

Reported relevance pathways between artificial intelligence applications in nursing practice and humanistic care: a focused scoping review

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Abstract

Background: Humanistic care is central to nursing, yet clinical complexity and administrative burdens constrain person-centered practice. AI is increasingly used in nursing, but its reported relevance to humanistic care, evidence maturity, and workflow integration remain unclear.

Objective: To examine, within a focused evidence sample, the reported direct and indirect relevance of AI applications to nursing practice and humanistic care, alongside application themes, evidence maturity, and workflow-integration reporting.

Methods: We conducted a focused scoping review following established guidance and PRISMA-ScR. Four databases were searched through December 18, 2025 for AI, nursing, and humanistic/person-centered care concepts. Direct versus indirect relevance was determined by full-text review. Two reviewers independently screened the studies and charted evidence maturity and workflow-integration features. No formal critical appraisal was undertaken.

Results: Eighteen studies were included, covering four themes: risk/need identification, proactive care management, emotion-focused conversational support, and workflow/resource optimization. Evidence was limited and unevenly reported: 11/18 studies reported development, technical validation, or usability/feasibility; 7/18 reported clinical evaluation or real-world implementation. Direct relevance clustered in communication and psychosocial support; indirect relevance clustered in workflow-oriented applications. Workflow reporting was often incomplete, especially regarding posttrigger actions, interoperability, and governance.

Conclusions: The included studies were organized by reported direct and indirect relevance to humanistic care. This review offers a cautious evidence map, not an exhaustive account of AI in nursing.

Trial registration: Not applicable.

Background

Humanistic nursing care (hereafter, humanistic care) is central to nursing practice and reflects commitments to empathy, respect, dignity, and holistic support for patients and families [1, 2]. This view is consistent with nursing perspectives that emphasize the therapeutic nurse–patient relationship, caring intent, and support for the whole person, as reflected in the work of Peplau and Watson [3, 4]. In contemporary healthcare settings, however, increasing patient complexity, workforce shortages, and administrative demands can constrain person-centered care and shift practice toward more routine, task-oriented work [5, 6].

In this context, artificial intelligence (AI) is being increasingly introduced into nursing tasks and workflows [7–9]. Prior work suggests that AI may support information processing, decision support, and selected routine tasks, potentially reducing administrative burden and preserving time and attention for direct patient care [8, 9]. These possibilities, however, do not constitute evidence of gains in humanistic care. Improvements in workflow alone do not demonstrate more relational, empathic, or dignity-preserving nursing practice.

Existing reviews provide broader overviews of AI in nursing and narrower syntheses of topics such as care organization or empathy-related comparisons between AI and human clinicians [8, 10–12]. This review adopts a different analytic lens. Rather than aiming for field-wide coverage of AI in nursing, it examines a deliberately focused evidence sample assembled around AI, nursing, and humanistic or person-centered care. Within this bounded sample, it asks how the included studies were reported to relate to humanistic care, whether that relevance was direct or indirect, how mature the supporting evidence appeared, and how workflow integration was reported. With this framing, the review is intended as a focused scoping review and a cautious organizing framework for interpreting a specific segment of the literature, not as an effectiveness review or an exhaustive mapping of all AI-supported nursing workflows.

Methods

Study Design

We conducted a focused scoping review following the Arksey and O'Malley framework [13] and JBI guidance for scoping reviews [14]. The search, screening, and inclusion criteria were reported in accordance with the PRISMA-ScR [15]. From the outset, the review was positioned as a focused evidence map rather than a search intended to capture all AI applications in nursing or all AI-supported workflow studies. The review did not have a prospectively developed or registered protocol. To improve transparency, the final review approach was retrospectively documented and submitted to the Open Science Framework (OSF) as an embargoed registration.

Research Questions

This scoping review addressed four questions: (1) Which AI applications in nursing practice within the included sample showed direct relevance or indirect enabling relevance to humanistic care, and in which care tasks or contexts were they used? (2) Which AI approaches and data sources did these applications use? (3) How mature was the available evidence, as reflected in the study design, evidence stage, and extent of clinical evaluation or real-world implementation? (4) How was workflow integration reported, including commonly reported implementation gaps and evidence gaps?

Inclusion Criteria

We defined eligibility using the population–concept–context (PCC) framework.

Population

We included studies involving care recipients (patients and, where relevant, family caregivers) and nursing-related care providers, primarily nursing staff and, in a small number of studies, paid caregivers explicitly involved in nurse-led, nurse-coordinated, or nursing-supervised care workflows. We also included studies focused primarily on care delivery, nursing workflows, or nursing management.

Concept

Eligible studies applied explicit AI methods or systems, such as machine learning (ML), deep learning (DL), natural language processing (NLP), computer vision (CV), conversational systems or robots, multimodal models, or rule-based expert systems, to nursing-related tasks and, upon full-text review, were judged to show direct relevance or indirect enabling relevance to humanistic care. Direct relevance was defined as applications explicitly targeting or assessing humanistic care-related processes or outcomes, such as communication quality, empathy, psychosocial outcomes, dignity, cultural sensitivity, patient experience, or other relational dimensions of nursing care [16].

Indirect enabling relevance was defined conservatively. To qualify, an application had to be nurse-facing, had to be embedded at an identifiable point in the care process, had to plausibly inform nursing action, care coordination, or conditions for nurse–patient interaction, and did not qualify solely on the basis of generic institutional efficiency [17]. Applications that reduced paperwork, information processing, coordination, or documentation burden were therefore not assumed by default to support humanistic care. Instead, inclusion required a plausible nurse-facing pathway to bedside care, care coordination, or nurse–patient interaction. Workflow gains were not automatically treated as gains in humanistic care. We also included interactive or educational tools used within care processes to support patient engagement, self-management, decision readiness, or shared decision-making when relevant to humanistic care [18].

To reflect the range of available evidence, we included studies on system development and technical validation, usability or feasibility assessment, clinical evaluation, and real-world implementation. For system development and usability or feasibility studies, we required at least one indicator of practice relevance: real-world nursing data or real-world user testing with nursing staff and, where relevant to the workflow, patients, family caregivers, or paid caregivers involved in nurse-linked care processes. Paid caregivers were considered only when they were embedded in nurse-led, nurse-coordinated, or nursing-supervised workflows.

We excluded digital tools or general information systems without explicit AI methods; studies reporting only technical performance without clear links to nursing tasks, workflows, or care processes; and algorithm validation studies based solely on simulated or scripted data without real-world nursing data or user testing. Borderline decisions, including indirect-pathway cases, were adjudicated at full-text review, using the decision rules summarized in Appendix 1.

Context

We placed no restrictions on disease or geographic location. Eligible settings included real-world or simulated real-world applications relevant to nursing practice, care delivery, or nursing workflows, such as hospitals, outpatient clinics, community settings, homes, and long-term care facilities. We included nursing education studies only when they were clearly linked to communication, empathy, humanistic care competencies, or clinical service delivery.

Operational Definition of AI Eligibility

To avoid conflating digital health tools with AI systems, studies had to specify the AI paradigm or system type and describe key workflow elements, including inputs, outputs, and integration points. In this review, AI was defined broadly to include data-driven methods and explicit knowledge-based or rule-based expert systems that supported a clear automated input–output–care action pathway within nursing workflows. When studies reported AI or machine learning in commercial or preexisting devices or platforms without disclosing model families or training details, we treated this as a reporting limitation rather than an exclusion criterion. Eligible studies also had to permit extraction from the full text of system-level input–output–care action pathways, such as risk stratification and alerting, care assessment, or coordination and disposition processes. We excluded studies that described systems as AI-based, ML-based, or intelligent without specifying the underlying analytical or generative mechanisms or a clear automated function or input–output pathway within workflows.

Information Sources and Retrieval

With support from information retrieval specialists, we developed search strategies around three concepts: AI-related technologies, nursing, and humanistic or person-centered care. We adapted the strategy for each database and searched PubMed, CINAHL Ultimate (EBSCOhost), Web of Science Core Collection, and Scopus. Searches were completed on December 18, 2025. Because the end-date options differed across databases, we set the Scopus end date to December 2025 and report December 18, 2025 as the final search date. In the Web of Science Core Collection, we searched the Topic field and refined the results by Web of Science categories (Nursing or Health Care Sciences Services). The complete search strings, fields, and hit counts are provided in Supplementary Material S1.

Direct relevance and indirect enabling relevance were not used as database-level filters but were adjudicated during full-text review and synthesis because indirect relevance may not be explicitly indexed in titles, abstracts, or subject headings. The search strategy was therefore designed to identify literature at the intersection of AI, nursing, and humanistic or person-centered care rather than every workflow-oriented AI study in nursing. As documented in the final

review record, we did not use a separate supplementary term set for workflow-related concepts at the database level; studies indexed primarily under workflow, documentation, staffing, triage, coordination, burden, or nurse-facing system terms may therefore have been underrepresented. The review was limited to English-language publications because the searches were conducted in English, and resources for translation and multilingual screening were unavailable. Given the aim of focused evidence mapping and our resource constraints, we excluded gray literature and did not conduct systematic reference or citation tracking.

Study Selection and Data Extraction

Two reviewers (LSH and WS) independently screened the records and assessed the full texts for eligibility using the operational definitions of direct relevance and indirect enabling relevance and the requirement for an identifiable nursing-practice pathway. The same two reviewers then independently charted the data using a standardized form that was developed a priori from the review objectives and pilot-tested on three included studies. The extracted variables included author and year, study population and context, AI type and data source, study design, relevance pathway, reported outcomes, reported limitations and implementation challenges, workflow-related features, practice relevance basis, and evidence stage. Disagreements at either stage were resolved through discussion, with input from a third author (ZY) as needed. For commercial or proprietary systems with undisclosed algorithm families or training details, the components were coded as not reported.

Quality Assessment

Because scoping reviews map the extent and distribution of available evidence but do not assess intervention effects or study quality, we did not conduct a formal critical appraisal of the included studies. This is consistent with scoping review guidance, which emphasizes evidence mapping over quality grading or effect inference [14, 19]. Evidence maturity was used only as a descriptive positioning framework and does not replace formal risk-of-bias assessment or certainty grading.

Evidence Synthesis and Analysis

We combined descriptive statistics with inductive content analysis to organize the evidence. Study characteristics, settings, AI approaches, data sources, relevance pathways, evidence maturity, and reported workflow-integration features are summarized in the tables. On the basis of the concept definitions above, we then conducted a narrative synthesis, grouping studies by application theme and examining direct or indirect enabling relevance to humanistic care, evidence maturity, and workflow-integration reporting. Workflow-integration reporting was summarized in terms of typical inputs, outputs or functions, triggering logic, embedding points, nurse actions, and reported feedback or outcomes. Evidence maturity was interpreted as the stage positioning within the available literature rather than as a marker of study quality or certainty.

Results

Results of the Literature Search and Screening Process

We retrieved 2,569 records from the database searches. After 371 duplicates and 10 retracted records were removed, we screened 2,188 titles and abstracts and excluded 1,722. Of the remaining 466 reports, full text could not be obtained for 12 reports. We assessed 454 full texts and excluded 436, leaving 18 studies for inclusion. This small final set reflected the intentionally focused scope of the review, which required either direct relevance or conservatively adjudicated indirect enabling relevance to humanistic care rather than capturing all AI applications in nursing. The main reasons for full-text exclusion were unclear AI methods or systems (n = 133), no direct humanistic care component and no eligible indirect nurse-facing workflow pathway (n = 100), nonoriginal empirical research (n = 99), and insufficient information on workflow integration or relevant outcomes (n = 96). Smaller numbers of studies were excluded because the population or setting fell outside the nursing practice (n = 7) or because the publication type was ineligible (n = 1) (Fig. 1).

[Insert Fig. 1 here]

Basic Characteristics of Included Studies

Eighteen studies were included (Table 1). Most were published between 2021 and 2025 and were conducted in hospital wards, outpatient follow-up, community settings, home care, and long-term care facilities. Nurses were the main professional group; patients, family caregivers, and, in a small subset of studies, paid caregivers also appeared within nurse-linked workflows. Technical approaches included ML, DL, NLP, CV, conversational systems or chatbots, social assistive robots, multimodal analysis, and rule-based expert systems. The data sources included electronic health records, nursing documentation and clinical text, patient-reported data, nurse–patient communication transcripts or corpora, and physiological or behavioral home monitoring data. The reported outcomes were heterogeneous and spanned patient-level indicators, nursing-process indicators, and system-level indicators. The evidence-stage positioning was uneven: 11/18 studies were at the system development, technical validation, or usability/feasibility stage, whereas 7/18 reported clinical evaluation or real-world implementation.

Table 1
Characteristics of the included studies and positioning variables (n = 18)

Author (Year)	Country	Study design	Evidence stage	AI Technology type	Humanistic/Nursing focus	Application theme	Application
Zhang et al. [20]	China	Mixed-methods usability study (nurse-led ICU delirium CDSS prototype)	Usability or feasibility assessment	Knowledge-based expert CDSS (if-then rules; forward inference to generate risk-based care recommendations)	Nurse-led delirium risk identification and modifiable risk factors	AI-Assisted Identification of latent risks and implicit care needs	ICU (nursing)
Kim and Kang [21]	Republic of Korea	Randomized controlled trial (CDSS for PES risk prediction)	Clinical evaluation	CDSS (ML risk prediction + NLP care recommendations)	Early identification of PES/symptom risks after TACE	AI-Assisted Identification of latent risks and implicit care needs	Oncology ward (nursing)
Zolnoori et al. [22]	USA	Observational data collection + model development/validation	System development and technical validation	NLP/ML classifier (speech transcripts + EHR features)	Screening for cognitive decline risk using nurse-patient communication	AI-Assisted Identification of latent risks and implicit care needs	Home (nursing adults; nursing notes)
Reunamo et al. [23]	Finland	Retrospective registry-based study (text classification)	System development and technical validation	Supervised ML text classification (BoW features; NN/RF/LR)	Identifying future psychosocial-support needs from nursing notes	AI-Assisted Identification of latent risks and implicit care needs	Pediatric oncology (nursing notes)
Vithanage et al. [24]	Australia	Model development and evaluation (NER on nursing notes)	System development and technical validation	NLP-NER (Clinical BioBERT + BiLSTM-CRF)	Extracting agitation symptoms to support person-centered care/interventions	AI-Assisted Identification of latent risks and implicit care needs	Residential (nursing)
Havreng-Théry et al. [25]	France	Retrospective controlled real-world evaluation + cost analysis	Clinical evaluation	AI-enabled remote monitoring device with proprietary ML risk prediction (algorithm model family NR; proprietary)	Person-centered home monitoring for early tailored intervention	Precision health management and proactive care management	Home (nursing living a)

Author (Year)	Country	Study design	Evidence stage	AI Technology type	Humanistic/Nursing focus	Application theme	Applica
Veyron et al. [26]	France	Multicenter uncontrolled pragmatic postimplementation study	Clinical evaluation	AI-enabled risk stratification/alerting with proprietary ML (algorithm model family NR; proprietary)	Person-centered monitoring to enable early intervention and avoid unplanned hospitalization	Precision health management and proactive care management	Assiste (older v adults)
Paulauskaite-Taraseviciene et al. [27]	Lithuania	System development + real-world scenario testing (nursing home)	System development and technical validation	IoT + CV deep learning (YOLOv3/AlphaPose) + rule-informed decision-tree decision support	Person-centered care-plan monitoring and adjustment support	Precision health management and proactive care management	Nursing term c
Ma et al. [28]	China	Retrospective cohort (app vs. usual care; 1:1 propensity score matching; PSM)	Clinical evaluation	AI coaching app (DL-OCR for data extraction; personalization details NR/partial)	Nurse-led person-centered CKD coaching to support continuity of care	Precision health management and proactive care management	Nondia (mobile
Zeng et al. [29]	China	Single-center retrospective before–after cohort (within-subject comparison)	Clinical evaluation	Smart PD system (app data + cloud AI analysis for real-time alerts) with DL-OCR	Nurse-led person-centered PD management for proactive coaching and early intervention	Precision health management and proactive care management	Home p dialysis platform
Wan et al. [30]	China	System development + single-center prospective RCT	Clinical evaluation	LLM chatbot (GPT-3.5 backbone; fine-tuning + site-specific prompt template; safety alerts with nurse oversight)	Empathy-centered communication support during outpatient reception	Interactive care support via emotion-focused conversational agents	Outpati (recept audio ii
Kaur et al. [31]	USA	Cross-sectional survey (HCP ratings of portal replies)	Clinical evaluation	GPT-3.5-turbo with prompt-engineering pipeline	Empathy-oriented messaging support for clinician–patient communication	Interactive care support via emotion-focused conversational agents	Patient messa (primary raters)
Yahagi et al. [32]	Japan (correspondence address: Hitachi, Ibaraki, Japan; affiliations list “San Francisco, CA”)	Single-blind RCT (standard nurse consult vs. ChatGPT interaction)	Clinical evaluation	ChatGPT-3.5 chatbot (interactive Q&A; anesthesiologist review for safety)	Emotion-supportive perioperative education and anxiety reduction	Interactive care support via emotion-focused conversational agents	Preope anesth (adult e

Author (Year)	Country	Study design	Evidence stage	AI Technology type	Humanistic/Nursing focus	Application theme	Applica
Yao et al. [33]	Taiwan, China	Retrospective cohort + external validation (NHAMCS + NTUH)	Clinical evaluation	Deep-learning triage engine (data-to-text EMR + CNN/RNN/attention fusion)	Triage prioritization support (hospitalization-risk prediction; potential to support prioritization and surge preparation)	AI-Supported Optimization of Nurse-Facing Workflows and Resource Management	ED triage data)
Nishi et al. [34]	Japan	Retrospective model development and evaluation (proof of concept)	Usability or feasibility assessment	NLP preprocessing (MeCab + vectorization) + feedforward ANN	Suggesting nursing diagnoses from progress records to reduce nurse workload	AI-Supported Optimization of Nurse-Facing Workflows and Resource Management	Critical notes + labels)
Macieira et al. [35]	USA	Methods study + workflow evaluation	Usability or feasibility assessment	RAG pipeline + GPT models for NIC mapping	Standardizing documented interventions and reducing mapper cognitive workload	AI-Supported optimization of nurse-facing workflows and resource management	EHR nu (4 hosp ed.)
Chen et al. [36]	USA	Methods study + single-site NICU case study (Epic audit logs)	Usability or feasibility assessment	Unsupervised ML clustering + task complexity metrics	Identifying high-burden EHR tasks to guide workflow optimization	AI-Supported optimization of nurse-facing workflows and resource management	NICU n (Epic a)
Pang et al. [37]	China	Retrospective cross-sectional analysis (model development/validation + DEA-based simulation verification)	Clinical evaluation	BPNN staffing prediction + DEA	Data-driven staffing decision support balancing safety and efficiency	AI-Supported optimization of nurse-facing workflows and resource management	55 nurse (tertiar Dec 20

Author (Year)	Country	Study design	Evidence stage	AI Technology type	Humanistic/Nursing focus	Application theme	Applicae
Abbreviations:							
NR = not reported.							
ICU = intensive care unit.							
CDSS = clinical decision support system.							
PES = postembolization syndrome.							
TACE = transarterial chemoembolization.							
BoW = bag-of-words.							
NN = neural network.							
RF = random forest.							
LR = logistic regression.							
NER = named entity recognition.							
BiLSTM = bidirectional long short-term memory.							
BioBERT = biomedical bidirectional encoder representations from transformers.							
ATHI = alert-triggered health intervention.							
CKD = chronic kidney disease.							
PSM = propensity score matching.							
PD = peritoneal dialysis.							
RCT = randomized controlled trial.							
GPT = generative pre-trained transformer.							
HCP = health care professional/provider.							
CNN = convolutional neural network.							
RNN = recurrent neural network.							
ANN = artificial neural network.							
RAG = retrieval-augmented generation.							
NIC = nursing interventions classification.							
NICU = neonatal intensive care unit.							
BPNN = backpropagation neural network.							
DEA = data envelopment analysis.							
Notes:							
For commercial or proprietary systems with incomplete disclosure of algorithm family details, undisclosed algorithm components were coded as NR. Evidence and technical validation, usability or feasibility assessment, clinical evaluation, or real-world implementation, on the basis of the study design and degree of stage positioning only and does not constitute formal quality appraisal or certainty grading. For early-stage studies, the practice relevance basis indicates whether nursing data, involved real-world user testing, or both.							

[Insert Table 1 here]

For thematic synthesis, we organized the studies around two reported pathways linking AI applications in nursing practice to humanistic care: direct relevance and indirect enabling relevance. Direct relevance was most common in studies explicitly targeting or assessing communication quality, patient experience, emotional or psychological support, the nurse–patient relationship, dignity, empathy, cultural sensitivity, or related humanistic-care processes; a subset of studies also used AI interactively to support patient engagement, shared decision-making, or self-management. Indirect enabling relevance was more common in workflow-integration and resource-related studies and in applications focused on risk identification, care coordination, documentation, or information-processing burden. Across these themes, the studies differed in how humanistic outcomes were defined and measured and in the level of detail provided regarding workflow integration. Descriptions of posttrigger actions, interoperability with existing information systems, user responsibilities, documentation updates, and ongoing operational governance were often incomplete or inconsistent. Using this framework, we grouped the included studies into four application themes.

Primary Application Themes and Reported Relevance Pathways in the Included Sample

Table 2 summarizes the included evidence from a workflow perspective, including typical inputs, system outputs, workflow integration points, and reported feedback or outcome indicators across themes.

Table 2
Cross-theme synthesis of workflow integration, humanistic relevance, and evidence maturity

Theme (n)	Typical inputs and AI approaches	Main AI outputs/functions	Alerting/triggering	Workflow embedding point & nurse action	Humanistic relevance pathway	Feedback/outcomes
Theme 1. AI-Assisted Identification of Latent Risks and Implicit Care Needs (n = 5)	EHR/nursing documentation, free-text notes, and communication transcripts; Knowledge-based expert CDSS, ML/NLP classifiers, and NER models	Risk/screening prompts; structured care-need signals	Rule-/threshold-/classifier-based triggering (where applicable); extraction outputs (e.g., NER)	Focused assessment and prioritization; follow-up questioning; care-plan initiation (variably reported)	Indirect	Model performance; usability; limited reporting of reassessment or documentation update
Theme 2. Precision Health Management Empowered by Intelligent Technologies (n = 5)	ePROMs, functional status measures, and home monitoring/IoT data; ML-based risk stratification, CV/DL monitoring, and app/cloud-based analytics	Risk stratification/alerts; status classification; follow-up recommendations	Push alerts; time-window risk flags	Tiered follow-up and referral; coordinated actions; reassessment	Mixed, primarily indirect	Follow-up data return; adherence/engagement process measures
Theme 3. Interactive Care Support via Emotion-Focused Conversational Agents (n = 3)	Patient portal messages and consultation text; LLM-based chatbots, prompt-engineered conversational AI, and generative models	Empathetic response drafts; education/reassurance messages	Draft generation with clinician review/approval (often nurse-led)	Nurse reviews/edits drafts and completes communication and education	Direct	Empathy/communication ratings; satisfaction; anxiety and other patient-reported measures
Theme 4. AI-Supported Optimization of Nurse-Facing Workflows and Resource Management (n = 5)	EHR data, progress notes, and audit logs/administrative data; DL triage models, NLP-ANN systems, generative AI pipelines, unsupervised ML, and BPNN-based prediction	Triage prioritization; diagnosis suggestions; workload/staffing predictions	Predictive outputs/recommendations or AI-assisted workflow step (not always real-time alerts)	Triage/throughput support; documentation decision support; staffing and workflow redesign	Indirect only	Efficiency, workload, workflow metrics; scalability

Theme (n)	Typical inputs and AI approaches	Main AI outputs/functions	Alerting/triggering	Workflow embedding point & nurse action	Humanistic relevance pathway	Feedback/outcomes
Abbreviations:						
EHR = electronic health record.						
CDSS = clinical decision support system.						
ML = machine learning.						
NLP = natural language processing.						
NER = named entity recognition.						
ePROMs = electronic patient-reported outcome measures.						
IoT = Internet of Things.						
CV = computer vision.						
DL = deep learning.						
LLM = large language model.						
AI = artificial intelligence.						
ANN = artificial neural network.						
BPNN = backpropagation neural network.						

[Insert Table 2 here]

AI-Assisted Identification of Latent Risks and Implicit Care Needs

Five studies were grouped under this theme. They described systems that converted risk-related information from clinical or care settings into alerts, predictions, or screening signals. The reported inputs included structured EHR data, free-text clinical notes, nurse-entered symptom and assessment information, and, in one study, transcripts of nurse–patient verbal communication. The methods included rule-based expert systems, machine learning, and natural language processing. Most studies on this topic were limited to system development, technical validation, or usability-related evaluation [20, 22–24], although one randomized controlled trial reported intervention-related outcomes [21]. Examples included a nurse-led delirium-management CDSS based on if-then rules [20], an ML-based system for predicting postembolization syndrome risk and generating care recommendations [21], and approaches to extract signals from nurses–patient communication transcripts or nursing notes to identify cognitive decline risk, psychosocial support needs, or agitation symptoms [22–24]. Within this focused sample, the reported relevance to humanistic care in this theme was primarily indirect, except in studies that more explicitly targeted psychosocial support needs or individualized follow-up. Reporting was often limited with respect to clinically meaningful thresholds, output interpretability, posttrigger actions, documentation updates, transferability across settings, and other implementation details.

Precision Health Management and Proactive Care Management

Five studies were included under this theme. They described systems using structured observational data, patient-reported outcome measures, home-monitoring data, or recent functional changes documented in care records to assign short-term risk levels, support follow-up coordination, or trigger alerts for higher-risk cases [25–29]. One home-care eHealth system used machine learning to analyze structured information entered after in-home visits and then alerted coordinating nurses when the estimated risk of emergency events or unplanned hospitalization increased over a 7–14 day horizon [25]. Another system in assisted living facilities used ePROMs and functional status measures to generate risk levels and alerts for high-risk patients, after which coordinators worked with the assigned nurses or physicians to verify the findings and initiate interventions [26]. Other studies combined continuous monitoring with automated analysis to support care plan assessment, dynamic updates, and longer-term follow-up coordination [27–29]. Examples include an elderly care management system integrating Internet of Things sensors, computer vision, and rule-informed decision support [27], a nurse-led chronic disease mobile health system that structured patient-uploaded data and generated personalized plans [28], and a peritoneal dialysis management system that generated anomalous alerts and supported timely nursing follow-up [29]. The reported relevance in relation to this theme was mixed but more often indirect than direct. Although some applications were explicitly person centered in aim, the reported relevance to humanistic care usually depended on how monitoring outputs, alerts, or recommendations were taken up in nurse-led follow-up and care coordination. This theme included more clinical evaluations than some other themes did, but the workflow-integration reporting remained variable, particularly with respect to responsibility boundaries, response windows, follow-up completion, interoperability, long-term outcome tracking, and governance.

Interactive Care Support via Emotion-Focused Conversational Agents

Three studies were included under this theme. Conversational generative AI, including large language models, was used to draft or deliver text-based, patient-facing care communication, and empathy or emotional experience was treated as an outcome or evaluation dimension [30–32]. The common aim was to improve the tone and responsiveness of emotionally oriented communication. One outpatient randomized trial reported higher ratings for overall quality and empathy, together with fewer negative emotions in the dialog, when nurses worked with a large language model-based triage chatbot [30]. In patient-portal messaging, AI-generated replies were rated favorably on communication dimensions such as empathy [31]. In terms of perioperative education, one randomized trial reported reduced preoperative anxiety with interactive question-and-answer use of ChatGPT, although the findings concerning patient

satisfaction and comprehension were mixed [32]. This theme was associated with the clearest evidence of direct relevance. However, the evidence remained limited and was centered largely on scripted or text-only exchanges, short follow-up, and single-scenario evaluations. Reports on deeper workflow integration, multimodal affective processing, safety governance, cross-context generalizability, and real-world deployment remain sparse.

AI-Supported Optimization of Nurse-Facing Workflows and Resource Management

Five studies were included under this theme. The studies addressed different workflow-related functions, including triage prioritization, diagnosis suggestion, documentation standardization, task-pattern analysis, and staffing prediction. Most studies drew on electronic health records, progress notes, or audit log data and applied deep learning, neural networks, generative AI, or other machine learning approaches [33–37]. The extent of routine workflow integration, however, varied across studies. Examples include a deep learning-based triage support system that predicted short-term hospitalization and supported prioritization [33], neural network-based nursing diagnosis suggestions derived from progress notes [34], the generative AI-assisted standardization of documented interventions [35], the audit-log-based identification of high-burden interaction patterns to inform workflow redesign [36], and predictive staffing models for workforce planning and flexible scheduling [37]. The reported relevance regarding this theme was indirect; in fact, this was the most distal of the four themes. The included reports described mainly documentation, coordination, prioritization, workflow, or staffing functions; direct evidence of improvement in humanistic care was not reported. Workflow-integration reporting was particularly limited, especially with respect to posttrigger actions, interoperability, maintenance costs, and governance.

Discussion

This focused scoping review should be read as a deliberately bounded, interpretive map rather than as a field-wide census of AI in nursing. Across four application themes, the included studies could be organized into two reported relevance pathways to humanistic care: direct relevance, which was more common in communication and psychosocial-support applications, and indirect enabling relevance, which was more common in risk identification, coordination, documentation, staffing, and other workflow-oriented functions. The review's contribution lies in positioning this heterogeneous evidence base by relating application themes to evidence maturity and workflow-integration reporting while avoiding assumptions that efficiency, monitoring, or prediction necessarily translate into empathic, relational, or dignity-preserving nursing care. The incomplete reporting of AI methods and workflow integration further limited comparability and constrained our ability to judge transferability.

The first theme, AI-assisted identification of latent risks and implicit care needs, was centered largely on assessment support and anticipatory follow-up. These systems process nursing notes, EHR data, or communication data to identify risks or cues that might otherwise remain less visible. In Peplau's framework, understanding of the patient's situation develops through observation and communication within the nurse–patient relationship [3]. From this perspective, the included systems are better understood as adjuncts that may make care-relevant information more visible while leaving contextual and relational interpretation, as well as subsequent action, to nurses [38]. The implication is not that humanistic care has improved but that some AI applications may support informational and assessment-related conditions that are relevant to later person-centered follow-up when embedded in clearly defined care processes.

The second theme, precision health management and proactive care management, pointed to a somewhat more developed segment of the evidence base, including several clinical evaluations. Here, AI was used to structure monitoring, identify higher-risk situations, and support coordinated follow-up across home care, chronic disease management, assisted living, and long-term care. These functions may be relevant to person-centered continuity of care, but their significance depends on how alerts or recommendations are incorporated into care processes and whether they are acted on in practice [39, 40]. In the included studies, workflow integration and follow-up processes were not always described in sufficient detail to clarify how responsibilities, escalation, and subsequent actions were operationalized. This theme therefore suggests a plausible pathway from monitoring to proactive care management, but in the reports reviewed, the processes linking detection to action were often only partly described.

The third theme, interactive care support via emotion-focused conversational agents, contained the clearest examples of direct relevance because empathy-related communication and emotional support were part of the intervention target itself. However, the evidence base was small and was limited mainly to text-based interactions, short-term outcomes, and narrowly defined scenarios. Watson's theory focuses on the role of humanistic nursing in caring consciousness, authentic presence, and transpersonal relationships rather than in technological ability alone [4]. The included evidence is therefore better interpreted as suggesting that conversational AI may support selected informational, educational, or emotionally oriented exchanges but not indicating that it can substitute for interpersonal nursing care [41]. This distinction is especially important when favorable empathy ratings are reported because such ratings do not eliminate the need for human oversight, contextual judgment, and relationship-based practice.

The fourth theme, AI-supported optimization of nurse-facing workflows and resource management, represented the most distal pathway to humanistic care. The included systems addressed triage, documentation, workload, and staffing rather than humanistic care processes directly. Their potential relevance lies in whether workflow changes free or redistribute time and staffing resources in ways that support more direct bedside nursing [8]. This is an organizational and practical question, not a result that can be inferred from efficiency metrics alone. Available reports described operational gains more often than how those gains translated into direct nurse–patient care or how transparency, accountability, fairness, and oversight were operationalized in routine use [42]. For that reason, this theme is best interpreted as evidence of organizational conditions that may matter for humanistic care, not as evidence that humanistic care has improved.

Across the themes, evidence maturity and workflow-integration reporting remained uneven. Most included studies were still at the development, technical validation, or usability/feasibility stages, and even clinically evaluated studies often left key workflow elements insufficiently described. These gaps, particularly in triggering, embedding, downstream actions, and governance, limited the interpretation of practice relevance because they obscured how the AI

outputs were translated into nursing action, highlighting the need for more specific reporting of workflow pathways, especially when indirect enabling relevance is claimed.

Limitations

This review has several limitations. Because the searches were anchored in AI, nursing, and humanistic or person-centered care concepts, studies framed directly around humanistic care were more likely to be identified than workflow-oriented studies with more indirect relevance were. The findings should therefore be read as a deliberately focused map rather than an exhaustive account of AI-supported nursing workflows. The review also applied conservative boundary rules to indirect-pathway studies, included paid caregivers only within nurse-linked workflows, and used a broad definition of AI that included eligible rule-based systems. Incomplete reporting in some commercial or proprietary systems further limits the technical comparability across studies. The review was also limited to English-language publications, excluded gray literature, and did not involve systematic reference or citation tracking or formal critical appraisal. Accordingly, our report organizes the literature descriptively by reported pathway, stage, and workflow-reporting characteristics rather than establishing the effectiveness or certainty of evidence.

Conclusions

Within this deliberately focused sample, the included studies could be interpreted as showing either direct relevance or indirect enabling relevance between AI applications in nursing practice and humanistic care. The main contribution of this review is the cautious organization of reported relevance pathways, evidence-stage distribution, and workflow-integration reporting gaps across four application themes. The available literature is limited, heterogeneous, and unevenly reported; therefore, further real-world evaluation and implementation research is needed to clarify how AI outputs translate into nursing actions and under what conditions they may support humanistic nursing practice.

Declarations

List of Abbreviations

Appendix (Abbreviation list)

Ethics Approval and Consent to Participate

Not applicable

Consent for Publication

Not applicable

Availability of Data and Materials

The dataset(s) supporting the conclusions of this article is(are) included within the article (and its additional file(s))

Competing Interests

The authors declare that they have no competing interests.

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Authors' Contributions

Conceptualization, LSH and WS; methodology, LSH and WS; formal analysis, LSH, WS and ZY; writing—original draft preparation, LSH and ZY; writing—review and editing, LZZ and WWC; supervision, PG; funding acquisition, WS. All the authors have read and agreed to the published version of the manuscript.

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Authors' Information

References

1. Reyes-Téllez Á, González-García A, Martín-Salvador A, Gázquez-López M, Martínez-García E, García-García I. Humanization of nursing care: a systematic review. *Front Med.* 2024;11:1446701.
2. International Council of Nurses. The ICN code of ethics for nurses. 2021. https://www.icn.ch/sites/default/files/2024-12/ICN_Code-of-Ethics_EN_Web.pdf. Accessed 8 Feb 2026.
3. Peplau HE. *Interpersonal relations in nursing: a conceptual frame of reference for psychodynamic nursing*. London: Springer Publishing Company; 1991.

4. Pajnikhar M, McKenna HP, Štiglic G, Vrbnjak D. Fit for practice: analysis and evaluation of Watson's theory of human caring. *Nurs Sci Q*. 2017;30:243-52.
5. Juvé-Udina ME, González-Samartino M, López-Jiménez MM, Planas-Canals M, Rodríguez-Fernández H, Duelt IJB, et al. Acuity, nurse staffing and workforce, missed care and patient outcomes: a cluster-unit-level descriptive comparison. *J Nurs Manag*. 2020;28:2216-29.
6. Vandekerckhof S, Malisse L, Steegen S, D'haenens F, Kindermans H, Van Haeken S. Providing compassionate care: a qualitative study of compassion fatigue among midwives and gynecologists. *Healthcare*. 2025;13:2908.
7. World Health Organization. Global strategy on digital health 2020-2027. Geneva, Switzerland: WHO; 2025.
8. Ventura-Silva J, Martins MM, Trindade LDL, Faria ADCA, Pereira S, Zuge SS, et al. Artificial intelligence in the organization of nursing care: a scoping review. *Nurs Rep*. 2024;14:2733-45.
9. Song Y, Gao J, Chen Y, Shi J, Zhang X, Luo D, et al. Nursing robots can reduce nursing workload in general adult wards: a two-phase study. *J Nurs Manag*. 2025;2025:9096837.
10. von Gerich H, Moen H, Block LJ, Chu CH, DeForest H, Hobensack M, et al. Artificial intelligence -based technologies in nursing: a scoping literature review of the evidence. *Int J Nurs Stud*. 2022;127:104153.
11. O'Connor S, Yan Y, Thilo FJS, Felzmann H, Dowding D, Lee JJ. Artificial intelligence in nursing and midwifery: a systematic review. *J Clin Nurs*. 2023;32:2951-68.
12. Howcroft A, Bennett-Weston A, Khan A, Griffiths J, Gay S, Howick J. AI chatbots versus human healthcare professionals: a systematic review and meta-analysis of empathy in patient care. *Br Med Bull*. 2025;156:ldaf017.
13. Arksey H, O'Malley L. Scoping studies: towards a methodological framework. *Int J Soc Res Methodol*. 2005;8:19-32.
14. Peters MDJ, Godfrey C, McInerney P, Munn Z, Tricco AC, Khalil H. Scoping reviews. In: Aromataris E, Munn Z, editors. *JBImanual for evidence synthesis*. JBI; 2024. p. 407-52.
15. Tricco AC, Lillie E, Zarin W, O'Brien KK, Colquhoun H, Levac D, et al. PRISMA extension for scoping reviews (PRISMA-ScR): checklist and explanation. *Ann Intern Med*. 2018;169:467-73.
16. Papadopoulos C, Castro N, Nigath A, Davidson R, Faulkes N, Menicatti R, et al. The CARESSES randomised controlled trial: exploring the health-related impact of culturally competent artificial intelligence embedded into socially assistive robots and tested in older adult care homes. *Int J Soc Robot*. 2021;14:245-56.
17. Duggan MJ, Gervase J, Schoenbaum A, Hanson W, Howell JT, Sheinberg M, et al. Clinician experiences with ambient scribe technology to assist with documentation burden and efficiency. *JAMA Netw Open*. 2025;8:e2460637.
18. Wu Y, Zhang J, Ge P, Duan T, Zhou J, Wu Y, et al. Application of chatbots to help patients self-manage diabetes: systematic review and meta-analysis. *J Med Internet Res*. 2024;26:e60380.
19. Aromataris E, Lockwood C, Porritt K, Pilla B, Jordan Z. *JBImanual for evidence synthesis*. 2024. <https://jbi-global-wiki.refined.site/download/attachments/355599504/JBI%20Manual%20for%20Evidence%20Synthesis%20Nov%202024.pdf?download=true>. Accessed 5 Feb 2026.
20. Zhang S, Ding S, Cui W, Li X, Wei J, Wu Y. Development and usability evaluation of a nurse-led clinical decision support system (AI-AntiDelirium) for management of intensive care unit delirium: a mixed methods study. *Appl Nurs Res*. 2025;82:151921.
21. Kim MS, Kang M. Development and effectiveness of a clinical decision support system for postembolization syndrome after transarterial chemoembolization: a randomized controlled trial. *Asian Nurs Res*. 2025;19:291-302.
22. Zolnoori M, Zolnour A, Vergez S, Sridharan S, Spens I, Topaz M, et al. Beyond electronic health record data: leveraging natural language processing and machine learning to uncover cognitive insights from patient-nurse verbal communications. *J Am Med Inform Assoc*. 2025;32:328-40.
23. Reunamo A, Moen H, Salanterä S, Lähteenmäki PM. Supervised machine learning applied in nursing notes for identifying the need of childhood cancer patients for psychosocial support. *Front Digit Health*. 2025;7:1585309.
24. Vithanage D, Zhu Y, Zhang Z, Deng C, Yin M, Yu P. Extracting symptoms of agitation in dementia from free-text nursing notes using advanced natural language processing. *Stud Health Technol Inform*. 2024;310:700-4.
25. Havreng-Théry C, Fouchard A, Denis F, Veyron J-H, Belmin J. Cost-effectiveness analysis of a machine learning-based ehealth system to predict and reduce emergency department visits and unscheduled hospitalizations of older people living at home: retrospective study. *JMIR Form Res*. 2025;9:e63700.
26. Veyron J-H, Deparis F, Al Zayat MN, Belmin J, Havreng-Théry C. Postimplementation evaluation in assisted living facilities of an ehealth medical device developed to predict and avoid unplanned hospitalizations: pragmatic trial. *J Med Internet Res*. 2024;26:e55460.
27. Paulauskaite-Taraseviciene A, Siaulyš J, Sutiene K, Petravičius T, Navickas S, Oliandra M, et al. Geriatric care management system powered by the IoT and computer vision techniques. *Healthcare*. 2023;11:1152.
28. Ma J, Wang J, Ying J, Xie S, Su Q, Zhou T, et al. Long-term efficacy of an AI-based health coaching mobile app in slowing the progression of nondialysis-dependent chronic kidney disease: retrospective cohort study. *J Med Internet Res*. 2024;26:e54206.
29. Zeng Y, Yin Y, Deng J, Chen D, Deng L, Wang D, et al. Effectiveness of a smart management system in improving adherence and clinical outcomes of patients receiving peritoneal dialysis: a retrospective cohort analysis. *BMC Nurs*. 2025;24:860.
30. Wan P, Huang Z, Tang W, Nie Y, Pei D, Deng S, et al. Outpatient reception via collaboration between nurses and a large language model: a randomized controlled trial. *Nat Med*. 2024;30:2878-85.
31. Kaur A, Budko A, Liu K, Eaton E, Steitz BD, Johnson KB. Automating responses to patient portal messages using generative AI. *Appl Clin Inform*. 2025;16:718-31.

32. Yahagi M, Hiruta R, Miyauchi C, Tanaka S, Taguchi A, Yaguchi Y. Comparison of conventional anesthesia nurse education and an artificial intelligence chatbot (ChatGPT) intervention on preoperative anxiety: a randomized controlled trial. *J PeriAnesth Nurs*. 2024;39:767-71.
33. Yao L-H, Leung K-C, Tsai C-L, Huang C-H, Fu L-C. A novel deep learning-based system for triage in the emergency department using electronic medical records: retrospective cohort study. *J Med Internet Res*. 2021;23:e27008.
34. Nishi R, Kashiwagi K, Yokota S, Ishii M, Miyo K. Construction and validation of artificial neural network model suggesting nursing diagnosis. *CIN Comput Inform Nurs*. 2025;43:e01293.
35. Macieira TGR, Bjarnadottir RI, Salgado PDO, Baranwal A, Semenov A, Priola KB, et al. Making nursing visible: AI-assisted standardization of electronic health record interventions using generative pre-trained transformer models and retrieval-augmented generation process. *Nurs Outlook*. 2025;73:102494.
36. Chen B, Alrifai W, Gao C, Jones B, Novak L, Lorenzi N, et al. Mining tasks and task characteristics from electronic health record audit logs with unsupervised machine learning. *J Am Med Inform Assoc*. 2021;28:1168-77.
37. Pang X, Pan J, Chen Z, Cao X, Shi J, Mao L. Development and validation of a backpropagation neural network model for predicting nursing unit staffing needs: a cross-sectional study. *Int J Nurs Stud*. 2025;172:105207.
38. Dailah HG, Koriri M, Sabei A, Kriry T, Zakri M. Artificial intelligence in nursing: technological benefits to nurse's mental health and patient care quality. *Healthcare*. 2024;12:2555.
39. Gholipour M, Dadashzadeh A, Jabarzadeh F, Sarbakhsh P. Challenges of clinical decision-making in emergency nursing: an integrative review. *Open Nurs J*. 2025;19:e18744346378311.
40. Pinto A, Santos C, Aguiar R, Oliveira S, Cunha D. The use of artificial intelligence in palliative care communication: a narrative review. *Cureus*. 2025;17:e80524.
41. Mohanasundari SK, Kalpana M, Madhusudhan U, Vasanthkumar K, Rani B, Singh R, et al. Can artificial intelligence replace the unique nursing role? *Cureus*. 2023;15:e51150.
42. Park CS-Y. Ethical artificial intelligence in nursing workforce management and policymaking: bridging philosophy and practice. *J Nurs Manag*. 2025;2025:7954013.

Figures

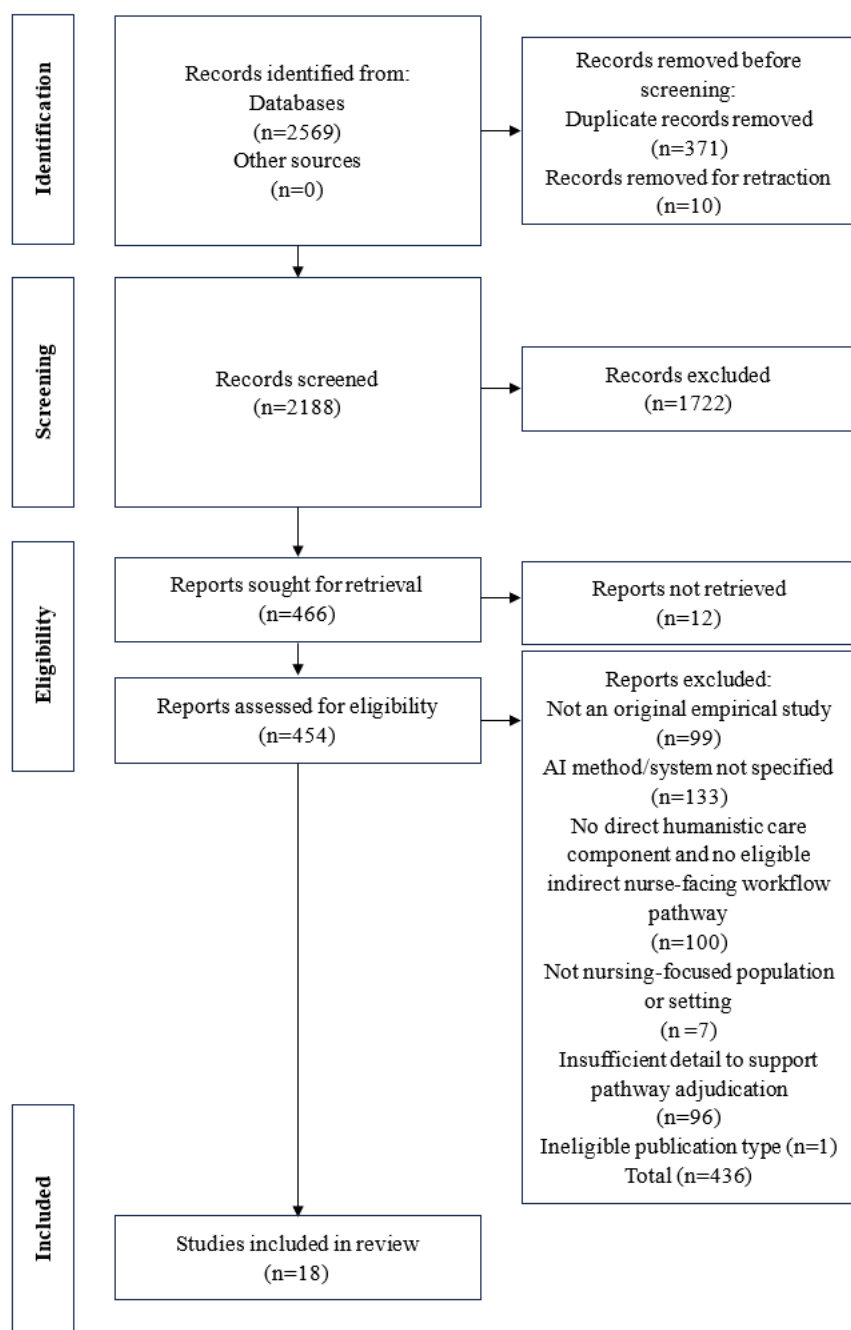


Figure 1

PRISMA-ScR flow diagram of the study selection process.

Supplementary Files

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