et al. note that when nursing AI relies on large volumes of patient data, insufficient anonymization can facilitate unauthorized access to—or leakage of—health records [15], while Ajibade and Madu highlight that once data are illicitly obtained, this can lead to identity theft and health-information–based discrimination [30].

Regarding algorithmic bias and fairness, 20 studies found that nursing predictive algorithms show systematic errors against ethnic minorities, older adults, and populations with low socioeconomic status, stemming from underrepresentation and distributional imbalance in training data, thereby exacerbating health inequities [15, 19–27, 29–36, 38, 39]. For example, Allam et al. reported that when training samples were predominantly White, accuracy for minority groups declined significantly, increasing the risk of misdiagnosis or delayed diagnosis [19], whereas Dreisbach et al. noted that structural racial bias can spill over into nursing resource allocation, leaving marginalized populations at a long-term disadvantage in healthcare accessibility [31].

Regarding Transparency and Explainability Risk, 10 studies indicate a widespread “black-box” problem: algorithms lack adequate explainability (and meaningful visualization), which undermines nurses’ understanding of predictive logic and their clinical judgment [19–22, 24, 25, 27, 32, 33, 38]. Salem Al-Faraj et al. note that the high complexity of deep learning models reduces transparency of the underlying mechanisms [22], while Hoelscher warns that adopting recommendations without understanding the algorithm’s reasoning can pose patient-safety risks [32].

Professional role and responsibility attribution risks

The ethical risks concerning professional roles and responsibility attribution primarily involve two aspects: the heightened complexity of responsibility allocation and legal accountability with the introduction of predictive tools, and the erosion of nurses’ professional autonomy and clinical judgment due to over-reliance on automation.

Table 2 Characteristics and quality ratings of the included studies

Author, Year	Country	Study Design	Study Population	Specific Nursing Setting	Key Findings	Score
Mohammed et al., 2025 [15]	Egypt	Systematic Review	17 nursing–AI ethics/regulation studies included from 2000–2024	Nursing decision support, predictive analytics/early warning, and nursing documentation	Distills five major themes: (1) enhancement of clinical decision-making and diagnosis; (2) ethical awareness and accountability; (3) support for routine nursing tasks; (4) algorithmic bias and inclusivity challenges; (5) public engagement and regulatory demands, calling for a nursing-specific ethical framework	2
Allam et al., 2024 [19]	Saudi Arabia	Narrative Review	Nursing workflows and patient data	Application of predictive analytics, clinical decision support systems, and wearable monitoring in early warning and nursing decision-making	Emphasizes the role of AI predictive analytics in early identification of clinical deterioration, resource optimization, and real-time intervention; discusses ethical challenges such as data privacy and algorithmic bias and offers adaptation and governance recommendations for nurses	2
Torres et al., 2024 [20]	Ecuador	Integrative Literature Review	Nursing practice and AI applications	Predictive analytics monitoring, clinical decision support, and nursing administrative automation	AI improves predictive monitoring and decision accuracy, reduces documentation time, and enables personalized nursing; highlights ethical challenges including data privacy and algorithmic bias	1
Carboni et al., 2024 [21]	Netherlands	Qualitative (Ethnographic Study)	Acute psychiatric nurses, AI violence-prediction algorithm	Two acute psychiatric wards in the Netherlands: predicting inpatient violence risk	Nurses appraise violence risk with a "skeptical–prudent" stance, whereas the algorithm's "pre-emptive" logic produces high-risk scores that tend toward over-punishment; nurses reinject uncertainty through questioning and contextualization, underscoring the ethical risks of algorithmic alerts	2

Table 2 (continued)

Author, Year	Country	Study Design	Study Population	Specific Nursing Setting	Key Findings	Score
Salem AL-Faraj et al., 2024 [22]	Saudi Arabia	Perspective Review	Nursing workflows and AI applications	Broad coverage—from primary care to chronic disease monitoring and prediction	Provides an overview of AI advantages in clinical decision support, predictive monitoring, and workload allocation; discusses ethical and implementation challenges including data privacy, algorithmic bias, and nurse training	1
Qahtani et al., 2024 [23]	Saudi Arabia	Systematic Review	10 studies (2020–2024) on AI and the nursing workforce/education/ethics	Broad themes (predictive analytics, robotics, education, leadership) without a specific nursing setting	Concludes that AI will create new positions and improve efficiency, while addressing challenges related to data privacy, algorithmic bias, training needs, and leadership	1
Koo et al., 2024 [24]	Malaysia	Systematic Review	Literature on AI-related nursing and medical practice	Comprehensive impact of AI on clinical decision-making, nursing workflows, and management, with no specific department or disease context	Summarizes that AI can enhance personalized nursing, predictive analytics, and administrative efficiency, and underscores ethical/regulatory points such as privacy, security, and algorithmic bias	1
Li et al., 2024 [25]	China	Scoping Review	48 articles on AI applications in psychiatric nursing	Psychiatric nursing (dementia, autism, schizophrenia, suicide risk, etc.)	Covers AI applications in symptom monitoring, risk assessment (suicide/violence), and individualized nursing, while signaling ethical challenges such as data bias and privacy	1
Lora & Foran, 2024 [26]	Australia	Integrative Literature Review	Various clinical nursing personnel	Multiple clinical settings (including perioperative care)	Reviews the potential advantages of AI technologies (including predictive analytics and robotic automation) in nursing and the improvement of workflow efficiency, highlighting nurses' ethical concerns about data privacy and deskilling; calls for training and organizational support	1

Table 2 (continued)

Author, Year	Country	Study Design	Study Population	Specific Nursing Setting	Key Findings	Score
Mani & Al-bagawi, 2024 [27]	Saudi Arabia	Scoping Review	Emergency nursing staff and systems	Emergency department (triage, monitoring, diagnosis, decision support, etc.)	Summarizes AI's role in emergency triage, continuous monitoring, diagnostic assistance, and decision support; emphasizes efficiency gains and data-driven alerts but also identifies ethical risks such as patient data security and algorithmic discrimination; calls for further validation studies	2
Nadaf et al., 2024 [28]	United Kingdom	Qualitative (Interpretative Phenomenological Study)	16 UK NHS registered nurses	Use of NEWS in acute adult wards to detect and manage clinical deterioration	Identifies three risk "bottlenecks" in NEWS use: (1) delegating vital-signs measurement to unregistered staff causes delays and uncertainty; (2) junior nurses over-rely on NEWS and overlook clinical intuition; (3) senior nurses tend to manage deteriorating patients independently, possibly missing timely escalation; underscores the ethical risk to patient safety posed by organizational culture and educational gaps	2
Alsayali et al., 2024 [29]	Saudi Arabia	Mixed Methods (Systematic Review + Meta-Analysis + Semi-Structured Interviews)	50 frontline nurses and literature sources	Nursing decision-making, triage, and resource allocation in crisis situations (pandemics, disasters, large-scale emergencies)	AI predictive analytics increased resource allocation efficiency by 30%; AI-based triage decision time decreased by 40%, reducing nurses' decision burden; yet insufficient training and ethical and privacy concerns remain the main barriers	2
Ajibade & Madu, 2025 [30]	United States	Review Commentary	Synthesis of literature and cases	AI-based predictive diagnosis and personalized regimens in neuro-oncology immunotherapy	Explores how AI predictive analytics improves diagnostic accuracy and individualized treatment; emphasizes data privacy, algorithmic bias, and nursing ethics	1

Table 2 (continued)

Author, Year	Country	Study Design	Study Population	Specific Nursing Setting	Key Findings	Score
Dreisbach et al., 2025 [31]	United States	Narrative Review	Literature and existing models	Early risk prediction across pregnancy, childbirth, and postpartum stages (pre-eclampsia, PPH, PPD, etc.)	Systematically reviews predictive models (AUC 0.7–0.9), emphasizing ethical risks such as insufficient external validation and racial bias, and highlights nurses' pivotal role in data quality and interpretation	2
Hoelscher, 2025 [32]	United States	Perspective Review	Literature and practical cases	Ethical impact of widely used AI in nursing work (generative AI, LLMs, NLP, AI-CDS, etc.) and the nurse's role	Systematically elaborates the advantages of AI in workload reduction, decision support, and patient education; analyzes risks of data bias, privacy, security, liability allocation, and "hallucination"; proposes nurses' responsibilities and participation pathways in data quality, model testing, and policy formulation	1
McCradden et al., 2024 [33]	Canada	Qualitative/Grounded Theory	16 participants (pediatric intensivists, nurses, respiratory therapists, etc.)	Machine-learning prediction of extubation success in the PICU and related clinical decision-making	Distills six reflective domains (medical knowledge, context, model information, model "knowledge," context–model fit, and patient best interests) and provides a clinical question checklist; notes that explanatory visualization may both aid and engender "automation bias"	2
Penner et al., 2025 [34]	United States	Conceptual Commentary	No specific study population (focused on obstetric nurses and perinatal women)	Informed consent and shared decision-making when using AI for prediction/decision support in obstetric nursing	Reviews AI technology types (predictive analytics, NLP, etc.) and their potential perinatal applications; proposes nurses' roles and strategies in interpreting AI outputs, mitigating power imbalances, and safeguarding informed patient choice; calls for an ethical framework and educational training	1
Rony et al., 2025 [35]	Bangladesh	Umbrella Review	Systematic review of AI in the nursing field	Multiple scenarios covering clinical decision support, patient monitoring, predictive analytics, workflow, and education	AI aids early warning, diagnostic support, and efficiency improvement; concurrently emphasizes data privacy, algorithmic bias, and gaps in ethics and training	1

Table 2 (continued)

Author, Year	Country	Study Design	Study Population	Specific Nursing Setting	Key Findings	Score
Seringa et al., 2025 [36]	Portugal	Qualitative Interview Study	13 participants—heart-failure clinicians (physicians, nurses) and data scientists	Early warning and intervention processes for decompensated heart failure predicted by machine learning	Interviewees consider ML helpful for early identification of high-risk patients, risk stratification, and personalized interventions; stress variable selection, wearable data collection, physiologic indicators, a three-tier risk level, and response models; raise technical and ethical challenges such as data quality, interoperability, privacy compliance, algorithmic bias, and clinical workflow integration, and recommend multidisciplinary collaboration, transparent explainability, and continuous maintenance	2
Sperling et al., 2025 [37]	United States	Qualitative Study (Focus Groups + Interviews)	52 participants—dialysis patients, their caregivers, and clinical staff (including nurses, technicians, social workers, etc.)	Ethics and trust in machine-learning mortality-risk prediction for dialysis nursing decisions and shared decision-making	Stakeholders generally accept ML prediction but are concerned about data sources, model factors, and accuracy; expect integration with clinical judgment and full explanation; stress transparency, fairness, and patient autonomy; require clarification of differential performance	2
Christine et al., 2020 [38]	Canada	Scoping Review	131 articles (including nurses, patients, managers, etc.)	Overview of AI (including predictive analytics, robotics, virtual assistants, etc.) and its potential impacts on nursing practice, management, policy, and research	AI has begun to reshape nursing roles and workflows; predictive analytics can optimize decision-making and workload, while robots/virtual assistants may enhance or diminish compassion; calls for nurses to participate in ethical design and implementation	1

Table 2 (continued)

Author, Year	Country	Study Design	Study Population	Specific Nursing Setting	Key Findings	Score
Laura et al., 2023 [39]	Canada	Mixed Methods (Computational Ethnography-Oriented)	Psychiatric emergency patients, nursing/medical staff, and their electronic health records	Prediction and early warning of potential violence/aggression in psychiatric emergency and inpatient wards	Explores ways to examine and mitigate intersectional group bias in ML violence-risk prediction; emphasizes that structural factors such as EHR data absence, coding errors, and police involvement may amplify inequities toward marginalized patients; proposes participatory design and knowledge mobilization with nursing teams and patients	2

Table 3 Summary of representative literature on the five Ethical-Risk dimensions and core themes of predictive analytics and early warning systems

Dimension	Theme	Representative Quote	Other Representative Support
Data- and Algorithm-Related Ethical Risks	Data Privacy and Security Risk	"The application of AI in nursing care demands a huge amount of patient data… This raises serious concerns about privacy, especially where data breaches or unauthorized access to health records may occur." [19]	[15, 22–27, 29, 30, 32, 34–36, 38]
	Algorithmic Bias and Fairness Risk	"Algorithmic bias emerges as another critical concern. … AI systems may perpetuate or even exacerbate existing healthcare disparities if not properly addressed." [15]	[19–27, 29–36, 38, 39]
	Transparency and Explainability Risk	"Algorithmic transparency and interpretability are necessary to maintain ethical standards and ensure patient safety when using AI in healthcare." [24]	[19–22, 25, 27, 32, 33, 38]
Professional Role and Responsibility Attribution Risks	Responsibility Attribution and Legal Accountability Risk	"In instances where nurses disagree with AI-generated assessments, the question of accountability becomes complex… particularly in cases where strict adherence to AI-driven protocols could lead to unintended patient harm or ethical conflicts." [36]	[15, 19, 22–24, 26, 27, 29, 30, 32, 33, 35, 38]
	Erosion of Professional Autonomy and Clinical Judgment risk	"Professional codes of ethics and standards of practice will require clear stipulations that the use of digital health technologies such as AI are intended to augment rather than replace nurses' clinical judgment." [38]	[15, 19, 21, 23, 26–30, 32, 33, 35, 36]
Patient Rights and Humane-Care Ethical Risks	Humanistic Care and Empathy Risk	"Several studies emphasize the irreplaceable role of empathy, compassion, and personal interaction in nursing, which AI cannot replicate." [35]	[15, 23, 25, 26, 38]
	Complex Informed Consent and Patient Autonomy Risk	"Patients… must be adequately informed regarding how AI is used in their care and the possible risks and benefits of AI-driven intervention. Informed consent under such circumstances then becomes all the more complex … rendering autonomy and control of decision-making capacities suspect." [30]	[15, 19, 20, 24]
Ethical-Governance and Misuse Risks	Regulatory Policy and Legal-Gap Risk	"One of the primary hurdles is the need for clear regulations and policies that govern AI use in clinical settings. Without standardized guidelines, there is a risk of inconsistent practices and potential misuse of AI technologies." [32]	[15, 23, 36]
	Systemic Misuse and Risk Issues	"…some participants raised concerns about potential use outside of direct clinical care decision-making for individual patients, such as broader use by health systems or insurers, including possibility of withholding treatment based on prediction results." [37]	[33]
Technological Accessibility and Social Acceptance Barriers	Technical Infrastructure and Digital Divide Risk	"Technical Barriers and Interoperability Issues: The healthcare system faces challenges related to compatibility between different systems, as it may be difficult to integrate AI systems with existing technology, which hinders the practical use of the technology." [22]	[27, 35, 36]
	Cultural and Social-Factor Risk	"Authors identified social determinants of health, such as the location of residence and education, in their study as top predictors for PPH." [31]	[39]

Regarding responsibility attribution and legal accountability, 14 studies report that when early warning systems provide erroneous assistance or inaccurate predictions, the boundaries of responsibility among nurses, healthcare institutions, and technology providers are unclear, triggering ethical disputes and legal conflicts [15, 19, 22–24, 26, 27, 29, 30, 32, 33, 35, 36, 38]. Allam et al. note, based on case analyses, that the absence of unified standards for responsibility determination leads to frequent disagreements among stakeholders [19]. Koo et al. further point out that when nurses act on AI recommendations and adverse outcomes occur, current regulations do not clearly define the scope of nurses' legal liability [24].

Regarding the erosion of professional autonomy and clinical judgment, 14 studies warn that although predictive tools can improve efficiency, their frequent use may weaken nurses' independent judgment and professional autonomy, reduce motivation to independently verify clinical information, and thereby diminish critical thinking, leading to degradation of core nursing skills [15, 19, 21, 23, 26–30, 32, 33, 35, 36, 38]. Carboni et al. emphasize that when algorithm-oriented decisions are detached from contextual complexity, they can result in inappropriate management and erode nurses' caregiving agency [21]. Hoelscher further notes that excessive prompts can induce alert fatigue, causing truly critical warnings to be overlooked [32].

Patient rights and Humane-Care ethical risks

The ethical risks to patient rights and humane care are primarily reflected in two aspects: first, technological intervention may displace humanistic care and empathy, weakening the emotional bond between nurses and patients; and second, within dynamic data flows and complex algorithmic contexts, the informed-consent process becomes increasingly complicated, thereby constraining patients' autonomous participation.

Regarding the Humanistic Care and Empathy Risk, six studies report that predictive tools can draw nursing attention disproportionately to data and alerts, leading to neglect of individualized needs and emotional care [15, 23, 25, 26, 35, 38]. For example, Christine et al. found that algorithm-dominated workflows reduce the depth and quality of nurse–patient emotional interactions [38], while Mohammed et al. warn that sustained reliance on automated judgments may evolve into a systemic risk of dehumanization [15].

Regarding the Complex Informed Consent and Patient Autonomy Risk, five studies indicate that continuous data collection and real-time risk updates raise patients' comprehension thresholds and weaken their effective participation in nursing decision-making [15, 19, 20, 24, 30]. Allam et al. report that most patients do not understand the actual role of AI within nursing workflows, making it difficult to assess its impact on their own decisions [19]. Ajibade and Madu further note that as AI becomes deeply embedded, the informed-consent process grows increasingly complex, and without clear explanations and safeguard mechanisms, patient autonomy may be implicitly eroded [30].

Ethical-Governance and misuse risks

The Ethical-Governance and Misuse Risks primarily involve two aspects: (1) regulatory policy and legal gaps—especially for cross-border data use and algorithm deployment—that create governance deficits; and (2) systemic misuse and risk issues arising from insufficient validation and improper application of these technologies.

Regarding the Regulatory Policy and Legal-Gap Risk, four studies indicate that regulatory policies and ethical guidelines for predictive technologies lag behind, leading to improper development and application [15, 23, 32, 36]. For example, Hoelscher notes that unclear regulations produce inconsistent implementation standards and misuse [32], while Qahtani et al. emphasize that many institutions lack systematic implementation norms, resulting in fragmented adoption that amplifies safety and ethical risks [23].

Regarding Systemic Misuse and Risk Issues, two studies explicitly note that deploying AI predictive tools without sufficient validation can lead to misunderstanding, misuse, and communication failures, thereby harming patient health and reducing nursing quality [33, 37]. McCradden et al. warn that when predictive results do not align with patient needs or nursing goals yet are nevertheless incorporated into decision-making, they can exacerbate adverse outcomes [33].

Technological accessibility and social acceptance barriers

Technological Accessibility and Social Acceptance Barriers are chiefly reflected in two aspects: disparities in technical infrastructure and digital literacy that constrain equitable application, and cultural and social-context differences that widen acceptance gaps and affect the clinical adoption and effectiveness of these tools.

Regarding the Technical Infrastructure and Digital Divide Risk, four studies note that nursing predictive systems depend on robust digital infrastructure and adequate training, and that imbalances in technology and resources can further widen service inequities [22, 27, 35, 36]. Rony et al. add that in resource-limited institutions, high costs and insufficient AI literacy hinder large-scale deployment, exacerbating disparities in care [35].

Regarding the Cultural and Social-Factor Risk, two studies indicate that patients and nursing staff from different cultural backgrounds show marked differences in acceptance of predictive tools, and insufficient cultural sensitivity in algorithms can trigger ethical conflicts and weaken generalizability [31, 39]. Sikström et al. further note that current development often overlooks deeper sociotechnical factors, allowing models to entrench cultural and structural biases, thereby undermining nursing equity [39].

Existing governance measures and mitigation strategies

Based on an inductive analysis of the included literature, governance measures and mitigation strategies for ethical issues arising from the use of predictive analytics and early warning systems in nursing practice can be organized into four overarching dimensions with sixteen themes: Technical–Data Governance (Data Governance and Privacy-Protection Recommendations; Algorithmic Bias Monitoring and Fairness-Audit Recommendations; Transparency and Explainability Recommendations); Clinical Human–Machine Collaboration (Nurse Training and Digital Literacy Enhancement Recommendations; Human–Machine Collaboration and Nurse-Led Decision-Making Recommendations; Patient Informed-Consent and Engagement Recommendations; Protection of Nurses' Clinical Judgment Recommendations; Simulation Training and Real-Time Feedback Mechanism Recommendations); Organizational-Capacity Building (Interdisciplinary Collaboration and Co-Creation Team Recommendations; Continuous Oversight and Ethical Supervision Recommendations; Digital Infrastructure and Technology-Gap Recommendations; Cautious Clinical Deployment and High-Risk Management Recommendations; Methodological Application and Data-Collection Optimization Recommendations); and Institutional–Policy Regulation (Policy and Regulatory Guidelines Recommendations; Contextual and Cultural Adaptation Recommendations; Value-Oriented Incentive Mechanism Recommendations). Detailed information is provided in Table 4.

Technical–Data governance

Technical–Data Governance encompasses Data Governance and Privacy Protection, Algorithmic Bias Monitoring and Fairness Audits, and Transparency and Explainability, emphasizing safeguards for AI use grounded in safety, fairness, and trustworthiness. First, 11 studies recommend establishing and rigorously implementing a data governance framework—including privacy protection, access control, and data encryption—with strict adherence to HIPAA and GDPR, and clear delineation of parties' data responsibilities and regulatory obligations, to prevent leakage of sensitive patient information and protect privacy and data security [19, 20, 22–25, 27, 30, 32, 35, 38]. Second, 13 studies call for the use of representative, diverse datasets and continuous auditing with across-group fairness evaluations to reduce algorithmic bias and enhance the fairness of predictive outputs, thereby avoiding systemic discrimination against specific populations [19, 20, 22–25, 27, 30–32, 35, 38, 39]. Third, 11 studies highlight the need to develop and deploy transparent, interpretable AI tools that provide clear, understandable rationales—for example, using Shapley additive explanations (SHAP) or Local Interpretable Model-agnostic Explanations (LIME) as explainable AI (XAI) techniques—to help nurses and patients interpret system outputs and strengthen trust and perceived safety [19, 20, 24–27, 30–32, 35, 37].

Clinical Human–Machine collaboration

Clinical Human–Machine Collaboration centers on Nurse Training and Digital Literacy Enhancement, Human–Machine Collaboration and Nurse-Led Decision-Making, Patient Informed-Consent and Engagement, Protection of Nurses' Clinical Judgment, and Simulation Training and Real-Time Feedback Mechanisms, underscoring AI's role in supporting—rather than replacing—clinical decision-making. Fourteen studies recommend building a continuous, tiered AI education-and-training system to strengthen nurses' understanding of AI tools and their critical-thinking skills, enabling effective integration into clinical nursing practice [19, 20, 22–24, 26, 27, 30–32, 34, 35, 37, 38]. Six studies emphasize clear positioning of AI as an augmentative aid within nurse-led decisions, with measures such as team case conferences or "dual-signature" workflows to prevent excessive technological interference with professional nursing judgment [15, 20, 29, 32, 33, 38]. Five studies stress that patients should clearly understand how AI is used in nursing, along with its potential risks and benefits, and be re-consented when tools are introduced, upgraded, or applied in new contexts; principles such as dynamic consent and data minimization help safeguard patients' rights and autonomy [19, 22, 30, 32, 34]. To preserve the professionalism and authority of nurses' clinical judgment, three studies encourage questioning and reflection on model outputs to avoid blind acceptance or over-reliance on AI [21, 33, 38]. Additionally, one study recommends high-fidelity simulation training with real-time feedback to strengthen practical skills and team coordination in AI-enabled care scenarios [28].

Organizational-Capacity Building

Organizational capacity building centers on Interdisciplinary Collaboration and Co-Creation Teams, Continuous Oversight and Ethical Supervision, Mitigation of Digital Infrastructure and Technology Gaps, Cautious Clinical Deployment with High-Risk Management, and Optimization of Methodological Applications and Data Collection, aiming to strengthen systemic capacity and application resilience. Eight studies emphasized the establishment of interdisciplinary co-creation

Table 4 Overview of representative literature on the Four-Dimensional Ethical-Governance framework and key measures for predictive analytics and early warning systems

Dimension	Theme	Representative Quote	Other Representative Support
Technical–Data Governance	Data Governance and Privacy-Protection Recommendations	"Privacy regulations, such as the Health Insurance Portability and Accountability Act (HIPAA), must be strictly adhered to when collecting, storing, and sharing patient data." [19]	[20, 22–25, 27, 30, 32, 35, 38]
	Algorithmic Bias Monitoring and Fairness-Audit Recommendations	"AI systems must be tested regularly for fairness and accuracy to avoid the reinforcement of biases that will negatively affect particular patient populations." [30]	[19, 20, 22–25, 27, 31, 32, 35, 38, 39]
	Transparency and Explainability Recommendations	"Ensuring that AI systems are designed and implemented in a way that is transparent and equitable is crucial for maintaining trust in these technologies." [20]	[19, 24–27, 30–32, 35, 37]
Clinical Human–Machine Collaboration	Nurse Training and Digital Literacy Enhancement Recommendations	"Preparing nurses for the future: Artificial intelligence education and training … Nurses should understand key AI concepts … Training and Educating Healthcare Professionals: Overcoming resistance… through educational programs and workshops that explain the benefits and uses of AI, helping professionals … develop skills to work with AI systems." [22]	[19, 20, 23, 24, 26, 27, 30–32, 34, 35, 37, 38]
	Human–Machine Collaboration and Nurse-Led Decision-Making Recommendations	"Collaboration between AI and human nurses should be seen as complementary, with AI serving as a tool to augment, rather than replace, human judgment." [38]	[15, 20, 29, 32, 33]
	Patient Informed-Consent and Engagement Recommendations	"Policy development should focus on the support of nurses to provide anticipatory guidance and seek informed consent before a nursing care procedure or AI is used." [34]	[19, 22, 30, 32]
	Protection of Nurses' Clinical Judgment Recommendations	"…other applications of machine learning in acute psychiatry are possible, they need to take into account, and indeed make central, the doubt at the heart of decision-making in these settings." [21]	[33, 38]
	Simulation Training and Real-Time Feedback Mechanism Recommendations	"Education to underpin the development of clinical judgement skills should be available, potentially utilising simulation-based education and underpinned by evidence-informed competency frameworks." [28]	-
Organizational-Capacity Building	Interdisciplinary Collaboration and Co-Creation Team Recommendations	"Collaboration between technologists, ethicists and healthcare providers is essential to develop comprehensive ethical guidelines and address these challenges to effectively integrate AI into psychiatric nursing." [25]	[19, 22, 26, 27, 32, 36, 38]
	Continuous Oversight and Ethical Supervision Recommendations	"The unintended consequences of AI include risks of harm, discrimination and erosion of human autonomy and accountability, which underscore the need for ethical frameworks, guidelines and oversight mechanisms to ensure the responsible development and deployment of AI in health care settings." [26]	[15, 21, 23, 24, 37, 38]
	Digital Infrastructure and Technology-Gap Recommendations	"Due diligence is required to ensure that vulnerable populations and people in rural and remote areas have access to continuous coordinated care." [38]	[31]
	Cautious Clinical Deployment and High-Risk Management Recommendations	"In health-care settings, the risk of misclassification may be substantial, … an AUC threshold for acceptability and clinical meaning may be held to a higher level….Research exploring how to discuss the risk scores generated by predictive analytics models with individuals and families is critically needed, as this may raise myriad ethical questions…" [31]	[36, 37]
	Methodological Application and Data-Collection Optimization Recommendations	"We pilot a novel computational ethnographic approach to studying bias in emergency psychiatric care, focusing on how patient data is compiled, interpreted and used to predict a risk of violence or aggression." [39]	[37]

Table 4 (continued)

Dimension	Theme	Representative Quote	Other Representative Support
Institutional–Policy Regulation	Policy and Regulatory Guidelines Recommendations	"Policymakers must establish clear regulations and guidelines to ensure the ethical use of AI in healthcare while prioritising patient privacy and autonomy." [24]	[15, 19, 20, 23, 25, 32, 38]
	Contextual and Cultural Adaptation Recommendations	"It is crucial that nurses understand the needs and preferences of residents before introducing socially assistive robots and must continuously monitor how the resident is responding." [38]	-
	Value-Oriented Incentive Mechanism Recommendations	"The presence of misaligned financial incentives within the health care system was recognized as a potential obstacle to the integration of ML models. This underscores the importance of establishing a successful reimbursement strategy to align interests among stakeholders." [36]	-

teams—including nurses, data scientists, ethicists, and administrators—to jointly develop, deploy, and govern AI tools, ensuring alignment with real-world nursing workflows and ethical imperatives [19, 22, 25–27, 32, 36, 38]. Seven studies proposed embedding routine oversight mechanisms and ethical supervision committees, complemented by regular Algorithmic Impact Assessments (AIA), phased rollouts, real-time monitoring, and rapid rollback strategies to maintain continuous ethical compliance and prevent adverse outcomes [15, 21, 23, 24, 26, 37, 38]. Two studies explicitly called for investment in digital infrastructure in rural or resource-limited areas to bridge technology gaps and promote equitable access to AI-enabled nursing innovations [31, 38]. Regarding cautious deployment in high-risk contexts, three studies recommended that in intensive care units and other critical scenarios, AI outputs should remain supplementary inputs for team deliberations rather than triggers for direct medical interventions, thereby minimizing potential risks [31, 36, 37]. Finally, two studies advocated applying innovative approaches such as computational ethnography and dynamic causal interaction to optimize data-collection processes, enhance nurses' and patients' understanding of factors shaping model predictions, and improve the quality of decision-making [37, 39].

Institutional–Policy regulation

Institutional–Policy Regulation encompasses Policy and Regulatory Guidelines, Contextual and Cultural Adaptation, and Value-Oriented Incentive Mechanisms, underscoring institutions' pivotal role in guiding the orderly and sustainable implementation of AI. At the policy and institutional level, eight studies recommend establishing unified national or organizational AI ethical guidelines, technical application standards, and regulatory accountability frameworks that clearly delineate the chain of responsibility for AI tools in nursing practice, while promoting professional guidelines and standardized procedures to facilitate appropriate clinical use [15, 19, 20, 23–25, 32, 38]. In addition, one study stresses that AI design and parameter tuning must fully incorporate contextual and cultural factors, with active participation by nursing personnel in the design process to ensure close alignment with specific nursing contexts and cultural adaptability [38]. Another study proposes adopting value-oriented incentive mechanisms that adjust performance-assessment models—linking clinical outcomes (e.g., reduced readmission rates) to the judicious use of AI tools—to encourage nursing institutions and nurses to apply predictive AI appropriately and effectively [36].

In summary, these governance measures and mitigation strategies constitute a cross-level collaborative governance pathway—spanning technical, clinical, organizational, and institutional domains—that can effectively address the ethical challenges posed by predictive analytics and early warning systems in nursing practice, thereby improving nursing quality and safeguarding patient safety.

Discussion

This study, using a systematic rapid review of 22 key studies published from 2015 to 2025, identifies and synthesizes—for the first time in a nursing context—five ethical-risk dimensions associated with predictive analytics and early warning systems in nursing practice, and proposes a closed-loop ethical framework encompassing four governance dimensions. The framework not only addresses the structural fragmentation of ethical analyses in prior work but also responds to the context-sensitive challenges of AI adoption in nursing. Theoretically, we move beyond single-issue discussions (e.g., data privacy, algorithmic bias, accountability) and systematically categorize ethical risks into Data- and Algorithm-Related Ethical Risks, Professional Role and Responsibility Attribution Risks, Patient Rights and Humane-Care Ethical Risks, Ethical-Governance and Misuse Risks, and Technological Accessibility and Social Acceptance Barriers. Building on these, we articulate four governance pathways—Technical–Data Governance, Clinical Human–Machine Collaboration, Organizational-Capacity

Building, and Institutional–Policy Regulation. This structured, closed-loop framework provides a clear analytical paradigm for nursing AI ethics and a theoretical foundation for future policy-making and system design.

The five ethical-risk dimensions do not exist in isolation but form a dynamically interacting risk chain within actual nursing workflows [40]. First, risks in the Data- and Algorithm-Related Ethical Risks dimension extend beyond traditional concerns about leakage: models' continuous ingestion of sensitive health data often lacks effective de-identification, encryption, and differential-privacy–style protections, creating persistent threats of privacy breaches and re-identification attacks [41]. Historical biases are inherited and amplified by algorithms, systematically distorting predictions across groups; meanwhile, "black-box" designs worsen nurses' inability to grasp system operations, producing a "privacy–bias–opacity" triple risk chain that undermines Transparency and Explainability [42]. Second, in Professional Role and Responsibility Attribution Risks, automation can erode nurses' clinical authority: when manual verification is marginalized and algorithmic outputs are treated as the sole standard, clinical judgment is compressed and responsibility attribution and legal accountability become ambiguous [43]. Third, within Patient Rights and Humane-Care Ethical Risks, technological integration can weaken humanistic care and empathy, pushing toward standardized, datafication of care processes [44]; at the same time, continuous data collection renders one-time informed consent ineffective, widening patients' understanding gaps about data use and algorithmic impact and eroding patient autonomy [45]. Fourth, Ethical-Governance and Misuse Risks are intensified by lagging institutional governance: policies remain largely declarative, lacking rapid-correction mechanisms and actionable anti-misuse provisions, which cannot keep pace with fast-moving technologies—exacerbating the imbalance between "fast technology and slow institutions" [46]. Fifth, under Technological Accessibility and Social Acceptance Barriers, the realization of system value depends on trust and acceptance: unequal resource allocation prevents some primary-level institutions from supporting high-performance models, and insufficient cultural sensitivity in algorithms can alienate marginalized groups, impeding the diffusion of fairness [47].

To address these multidimensional ethical risks, we propose a structured four-dimension closed-loop governance framework—Technical–Data Governance, Clinical Human–Machine Collaboration, Organizational-Capacity Building, and Institutional–Policy Regulation—to align ethical principles with practical implementation. Under Technical–Data Governance, organizations should adhere to hierarchical access control, data minimization, and end-to-end encryption, alongside continuous algorithmic-bias monitoring, cross-population fairness audits, and explainability tools (e.g., model cards) to strengthen transparency and accountability [48, 49]. Within Clinical Human–Machine Collaboration, systematic programs in digital literacy and ethics training, combined with scenario-based simulation and real-time feedback, can sharpen nurses' recognition of model limitations; in high-risk early-warning contexts, team consultations should be used to ensure nurse-led clinical decision-making [50, 51]. At the same time, dynamic informed-consent processes and explainable interfaces can safeguard patients' ongoing participation during model updates and deployment changes [52]. In Organizational-Capacity Building, healthcare institutions should establish AI ethics governance committees responsible for ethical review, phased rollouts, and rapid rollback, while investing in infrastructure for resource-limited settings to promote equitable implementation. The Mayo Clinic's internal review mechanisms offer a feasible example of advancing technological innovation in parallel with ethical oversight [53, 54]. Under Institutional–Policy Regulation, governance should establish both baseline rights protections and clear pathways for compliant use. In Europe, the General Data Protection Regulation (GDPR) sets fundamental principles—data minimization, purpose limitation, and transparent processing—to safeguard individual rights and compliance responsibilities [55], while the European Health Data Space (EHDS), as a health-sector regulation, further specifies responsibilities for cross-border data sharing, secondary use, and health data intermediaries, aiming to enable responsible reuse of health data for the public interest and research and innovation [56]. Together, this dual-track design illustrates a balance between rights protection and data-value realization, differing from approaches that rely more on industry self-regulation or ex post accountability. Accordingly, our localized governance framework cautions against one-sided logics of "protection without use" or "use without protection," and seeks a practical balance among safety, efficiency, and feasibility across institutional contexts.

This framework not only advances theory but also offers actionable ethical-governance pathways tailored to different nursing roles. For frontline nurses, their role should extend beyond passive end users to active participation in early-warning triage, model interpretation, and patient communication. Introducing dynamic informed-consent processes and explainable interfaces, supplemented by scenario-based simulation and real-time feedback training, can strengthen critical judgment and clinical autonomy, addressing accountability ambiguities and the dilution of professional authority associated with algorithmic "black boxes." For nursing managers, dual investments in organizational governance structures and digital infrastructure are key: establish ethics committees, implement phased rollouts with rapid rollback and continuous monitoring, and prioritize technology investment in resource-limited settings to ensure accessibility and equity. For nursing informatics practitioners, early, deep involvement in model development—through data design, bias identification, and explainability modeling via interdisciplinary collaboration—can better align technology with nursing needs and reduce barriers to clinical implementation.

Future research should employ multicenter prospective cohort studies and randomized controlled trials to further test the practical feasibility and ethical effectiveness of this governance framework, as well as to quantify its specific impacts on patient safety, nursing efficiency, and nurses' workload [57]. Moreover, cultural and social contextual factors play a critical moderating role in shaping the acceptance of predictive tools among nursing personnel and patients, particularly in low-resource settings and among minority groups. For instance, multilingual populations, ethnic minorities, and individuals with low health literacy may struggle to interpret standardized risk-scoring models, resulting in technological alienation and cooperation barriers; in some non-Western contexts, collective decision-making preferences and high trust in medical authority may further undermine the acceptance of dynamic consent mechanisms [58]. To address these challenges, future research should prioritize the development of culturally adaptive explainable interfaces and the integration of fairness metrics into performance-evaluation systems to foster localized governance and multicultural participation. At the same time, explainable AI tools tailored to the nursing context should be developed and validated, with particular attention to their effects on nurses' decision accuracy and trust levels [59]. Looking further ahead, we recommend the establishment of a "continuous ethics database" to track attributable ethical events associated with predictive-system use, including data breaches, algorithmic discrimination, accountability ambiguities, and the erosion of patients' decision-making rights. Embedding an anonymous, non-punitive ethics-monitoring module within existing incident-reporting systems—supplemented by multi-party review and de-identification mechanisms—would enable dynamic sensing and system-level assessment of ethical risks. Such mechanisms could shift ethical governance from static regulation to dynamic response, thereby providing long-term, robust empirical support for the responsible implementation of predictive analytics and early warning systems [60].

Limitations

Although this review systematically delineates the ethical risks and governance pathways for predictive analytics and early warning systems in nursing practice, the current evidence landscape is structurally dominated by theoretical and review-based work, with a relative paucity of rigorous, large-sample empirical studies. This limits, to some extent, the external validity and generalizability of our conclusions and underscores the need for multicenter, prospective, and mixed-methods empirical research to strengthen the evidence base. As a systematic rapid review, this study was constrained by time and resources and therefore did not perform detailed item-by-item risk-of-bias assessments for each article—an acknowledged methodological limitation that may affect the granularity of the findings. Moreover, we excluded non-English publications, which may underestimate practices and ethical concerns in certain regions or contexts and reduce the comprehensiveness of our synthesis. Taken together, while faithfully reflecting the existing evidence landscape, this review also highlights priority directions to address methodological and geographic gaps in future research.

Conclusion

In sum, predictive analytics and early warning systems are profoundly reshaping nursing practice, enhancing clinical efficiency and patient safety while introducing multidimensional ethical challenges. This study, for the first time, proposes a "five ethical-risk dimensions–four governance pathways" framework, which offers nurses practical guidance for balancing technological use with professional autonomy and clinical judgment, provides healthcare institutions with feasible routes to strengthen data governance, establish ethical oversight, and promote interdisciplinary collaboration and continuous education, and furnishes policymakers with a basis for context-sensitive, actionable regulatory guidelines. Looking ahead, cross-cultural and multi-setting empirical evaluations—leveraging real-world data—are urgently needed to test the framework's applicability and dynamic adjustment mechanisms across diverse institutional and resource environments, and to analyze implementation challenges such as resource constraints, organizational coordination, and variations in acceptance. Advancing along these lines can help move the framework from theory to practice and more comprehensively achieve the dual goals of maximizing technological benefits and minimizing ethical risks.

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Supplementary Information

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Supplementary Material 1

Authors' contributions

Yucheng Cao: Conceptualization (lead); Data Curation (equal); Formal Analysis (lead); Investigation (equal); Methodology (lead); Software (lead); Validation (lead); Visualization (lead); Writing – Original Draft Preparation (lead).Lili Deng: Conceptualization (supporting); Formal Analysis (supporting); Writing – Review & Editing (supporting).Xusheng Liu: Conceptualization (supporting); Formal Analysis (supporting); Writing – Review & Editing (supporting). Zhixian Feng: Project administration (supporting).Yu Gao: Conceptualization (supporting); Data Curation (equal); Formal Analysis (supporting); Project Administration (lead); Supervision (lead); Validation (supporting); Writing – Original Draft Preparation (supporting); Writing – Review & Editing (lead).

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Data availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Declarations

Ethics approval and consent to participate

The review protocol was prospectively registered in PROSPERO (registration number: CRD420251079212).

Consent for publication

Not applicable.

Conflict of interest

The authors declare that they have no conflicts of interest.

Competing interests

The authors declare no competing interests.

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