Review Article

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Artificial Intelligence in Trauma and Surgical Nursing: A Scoping Review of Nursing Roles, Workflow Integration, and Evidence Gaps

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Received: April 30, 2026

Revised: September 12, 2026

Accepted: October 13, 2026

Citation: Mohsenizadeh SM, Salehi H. Artificial Intelligence in Trauma and Surgical Nursing: A Scoping Review of Nursing Roles, Workflow Integration, and Evidence Gaps. J Surg Trauma. 2027(In Press).

Abstract

Artificial intelligence (AI) is increasingly applied across trauma and surgical care, yet the evidence specifically addressing nursing roles, nursing workflows, and nursing-sensitive outcomes remains insufficiently synthesized. This scoping review aimed to map the intersection of AI technologies with trauma and surgical nursing practice to systematically identify use cases, evidence gaps, and implications for research and practice. This scoping review was conducted according to Joanna Briggs Institute (JBI) methodology and the Arksey and O'Malley framework. The review protocol was not prospectively registered. The review was conducted in accordance with JBI and PRISMA-ScR methodological standards to ensure transparency and reproducibility. PubMed, CINAHL, Web of Science, Scopus, and Embase were searched for studies published between January 2015 and November 2025. Two independent reviewers screened titles, abstracts, and full texts using Covidence. Data charting captured study characteristics, AI technology types, clinical application domains, nursing role descriptions, outcomes stratified across patient, system, and nursing levels, and implementation science considerations. From 2,356 initial records, 31 studies met inclusion criteria. Five primary thematic domains emerged: (1) AI-assisted triage and clinical decision support (n=10, 32%), (2) AI-enabled complication prediction and postoperative surveillance (n=8, 26%), (3) AI-supported massive transfusion protocol optimization (n=5, 16%), (4) AI-enabled documentation and workflow efficiency (n=5, 16%), and (5) AI-supported interprofessional communication and team dynamics (n=3, 10%). Machine learning was the predominant AI modality (71%). Outcomes were distributed across three non-mutually exclusive tiers: patient outcomes were most frequently reported (81%), system outcomes followed (55%), while nursing outcomes were measured in only 3 of 31 studies (10%). Implementation science frameworks were used in four studies (13%). Across domains, studies prioritized model performance over clinically meaningful nursing outcomes. AI may augment trauma and surgical nursing practice, yet the evidence base remains dominated by early-phase model development. Without integrating nursing-sensitive metrics and implementation science frameworks, the clinical value of AI for nursing practice will remain incompletely defined.

Key words: Artificial Intelligence, Nursing Roles, Surgical Nursing, Trauma Nursing

Introduction

Trauma and surgical nursing operate at the nexus of time-sensitive decision-making, complex interdisciplinary coordination, and high-acuity patient monitoring. Nurses in these settings must simultaneously manage hemodynamic instability, anticipate life-threatening complications, coordinate massive transfusion protocols, and maintain meticulous documentation all within environments where minutes directly determine patient outcomes (1, 2). These cognitive and logistical demands create conditions where artificial intelligence (AI) augmentation may be valuable, yet the specific role of AI in supporting nurses within trauma and surgical contexts remains insufficiently characterized. Prior reviews have systematically examined AI applications across trauma care or nursing practice broadly; however, none has isolated the specific intersection of AI with trauma and surgical nursing workflows, nor

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mapped the extent to which nursing-sensitive outcomes are incorporated into AI evaluation studies (3–5). When nursing is discussed, it is often peripherally as users of AI-driven alerts rather than as primary beneficiaries or evaluators of AI systems (6). The specific question that remains unanswered is: To what extent do current AI applications in trauma and surgical settings address nursing workflow needs, measure outcomes relevant to nursing practice, and incorporate nurses as active participants in AI design and evaluation rather than passive end-users?

Parallel literature in general nursing has explored broader AI integration themes, including clinical decision support, predictive analytics, and documentation (7–9). Yet none of these reviews isolated the specific demands of trauma and surgical contexts—environments with compressed decision-making timeframes and the constant risk of rapid patient deterioration. The gap between AI development and nursing-focused implementation is particularly evident in the surgical domain, where the nursing role is often framed as equipment management rather than cognitive and care coordination expertise (10, 11). A survey demonstrated that surgical nurses experience significant moral distress when their clinical judgment is overridden or dismissed (12). Beyond technical performance, the integration of AI into trauma and surgical nursing raises substantive professional concerns. Surveys of surgical nurses have documented resistance to AI adoption stemming from perceived threats to professional autonomy, concerns about erosion of clinical judgment, and uncertainty regarding legal accountability when algorithmic recommendations conflict with nursing assessment (13). Privacy and ethical considerations including data security, algorithmic bias, informed consent for AI-driven care, and the potential for AI to exacerbate rather than mitigate health inequities have been identified as critical yet underexplored issues in nursing contexts (7,14). These concerns are particularly acute in trauma settings, where time pressure may limit the opportunity for critical reflection on AI-generated recommendations (15).

The development and integration of AI technologies into healthcare represents a paradigm shift with implications for nursing practice (16,17). However, successful AI implementation depends on effective integration with existing clinical workflows and meaningful engagement of end-users in the design and evaluation process (13,15). For trauma and surgical nursing, where workflow interruptions are frequent and cognitive demands are high, understanding how AI tools intersect with nursing practice is essential. A scoping review was selected as the appropriate methodology because the aim was to map a broad, heterogeneous, and emerging body of literature to identify evidence clusters, characterize existing research, and pinpoint gaps rather than to answer a narrow clinical effectiveness question or assess study quality.

Methods

Protocol and Design

This scoping review followed the methodological framework established by Arksey and O'Malley (18), with refinements by Levac and colleagues (19) and the Joanna Briggs Institute (JBI) Manual for Evidence Synthesis (20). The Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR) guidelines informed reporting (21). The review protocol was not prospectively registered. The review was conducted according to JBI and PRISMA-ScR standards. Given the exploratory nature of the research question and the heterogeneity of anticipated studies, a scoping review approach was appropriate to map a body of literature that had not yet been comprehensively reviewed.

Research Question

Guided by the Population-Concept-Context (PCC) framework (20), the primary research question was: What AI technologies are being applied in trauma and surgical nursing practice, and what roles do nurses assume in using these tools? Secondary questions included: What outcomes are measured at patient, system, and nursing levels? How are nursing-sensitive outcomes incorporated? What implementation science considerations are addressed? What barriers to AI integration are identified?

Search Strategy

A comprehensive search was conducted in five electronic databases: PubMed (including MEDLINE), CINAHL (Cumulative Index to Nursing and Allied Health Literature), Web of Science Core Collection, Scopus, and Embase. The search strategy combined three concept groups using Boolean operators: (1) artificial intelligence terms, (2) clinical context terms, and (3) nursing

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role terms. Database-specific controlled vocabulary (MeSH terms, CINAHL headings, Emtree) was incorporated where applicable. Searches were limited to English-language publications between January 2015 and November 2025. The 2015 cutoff reflects the clinical emergence of modern neural network-based deep learning approaches in healthcare contexts (16,17). The search end date of November 2025 was determined by the study timeline, with data extraction and analysis conducted between November 2025 and January 2026. Articles published after this date were not captured.

Inclusion and Exclusion Criteria

Studies were eligible for inclusion if they were original research articles examining AI applications with direct relevance to nursing practice in trauma, emergency surgical, or perioperative settings. Nursing relevance was defined as explicit involvement of nurses in the use, evaluation, or impact of the AI tool on nursing workflow or outcomes. This definition was chosen to ensure reproducibility and clarity of inclusion criteria in the absence of standardized reporting of nursing roles in AI literature. It may have excluded studies where nursing roles were implicit but not explicitly reported. Only articles published in English between January 2015 and November 2025 were considered. To avoid conflation of evidence levels, review articles, systematic reviews, and scoping reviews were excluded from primary analysis; these were catalogued separately as background context. Studies were excluded if they focused exclusively on AI for radiological image interpretation without nursing workflow implications, addressed robotic surgery solely from a surgeon technical perspective without documented nursing components, consisted of conference abstracts without full-text availability, were editorials or commentaries without original data, or were not available in full text despite interlibrary loan requests (21,22).

Study Selection and Data Charting

Two reviewers independently screened titles and abstracts against eligibility criteria, followed by full-text review of potentially eligible studies. Disagreements were resolved through consensus or consultation with a third reviewer. Covidence systematic review software was used to manage the screening process (23). Data charting was conducted in accordance with JBI recommendations for scoping reviews (20). A standardized data charting form captured: study characteristics (design, country, setting, sample size, year), AI technology type, clinical application domain, nursing role description, outcomes stratified across three tiers—patient outcomes (e.g., mortality, complications), system outcomes (e.g., time to intervention, length of stay), and nursing outcomes (e.g., documentation time, cognitive workload, nurse satisfaction). Outcomes were not mutually exclusive; studies could report multiple outcome categories. The form also captured implementation science considerations and barriers to implementation reported by authors. The form was piloted on five included studies and refined iteratively (19).

Quality Appraisal

Consistent with JBI guidance for scoping reviews, formal critical appraisal was not undertaken, as the objective was to map the nature and extent of evidence rather than to assess the effectiveness of interventions (20, 21). However, methodological characteristics and limitations were narratively described where relevant to the review's mapping objectives. Most included studies were retrospective and single-center (21 of 31, 68%), with limited external validation, which may restrict the generalizability of findings.

Data Synthesis

Findings were synthesized using a narrative approach, organized thematically around AI application domains identified through iterative reading and coding of included studies (18, 19). Frequency counts of study types, technologies, and clinical contexts supplemented qualitative description of nursing role representation.

Results

Study Selection

The search strategy yielded 2,356 records across the five databases. After removing 509 duplicates, 1,847 records underwent title and abstract screening. Of these, 241 were deemed potentially eligible and sought for retrieval. Full texts could not be retrieved for 15 records. The remaining 226 full-text articles were assessed for eligibility. Following full-text review, 195 records were excluded: 84 focused exclusively on radiological interpretation without nursing relevance, 52 addressed robotic surgery from a purely surgical technical perspective, 29 were conference abstracts

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only, 18 were editorials or commentaries without original data, and 12 were excluded for other reasons. Ultimately, 31 studies met the inclusion criteria.

The high exclusion rate (98.3% of unique records) reflects the deliberately broad search strategy, which was designed to maximize sensitivity for an emerging and heterogeneous literature. The search strategy intentionally combined a comprehensive set of AI-related terms with broad clinical context and nursing role terms to ensure capture of all potentially relevant studies. This approach inevitably retrieved a large volume of records where AI was mentioned but not the primary focus (e.g., radiological image interpretation without nursing workflow implications, robotic surgery from an exclusively surgeon technical perspective, or studies where nurses were mentioned only incidentally as data collectors rather than as users or evaluators of AI tools). The 210 full-text exclusions are documented with specific reasons in the PRISMA flow diagram (Figure 1). This pattern is consistent with scoping reviews in emerging interdisciplinary fields, where broad initial search strategies are recommended to map the full extent of available evidence before applying focused inclusion criteria. The PRISMA-ScR flow diagram is presented in Figure 1.

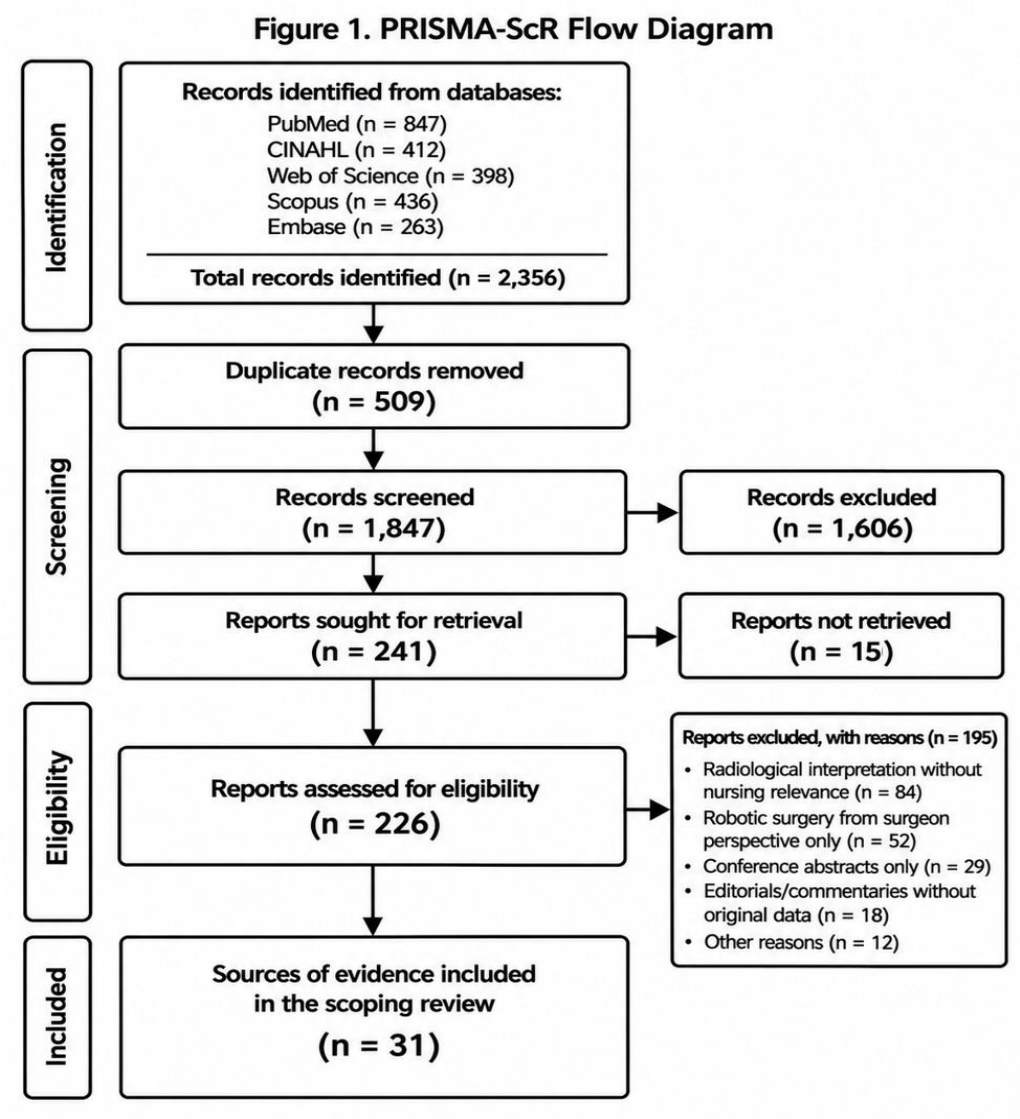

Figure 1. The PRISMA-ScR flow diagram

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Study Characteristics

The 31 included studies spanned publication years from 2016 to 2025, with an increase in publications after 2020 (n=23, 74%). Geographically, studies originated predominantly from the United States (n=14, 45%), followed by the United Kingdom (n=5, 16%), Australia (n=4, 13%), Canada (n=3, 10%), continental Europe (n=3, 10%), and Asia (n=2, 6%). Study designs included retrospective cohort studies (n=9, 29%), prospective observational studies (n=6, 19%), quality improvement projects (n=4, 13%), prospective implementation studies (n=4, 13%), qualitative studies (n=3, 10%), and mixed-methods studies (n=5, 16%). The majority were conducted in Level I trauma centers or academic medical centers (n=21, 68%). Sample sizes ranged from 38 patients in a pilot implementation to over 280,000 patients in large database analyses. Table 1 summarizes the characteristics of included studies.

Table 1. Characteristics of Included Primary Studies (n=31)

Characteristic	Category	n (%)
Year of publication	2016-2019	8 (26)
	2020-2022	12 (39)
	2023-2025	11 (35)
Country	United States	14 (45)
	United Kingdom	5 (16)
	Australia	4 (13)
	Canada	3 (10)
	Europe (other)	3 (10)
	Asia	2 (6)
Study design	Retrospective cohort	9 (29)
	Prospective observational	6 (19)
	Quality improvement	4 (13)
	Implementation study	4 (13)
	Qualitative	3 (10)
	Mixed-methods	5 (16)
Setting	Level I trauma center	21 (68)
	Multicenter	7 (23)
	Community hospital	3 (10)
AI technology	Machine learning (including ensemble methods)	22 (71)
	Deep learning	9 (29)
	Natural language processing	6 (19)
	Clinical decision support system	11 (35)
	Large language model	2 (6)
	Computer vision	3 (10)

Note: Percentages may exceed 100% as some studies used multiple AI technologies. AI = artificial intelligence.

Nursing Roles Across Included Studies

Across the 31 included studies, nursing roles were categorized into four non-mutually exclusive types. Nurses served as end users of AI tools in 26 studies (84%), most commonly as recipients of AI-generated alerts or decision support recommendations. In 8 studies (26%), nurses participated in usability testing or provided feedback on AI tool design. In 3 studies (10%), nurses were involved as co-investigators or members of the AI development team. Only 2 studies (6%) included nurses in algorithm development or feature selection. No study reported nurses in a leadership or principal investigator role for AI development. This distribution indicates that nursing involvement remains predominantly at the implementation stage of the AI development pipeline rather than at the design and conceptualization stage.

Thematic Domains

Five primary thematic domains emerged, each representing a distinct intersection of AI technology with trauma and surgical nursing practice. Studies were assigned to a single primary thematic domain based on the principal AI application examined. The following assignment rules were applied: (1) if the AI tool's primary function was to generate risk scores or treatment recommendations during initial assessment, the study was assigned to Domain 1 (AI-assisted triage and clinical decision support); (2) if the primary function was to predict post-admission complications using continuous monitoring data, it was assigned to Domain 2 (AI-enabled complication prediction); (3) if the primary function was to guide blood product administration, it was assigned to Domain 3 (AI-supported MTP optimization); (4) if the primary function was to automate or augment clinical documentation, it was assigned to Domain 4 (AI-enabled documentation); (5) if the primary function was to analyze or enhance team interactions, it was assigned to Domain 5 (AI-supported team communication). We acknowledge that some studies addressed functions spanning multiple domains; in such cases, assignment was determined by the explicitly stated primary objective of the study. Table 2 provides a structured overview.

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Table 2. Thematic Domains with Evidence Translation Stage and Nursing Practice Implications

Domain	Primary evidence	Nursing-sensitive outcomes measured	Stage of AI translation	Identified gaps	Clinical implication for nurses
AI-assisted triage & decision support	Retrospective cohort, prospective observational	Nurse activation time (2 studies)	Model development / internal validation	Alarm fatigue; no nursing-sensitive endpoints	Efficient triage support available but may increase cognitive workload
AI-enabled complication prediction	Retrospective cohort	None directly measured	Model development	Absence of failure-to-rescue as outcome	High predictive accuracy, yet unlinked to bedside nursing interventions
AI-supported MTP optimization	Quality improvement, retrospective cohort	Protocol adherence (1 study)	Early implementation	Workflow disruption; communication at transitions of care	Activation speed gains offset by alert fatigue
AI-enabled documentation	Mixed-methods, qualitative	Documentation time (2 studies); satisfaction (1 study)	Early implementation	Accuracy concerns; loss of clinical nuance	Time savings promising, but narrative quality may be compromised
AI-supported team communication	Feasibility studies, qualitative	Communication frequency (1 study)	Conceptual	Small samples; no multisite validation	Objective feedback possible; requires larger-scale testing

Note: MTP = massive transfusion protocol. Stage of AI translation categorized using an adapted taxonomy informed by translational AI mplementation frameworks in clinical research, as described by Bates et al. (2021) (15) and Cobianchi et al. (2023) (13): conceptual → model development → internal validation → external validation → early implementation→mature implementation/scale-up.

Domain 1: AI-Assisted Triage and Clinical Decision Support (n=10)

The largest thematic domain comprised studies examining data-driven tools designed to support nursing clinical decision-making during trauma resuscitation and triage. Machine learning-based early warning scores integrated into electronic health records were the most frequently described application. Several studies reported that AI-guided triage protocols were associated with reduced time to definitive intervention. Studies also noted the challenge of alarm fatigue when sensitivity was prioritized over specificity. Cognitive workload assessment emerged as a subtheme; one prospective observational study found that AI-generated decision prompts were associated with reduced time to task completion, while increasing perceived cognitive workload in less experienced clinicians (24).

Domain 2: AI-Enabled Complication Prediction and Postoperative Surveillance (n=8)

Studies in this domain described machine learning models leveraging continuous physiological data to anticipate coagulopathy, venous thromboembolism, and sepsis onset before clinical deterioration becomes apparent through conventional monitoring (5). These studies reported area under the curve (AUC) values typically ranging from 0.78 to 0.94 for outcomes such as postoperative sepsis, surgical site infection, and unplanned intensive care unit admission (4, 11, 15). All studies in this domain relied on retrospective, single-center datasets. None had been tested for impact on failure-to-rescue or time to nursing intervention (3).

Domain 3: AI-Supported Massive Transfusion Protocol Optimization (n=5)

AI models predicting the need for massive transfusion and supporting MTP activation timing were examined. Models incorporating vital signs,

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FAST results, and laboratory values achieved sensitivity above 85% in several studies (1, 6). One quality improvement study found that AI-based clinical decision support was associated with reduced time to MTP activation by a mean of 8 minutes (25). A separate study highlighted coordination challenges during transitions of care when AI-generated recommendations were not smoothly communicated between departments (1).

Domain 4: AI-Enabled Documentation and Workflow Efficiency (n=5)

Natural language processing (NLP) and large language models (LLMs) were explored to reduce documentation burden. Studies reported that trauma nurses spend approximately 21–34% of their shift time on documentation tasks, with documentation during active resuscitation identified as a source of cognitive interruption (8,24). One pilot study implementing an NLP-based trauma flow sheet automation tool reported a 23% reduction in nursing documentation time; nurses expressed concerns about accuracy and the need to maintain clinical narrative nuance (26).

Domain 5: AI-Supported Interprofessional Communication and Team Dynamics (n=3)

AI applications for team performance assessment and communication enhancement were examined. Research has shown that data-driven analysis of trauma team activations can classify team leader utterances, measure communication frequency between professional groups, and identify patterns associated with more efficient resuscitations (27). Although not AI-driven, the foundational studies in this domain provide essential evidence for communication structures—such as crew resource management and SBAR frameworks—that emerging AI-based analytics aim to quantify and optimize (28, 29). All three included studies were classified as feasibility or proof-of-concept work.

Outcome Distribution Across Tiers

Outcomes reported across the 31 included studies were categorized into three non-mutually exclusive tiers. Patient outcomes (mortality, complication rates, physiological parameters) predominated, appearing in 25 studies (81%). System outcomes (time to intervention, length of stay, protocol adherence) were reported in 17 studies (55%). Nursing outcomes (documentation time, nurse-assessed cognitive workload, nurse satisfaction with AI tools) were measured in only three studies (10%) and were documented in fewer than five studies each across the entire sample (7, 24, 26). The most commonly reported individual outcomes were in-hospital mortality (n=14, 45%), time to definitive intervention (n=11, 35%), and prediction model performance statistics (n=26, 84%).

Implementation Science Considerations

Implementation science frameworks were utilized in four of 31 included studies (13%). The most common frameworks were the Consolidated Framework for Implementation Research (CFIR) and the Reach, Effectiveness, Adoption, Implementation, Maintenance (RE-AIM) framework. Studies applying formal implementation frameworks were more likely to report contextual factors influencing AI adoption, including organizational readiness, leadership support, and end-user training infrastructure. The remaining studies addressed implementation informally, typically in discussion sections.

Implementation Barriers

Technical barriers included limited interoperability between AI tools and existing electronic health record systems (n=8, 26%), insufficient external validation of models (n=7, 23%), and concerns regarding algorithmic bias and equity (n=6, 19%) (3, 7, 8, 14). Human factors barriers were cited more frequently: alarm fatigue and alert desensitization (n=9, 29%), workflow disruption (n=11, 35%), lack of end-user engagement during tool development (n=8, 26%), and inadequate AI literacy among nursing staff (n=10, 32%). Ethical considerations including governance frameworks, informed consent, data security, and equity audits were identified as critical requirements (7, 14).

Discussion

This scoping review maps the published literature on AI applications relevant to trauma and surgical nursing practice, identifying five primary domains of activity. While the volume of published research has increased since 2020, the evidence base remains characterized by early-phase model development rather than mature implementation science (3,4,16). As shown in Table 2, the majority of studies in Domain 1 (AI-assisted triage) and Domain 2 (complication prediction) remain at the model development or internal validation stage,

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which limits conclusions about real-world implementation and clinical effectiveness. The three-tier outcome analysis reveals a pronounced imbalance: patient and system outcomes dominate, while nursing outcomes are rarely measured.

Unlike the integrative review by El Arab et al. (2025) (7), which examined AI in nursing broadly and proposed a general Nursing AI Integration Roadmap, or the systematic review by Abdelmohsen and Al-Jabri (2025) (8), which assessed AI impact on nursing practice and patient outcomes across all healthcare settings, this review specifically focuses on trauma and surgical environments as distinct practice contexts. The scoping review by Von Gerich et al. (2022) (9) mapped AI-based technologies in nursing but did not examine practice setting-specific demands. Each of these prior reviews left unaddressed the specific intersection of AI with trauma and surgical nursing workflows and the extent to which nursing-sensitive outcomes are incorporated into AI evaluation studies. This review maps the literature through three lenses not previously applied together: nursing scope, workflow integration, and nursing-sensitive outcomes. In doing so, it highlights a persistent pattern that has received limited attention in prior reviews—namely, that AI tools are being developed for functions aligned with nursing practice, yet the evidence used to evaluate these tools systematically excludes nursing-relevant endpoints.

Despite technical sophistication in the evidence base, critical gaps require attention. The limited number of studies measuring nursing-sensitive endpoints is a prominent finding. Failure-to-rescue, a nurse-sensitive indicator with established validity in surgical populations, was not assessed in any included study (8,11). The three-tier outcome analysis underscores this gap: while patient outcomes were reported in 81% of studies, nursing outcomes appeared in only 10%. Several factors may explain why nursing-sensitive outcomes were measured in only 3 of 31 studies. First, AI research in acute care settings is predominantly led by data science and medical teams, whose outcome priorities center on physiological and clinical endpoints rather than nursing-specific metrics. Second, validated nursing-sensitive metrics specifically designed for AI evaluation contexts remain limited; existing nurse-sensitive indicators such as failure-to-rescue were developed for quality improvement rather than AI performance assessment. Third, publication bias may favor reporting of model performance statistics over implementation outcomes. Fourth, the absence of nursing representation on AI research teams during study conceptualization may result in nursing-relevant endpoints being omitted from study design. The predominance of retrospective, single-center designs raises questions about generalizability, particularly given emerging evidence regarding algorithmic bias in healthcare AI (3,14). Alarm fatigue and workflow disruption were the most frequently cited barriers, aligning with human factors research (13,24,25). Greater integration of implementation science frameworks, which remain underutilized (13% of studies), may accelerate translation of technically sound AI models into clinically meaningful nursing tools (15,19,25).

For nursing practice, AI tools show potential to support decision-making, surveillance, MTP activation, and documentation. However, current evidence does not support autonomous use without nursing clinical judgment. Nurses should retain authority and develop competence to interpret AI outputs critically (7,13). For education, AI literacy curricula are needed in pre-licensure and continuing professional development, addressing technical aspects, critical appraisal, bias awareness, and ethical governance (13,25,26). For policy, governance structures should include nursing representation on AI implementation committees. Embedding nursing perspectives into AI design and evaluation is essential to ensure safe, equitable, and clinically meaningful implementation.

Prospective implementation studies with nursing-sensitive primary endpoints are needed, examining whether AI deployment changes failure-to-rescue rates, time to nursing intervention, documentation accuracy, and nurse-assessed quality of care. Participatory design research engaging nursing end-users from conceptualization through evaluation is essential. Multisite external validation across diverse populations is required before routine clinical adoption. Studies examining AI's impact on team dynamics during high-stakes events would address an understudied area.

This review has several limitations. The search was limited to English-language publications, which introduces potential selection bias and may have omitted relevant studies published in other languages, particularly from Asian, Middle Eastern, and South American trauma systems. The search end date of November 2025 means that articles published in late 2025 and 2026—a period of rapid

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advancement in large language model applications—were not included, and the review may not reflect the most current AI developments. Publication bias—where studies with positive results are more likely to be published—may have influenced the composition of the evidence base. Grey literature searching was not systematically conducted, which may have resulted in the exclusion of relevant non-indexed studies, particularly implementation reports and quality improvement initiatives not published in peer-reviewed journals. The reliance on author-reported descriptions of nursing roles may have introduced reporting bias, as nursing contributions are often underreported in multidisciplinary studies. The operational definition of nursing relevance may have led to exclusion of studies where nursing roles were implicit but not explicitly reported. The heterogeneity of AI models—from classical machine learning to large language models—may limit comparability across studies and synthesis of findings. The review protocol was not prospectively registered, which may limit transparency and reproducibility; all methodological stages were, however, predefined and documented prior to data extraction. Heterogeneity of study designs precluded meta-analysis. Consistent with scoping review methodology, formal quality appraisal was not performed; as no critical appraisal was conducted, the findings should be interpreted as a mapping of evidence rather than an assessment of effectiveness or methodological robustness.

Conclusions

This scoping review maps AI applications relevant to trauma and surgical nursing across five domains: AI-assisted triage, AI-enabled complication prediction, AI-supported MTP optimization, AI-enabled documentation, and AI-supported team communication. A three-tier outcome analysis reveals that patient and system outcomes dominate the evidence base, while nursing outcomes are measured in only 3 of 31 studies (10%). Across all domains, the evidence shows technical promise but is limited by gaps in prospective implementation, nursing-sensitive outcome measurement, and human factors consideration. AI is currently best positioned as a decision support adjunct a tool to support, not replace, nursing clinical judgment. A key priority for future research is prospective implementation studies that measure nursing-sensitive outcomes such as failure-to-rescue rates, time to nursing intervention, documentation accuracy, and nurse-assessed quality of care as primary endpoints. Without this evidence, the clinical value of AI for nursing practice will remain incompletely defined. Embedding nursing perspectives into AI design and evaluation is essential to ensure safe, equitable, and clinically meaningful implementation.

Ethics Approval and Consent to Participate

Ethical approval was obtained from the relevant institutional review board of Birjand University of Medical Sciences(code: IR.BUMS.REC.1405.229).

Consent for Publication

Not applicable.

Data Availability Statement

The data extracted and synthesized during the current study are available from the corresponding author upon reasonable request.

Funding Statement

No funding was received for this study.

Acknowledgements

The authors gratefully acknowledge the researchers, clinicians, and interdisciplinary teams whose original work formed the evidence base for this scoping review. Their contributions to artificial intelligence research and trauma nursing practice made this synthesis possible. We also thank the library services at Birjand University of Medical Sciences for their assistance with database access and full-text retrieval.

Authors' Contribution

SMM conducted the literature search, synthesized the data, and wrote the first draft of the manuscript. HS supervised the study, validated the content, and critically revised the manuscript. Both authors reviewed and approved the final version of the manuscript.

Conflict of Interest

The authors declare no conflicts of interest.

Declaration of Generative Artificial Intelligence (AI) in Scientific Writing

ChatGPT version 5.2 was used to improve the English grammar of the work.

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