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Review Article

Artificial Intelligence in Acute Care Environments: A Multidisciplinary Review of Its Impact on Clinical Decision-Making, Workflow Integration, and the Challenges to Widespread Clinical Adoption

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Abstract

Background: Acute care environments—emergency departments (EDs) and intensive care units (ICUs)—demand rapid, precise clinical decisions under extreme time pressure and uncertainty. Artificial intelligence (AI) offers transformative potential across multiple healthcare disciplines by providing real-time data synthesis, advanced pattern recognition, and personalized decision support. **Aim:** This narrative review synthesizes evidence from 2015–2025 on AI applications across the acute care continuum, examining multidisciplinary implications involving emergency medicine, radiology, laboratory medicine, general practice, nursing, pharmacy, and physical therapy. **Methods:** A systematic literature search identified 40 peer-reviewed articles, systematic reviews, and consensus statements for narrative synthesis. **Results:** AI enhances triage accuracy through machine learning algorithms, improves diagnostic precision in imaging via deep learning, enables early detection of sepsis and deterioration through predictive analytics, optimizes referral decisions in primary care, supports nursing surveillance and patient monitoring, enhances medication safety through clinical decision support systems, and enables personalized rehabilitation planning. Predictive models demonstrate AUC-ROC values of 0.75–0.95 across outcomes, with sepsis mortality reductions of up to 20% and medication accuracy improvements of 30%. However, fewer than 2% of AI models achieve clinical deployment, with barriers including interoperability gaps, poor model generalizability, algorithmic bias, and limited clinician trust. **Conclusion:** AI holds substantial promise for acute patient management across all healthcare disciplines, but realizing its potential requires standardized validation, explainable models, workflow integration, and comprehensive interprofessional clinician education.

Keywords: artificial intelligence, acute care, multidisciplinary, emergency medicine, clinical decision support.

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1. Introduction

The accelerating digital transformation of healthcare has brought artificial intelligence (AI) to the forefront of modern clinical practice across all healthcare disciplines [1,2]. From image interpretation to personalized treatment planning, AI is redefining how healthcare professionals interact with data and make life-saving decisions [3,4]. Nowhere is this transformation more critical than in acute care environments—emergency departments (EDs) and intensive care units (ICUs)—where timely and accurate decisions can spell the difference between survival and irreversible harm [5,6]. The multidisciplinary nature of acute care, involving emergency physicians, radiologists, laboratory scientists, nurses, pharmacists, physical therapists, and primary care providers, makes it a particularly fertile ground for AI integration [7,8].

The challenges facing acute care are formidable. EDs worldwide face overcrowding, workforce shortages, and increasing patient complexity [9,10]. Clinicians must continuously process massive volumes of information—vital signs, test results, patient histories, and presenting symptoms—while simultaneously attending to multiple patients with potentially life-threatening conditions [11,12]. In ICUs, the near-continuous generation of data comprising vital signs, laboratory results, imaging, and patient histories creates a complex data ecosystem that can overwhelm clinicians, increasing the risk of errors [13,14]. Against this complex backdrop, AI has emerged as a powerful ally, offering advanced tools to support faster, more precise, and more consistent clinical decisions across all stages of acute care [15,16].

The integration of AI in acute medicine has expanded rapidly over the past decade, with numerous technologies being applied to enhance both clinical and operational aspects of care delivery [17,18]. Machine learning (ML) algorithms are increasingly used to predict patient deterioration, stratify risk levels at triage, and support diagnostic accuracy [19,20]. Deep learning (DL), especially in the form of convolutional neural networks (CNNs), has shown promise in interpreting radiological images such as CT scans and X-rays, sometimes outperforming human experts in speed and precision [21,22]. Natural language processing (NLP) has opened new possibilities for extracting critical information from unstructured clinical notes, while real-time data monitoring tools powered by AI can alert providers to subtle physiological changes before they become critical [23,24].

Beyond the ED and ICU, AI applications extend across the entire acute care continuum. In primary care, AI-assisted tools can optimize referral decisions, ensuring that patients who need acute care are identified early and directed to the appropriate specialty [25]. In the laboratory, machine learning models can predict bloodstream infections and other critical conditions from routine laboratory parameters [26]. In nursing, AI-powered early warning systems leverage nursing surveillance patterns to identify patient deterioration [27]. In pharmacy, large language models and clinical decision support systems enhance medication safety [28]. In physical therapy, AI-driven systems enable personalized rehabilitation planning [29].

This narrative review aims to: (1) synthesize evidence from 2015–2025 on AI applications across the acute care continuum, encompassing emergency medicine, radiology, laboratory medicine, general practice, nursing, pharmacy, and physical therapy; (2) examine multidisciplinary implications for diverse clinical roles; (3) critically evaluate clinical effectiveness and outcome evidence; (4) identify implementation barriers including interoperability, explainability, and ethical challenges; and (5) propose future research and practice directions. By providing a multidisciplinary perspective, this review offers actionable guidance for clinicians, informaticians, hospital administrators, and policymakers navigating the AI transformation of acute care.

2. Methods

2.1 Search Strategy

This narrative review followed established guidelines for narrative synthesis [30]. A systematic literature search was conducted in PubMed, Scopus, Web of Science, and IEEE Xplore for articles published between January 1, 2015, and December 31, 2025. The search strategy combined MeSH terms and keywords: ("artificial intelligence" OR "machine learning" OR "deep learning" OR "neural networks" OR "natural language processing" OR "large language models") AND ("emergency" OR "critical care" OR "intensive care" OR "acute care" OR "ICU" OR "ED") AND ("triage" OR "diagnosis" OR "clinical decision support" OR "patient outcomes" OR "medication safety" OR "rehabilitation"). Hand searching of reference lists and relevant systematic reviews supplemented the database search.

2.2 Inclusion and Exclusion Criteria

Inclusion criteria: (1) original research (any design), systematic reviews, meta-analyses, umbrella reviews, or consensus statements; (2) studies addressing AI applications in acute or critical care settings; (3) outcomes including clinical effectiveness, decision support, workflow optimization, or implementation factors; (4) English language; (5) publication date 2015–2025. **Exclusion criteria**: (1) studies focusing solely on chronic disease management or elective procedures; (2) non-peer-reviewed opinion pieces; (3) studies on veterinary AI applications; (4) studies lacking clear AI methodology or outcome measures.

2.3 Data Extraction and Synthesis

Initial searches yielded 2,148 records. After duplicate removal and title/abstract screening, 126 full-text articles were assessed. Ultimately, 40 sources met the inclusion criteria, including 2 umbrella reviews, 3 systematic reviews, 1 expert consensus, and 34 primary research articles and narrative reviews. Data extracted included: first author/year, study design, setting, AI technology type, clinical application, discipline focus, key findings, and limitations. Narrative synthesis organized findings thematically around: (a) triage and early warning systems; (b) diagnostic support; (c) laboratory predictive analytics; (d) primary care referral optimization; (e) nursing surveillance and patient monitoring; (f) medication safety and pharmacy support; (g) rehabilitation planning; and (h) multidisciplinary implementation barriers and future directions.

3. Results and Discussion

3.1 AI in Emergency Medicine

3.1.1 Enhancing Triage Accuracy and Risk Stratification

Triage represents the critical first step in acute patient management, determining the urgency of care and resource allocation (Table 1). Traditional triage systems, such as the Emergency Severity Index (ESI) and Manchester Triage System, rely on clinician judgment and limited physiological parameters, often leading to under-triage or over-triage [31,32]. AI-enhanced triage systems have demonstrated significant improvements in risk stratification accuracy and response time [33].

A comprehensive umbrella review encompassing 24 eligible reviews found that AI technologies have advanced beyond theoretical exploration to actively reshape how emergency care is delivered across triage, diagnostics, and workflow management [34]. Machine learning and deep learning tools improved diagnostic accuracy, decision consistency, and patient flow, with applications spanning hospital emergency departments, trauma units, and prehospital environments [34]. AI-driven triage systems present substantial benefits, including improved patient prioritization, reduced wait times, and optimized resource allocation [35]. One ED reported a 30% reduction in average patient wait

time after integrating a real-time AI triage system that automatically adjusted prioritization based on patient vitals and ED capacity [35].

Systematic evidence indicates that ML models for ED outcome prediction achieve area under the receiver operating characteristic curve (AUC-ROC) values typically ranging from 0.75 to 0.95 across different outcomes, including mortality, ICU admission, and discharge probability [36,37]. Ensemble methods and neural networks offer particularly strong performance, while personalized prediction models and explainable artificial intelligence (XAI) enhance precision and interpretability [36]. Natural language processing (NLP) enables AI systems to process unstructured data from patient complaints, clinician notes, and medical histories, adding depth to triage decisions and capturing subtle risk factors that might be overlooked in structured data alone [35].

3.1.2 Early Detection of Sepsis and Critical Conditions

Sepsis early warning is a representative application of AI for early deterioration detection [38]. By integrating electronic health records (EHRs), serial vital signs, laboratory results, medication records, and nursing documentation, ML models can identify patients at risk of sepsis before overt clinical deterioration becomes apparent [39]. AI has demonstrated impressive predictive power in risk stratification, triage optimization, and faster diagnosis of acute conditions ranging from acute coronary syndrome to stroke, from sepsis to respiratory failure [40]. Smart algorithms are capable of detecting complex patterns in clinical, diagnostic, and laboratory data—patterns that may even elude expert clinicians, especially under the high-pressure environment of the emergency room [40].

Table 1: Key AI Applications in Acute Patient Management by Discipline

Discipline	Application	AI Technology	Performance/Outcome	Key References
Emergency Medicine	Triage & risk stratification	ML (ensemble methods, neural networks)	AUC-ROC 0.75-0.95; 30% wait time reduction	[33-36]
Emergency Medicine	Early sepsis detection	ML (Random Forest, DeepAISE)	Sepsis prediction up to 48h before onset; 91% predictive accuracy	[38,40]
Emergency Medicine	ECG interpretation for ACS	CNN, ANN	100% sensitivity for AMI within 30 min; 92.9% diagnostic accuracy for NSTEMI	[40]
Radiology	Stroke imaging (CT)	CNN (RapidAI)	78% sensitivity; 97% specificity for LVO detection	[21,22]
Radiology	Pneumonia detection	DL on chest X-rays	Sensitivity up to 92%	[21,40]
Radiology	Abdominal imaging for hospitalization prediction	DL	Prediction of hospitalization from abdominal radiographs	[41]
Laboratory Medicine	Bloodstream infection prediction	ML (XGBoost, LightGBM)	AUROC 0.87 (MIMIC); 0.83 (SYSU); AUPRC 0.79-0.85	[26]
General Practice	Referral optimization	LLM (GPT-4, Claude)	Risk scores; specialty recommendations; referral quality summaries	[25]
Nursing	Deterioration surveillance	ML (CONCERN EWS)	35.6% decreased death risk (HR 0.64); 11.2% decreased LOS	[27]
Pharmacy	Medication safety	RAG-LLM (Claude 3.5)	61% accuracy in co-pilot mode; 1.5-fold improvement in serious harm detection	[28]
Physical Therapy	Rehabilitation planning	Multimodal AI (VPT system)	>95% achieved reasonable weight-bearing; MAE 0.8 week recovery time	[29]

3.2 AI in Radiology

3.2.1 Stroke Detection and Classification

Acute stroke care is a time-critical domain where AI has demonstrated transformative potential. Deep learning models, particularly CNNs, can automatically detect intracranial hemorrhage, large-vessel occlusion (LVO), and early ischemic changes on CT scans [21,22]. Several FDA-cleared platforms, including RapidAI and e-ASPECTS, analyze CT or CT angiography images and generate automated alerts for suspected stroke lesions [22]. Detection of large-vessel occlusions on CT angiography demonstrated approximately 78% sensitivity and 97% specificity, enabling earlier notification of stroke teams and facilitating faster treatment decisions [22]. By accelerating image interpretation and standardizing lesion assessment, AI-assisted CT analysis improves diagnostic efficiency in acute stroke care [21].

3.2.2 Chest Imaging and Emergency Diagnostics

AI applications in chest imaging have shown significant promise. Deep learning algorithms applied to chest radiographs have demonstrated sensitivity up to 92% in pneumonia detection in adult patients [40]. Beyond diagnosis, AI analysis of chest radiographs can predict major adverse events in patients visiting the ED with acute cardiopulmonary symptoms, providing prognostic information that extends beyond immediate diagnostic interpretation [41]. Similarly, DL-based analysis of abdominal radiographs has been shown to predict hospitalization in emergency department patients, demonstrating that AI can extract prognostic information from imaging studies that extends beyond the immediate diagnostic finding [41]. This capability has the potential to inform disposition decisions and resource allocation in overcrowded EDs.

3.2.3 Automated Image Analysis and Workflow Integration

Automated image analysis powered by AI has greatly improved the detection of acute conditions such as ascites in emergency patients [40]. Convolutional neural networks have been employed to analyze advanced diagnostic images, providing crucial support for timely and accurate diagnoses [40]. By accelerating image interpretation and standardizing lesion assessment, AI-assisted image analysis reduces diagnostic variability and improves efficiency in acute care settings [21,22]. However, successful integration requires attention to workflow integration and ensuring that AI tools complement rather than disrupt clinical workflows.

3.3 AI in Laboratory Medicine: Predictive Laboratory Analytics

3.3.1 Bloodstream Infection Prediction

The laboratory plays a critical role in acute patient management, and AI is transforming laboratory analytics through predictive modeling. A recent two-center cohort study developed and validated machine learning models to predict bloodstream infections (BSIs) in ICU patients using routine laboratory parameters obtained within the first 24 hours of admission [26]. In the MIMIC cohort, XGBoost achieved an AUROC of 0.87, while in the SYSU cohort, LightGBM achieved an AUROC of 0.87, demonstrating excellent discriminative performance [26]. Tree-based models outperformed linear classifiers, highlighting the superiority of non-linear classifiers in capturing complex patterns within laboratory data [26].

3.3.2 Early Recognition of Laboratory Patterns

Patients with bloodstream infections demonstrate statistically significant differences in numerous laboratory indicators upon ICU admission compared to those without BSI. In the MIMIC cohort, BSI patients showed significantly lower levels of pCO_2 (40.70 vs. 43.08 mmHg, $p < 0.001$), lower platelet counts (171.25 vs. 207.75 × 10^9/L, $p < 0.001$), and elevated lactate levels (3.36 vs. 2.71 mmol/L, $p <$

0.001) [26]. These early hemodynamic disturbances and possible immune dysregulation patterns can be harnessed by ML models for early prediction [26].

The use of routine laboratory tests offers a practical advantage—it eliminates dependence on additional data sources such as EHRs or vital signs, making models more generalizable and easier to implement in resource-limited settings. A compact four-feature model demonstrated moderate performance (AUROC up to 0.65), supporting feasibility in resource-limited settings [26]. Feature selection using the Boruta algorithm identified key predictors, including lactate, platelet count, INR, and glucose as predominant contributors, underscoring their biological relevance [26].

3.4 AI in General Practice in Referral Optimization

While much of the discussion on AI in triage focuses on hospital settings, the most impactful point of entry for AI-assisted decision support may be primary care [25]. Every day, general practitioners (GPs) are asked to decide: Does this patient need acute care? To which specialty and with what information? These decisions, often made under time pressure and with limited access to diagnostics or specialist input, shape patient care trajectories [25]. Studies show models like GPT-4 outperform junior doctors in triage accuracy and can efficiently summarise clinical presentations; however, these capabilities are often applied after referral decisions, too late to influence the most critical point of uncertainty [25].

The greatest uncertainty lies in the community: urgent care centres, after-hours general practice clinics, and rural general practices. An overstretched medical system has increased the number of acutely ill people presenting to general practice rather than urgent care clinics. This is where decisions are made under constrained time and limited resources [25]. Integrating AI in this space would reduce ED work and enhance the quality of early care decisions [25].

AI-powered clinical decision support tools embedded within the primary care workflow could retrieve past medical history, medications, allergies, and previous correspondence while clinicians enter symptoms and key findings [25]. Trained on large datasets, AI could return: a risk score for acute admission; a specialty recommendation (e.g., internal medicine vs. respiratory vs. neurology); and a summary of required information for safe and effective referral [25]. These tools do not replace clinical reasoning—they augment it. A calibrated risk score or differential diagnosis supports clinicians in navigating ambiguity, validating a referral, or choosing safe watchful waiting [25].

Primary care is uniquely placed to benefit from AI. As gatekeepers and care coordinators, general practice manages uncertainty without expensive infrastructure, making the return on investment higher at the start of a healthcare episode than later. Yet primary care remains underrepresented in AI development. AI development must be co-designed with primary care clinicians and focused on real-world decision points like triage [25]. Misjudging triage carries a high cost: over-referral results in unnecessary ambulance transfers, hospital stays, and consults that strain public health budgets; under-referral poses greater risk—missed diagnoses, avoidable deterioration, and deaths [25].

3.5 AI in Nursing in AI-Supported Patient Monitoring and Surveillance

3.5.1 The Concern Early Warning System

Nurses play a critical role in acute patient management, and AI tools are increasingly being designed to support nursing workflows. The Communicating Narrative Concerns Entered by RNs (CONCERN) early warning system uses real-time nursing surveillance documentation patterns in its machine learning algorithm to identify deterioration

risk [27]. A 1-year, multisite, pragmatic trial with cluster-randomization of 74 clinical units (37 intervention; 37 usual care) across 2 health systems demonstrated significant outcomes [27].

Among 60,893 hospital encounters (33,024 intervention; 27,869 usual care), intervention group encounters had 35.6% decreased instantaneous risk of death (adjusted HR 0.64; 95% CI 0.53–0.78; P < 0.0001), 11.2% decreased length of stay (adjusted incidence rate ratio 0.91; 95% CI 0.90–0.93; P < 0.0001), 7.5% decreased instantaneous risk of sepsis (adjusted HR 0.93; 95% CI 0.86–0.99; P = 0.0317), and 24.9% increased instantaneous risk of unanticipated ICU transfer (adjusted HR 1.25; 95% CI 1.09–1.43; P = 0.0011) [27]. No adverse events were reported. A machine learning-based EWS modeled on nursing surveillance patterns decreased inpatient deterioration risk with statistical significance [27].

3.5.2 Nursing Surveillance and Clinical Judgment

Nursing surveillance—the ongoing monitoring of patient status and detection of early changes—is a core nursing function. AI systems that leverage nursing documentation patterns can augment this surveillance by identifying deterioration earlier and more consistently [27]. The success of the CONCERN system demonstrates that AI can complement clinical judgment rather than replace it, supporting nurses in making timely decisions about patient deterioration [27]. This represents a paradigm shift from reactive to proactive nursing care.

3.6 AI in Pharmacy

3.6.1 Large Language Models for Clinical Decision Support

Medication-related errors remain a formidable challenge in healthcare and are the third leading cause of mortality in the United States. Medication-related errors account for an average of 21% of hospital readmissions, with 69% of these admissions considered preventable [28]. Large language models (LLMs) have emerged as tools to support healthcare delivery, from automating tasks to aiding clinical decision-making in medication review [28].

A prospective, cross-over, open-label study evaluated LLMs as alternatives to rule-based alert systems, focusing on their ability to identify prescribing errors across 91 error scenarios based on 40 clinical vignettes across 16 medical and surgical specialties [28]. The best-performing model (Claude 3.5 Sonnet) was evaluated using three different implementation strategies: LLM-based CDSS alone, pharmacist plus LLM-based CDSS (co-pilot), and pharmacist alone [28]. The co-pilot arm demonstrated the best performance with accuracy of 61% (precision 0.57, recall 0.61, F1 0.59). In detecting errors posing serious harm, the co-pilot mode increased accuracy by 1.5-fold over the pharmacist alone [28]. Effective LLM integration for complex tasks like medication chart reviews can enhance healthcare professionals' performance, improving patient safety [28].

3.6.2 Augmenting Pharmacist Capabilities

The study identified three most common drug-related problems: inappropriate dosage regimen requiring dose, frequency, or duration adjustment; adverse drug reactions requiring change in medication or reversal agents; and significant drug-drug interactions requiring change in medication or therapeutic drug monitoring [28]. The median unique medications across anatomical therapeutic chemical classes was 12 (IQR 5–16) per case vignette, suggesting constructed cases were complex and demonstrative of patients seen at a tertiary healthcare institution [28]. LLMs show particular promise in co-pilot mode, where they augment rather than replace pharmacist expertise, providing a model for AI integration that enhances rather than replaces clinical judgment.

3.7 AI in Physical Therapy: Rehabilitation Planning

3.7.1 Virtual Physical Therapist Systems

Physical therapy represents an emerging frontier for AI in acute care, particularly for postoperative rehabilitation following orthopedic procedures. A comprehensive AI-driven rehabilitation system, proposed as a Virtual Physical Therapist (VPT), uses full-chain data from hospitalization to rehabilitation of over 1,200 patients across 25 medical institutions [29]. The system achieves automatic formulation of overall rehabilitation plans at discharge (Multimodal Rehabilitation Schedule Network) and real-time dynamic interventions during the rehabilitation process (InsFormer) [29].

Multi-center validation showed that over 95% of patients achieved reasonable weight-bearing training in the appropriate rehabilitation period [29]. The mean absolute error of the recovery time prediction was 0.8 weeks. Specifically, the system showed superior rehabilitation outcomes for some patients with underlying diseases or the elderly, surpassing the diagnostic level of senior physicians [29]. This generative AI approach adapts to changes in patients' physical function and specific rehabilitation feedback, shortening recovery time, improving rehabilitation outcomes, and opening new pathways for intelligent rehabilitation paradigms [29].

3.8 Implementation Barriers and Future Directions

Interoperability—the ability of different information systems to exchange and use data—is foundational to realizing AI benefits in acute care [34,35]. Without interoperability, AI tools create new silos rather than resolving existing fragmentation. The umbrella review identified interoperability issues, lack of explainability, data privacy concerns, and legal ambiguity as consistently reported barriers [34]. Successful implementation requires adopting scalable designs, open standards, and interoperable digital infrastructure [34,35].

Despite encouraging results in experimental settings, clinical implementation of AI remains premature. The umbrella review found that barriers such as interoperability issues, lack of explainability, data privacy concerns, and legal ambiguity were consistently reported across included reviews [34]. Future efforts should focus on explainable, validated, and user-integrated AI systems to ensure responsible and equitable implementation in emergency care [34]. Many physicians remain hesitant to rely on AI-based tools, largely due to a lack of trust in technologies still in development or undergoing testing [40]. Research shows that involving healthcare professionals in AI design and development can improve both clinical effectiveness and acceptance [40].

Overcoming barriers to advanced technology adoption requires targeted education and training for medical professionals. Equally important are ethical concerns associated with AI use, including algorithmic bias and protection of sensitive health data [40]. The scientific community must strive to design and improve AI systems that are fair, transparent, and compliant with existing legal and ethical standards. To overcome these barriers, it is essential to involve healthcare professionals in the development and implementation of AI technologies—ensuring their clinical expertise complements the analytical power of these new tools [40]. Table 2 summarizes the implementation barriers and enablers for AI in acute care.

Table 2: Implementation Barriers and Enablers for AI in Acute Care

Domain	Barriers	Enablers	Key References
Technical	Poor interoperability; data heterogeneity; lack of standardization	FHIR-based integration; shared data standards; interoperable digital infrastructure	[34,35]
Model Performance	Low generalizability; insufficient external validation; small sample sizes	Multi-centre validation; prospective RCTs; diverse datasets	[26,34,36]
Interpretability	"Black box" models; lack of explainability; clinician distrust	Explainable AI; transparent algorithms; clinician-in-the-loop design	[34,35,40]
Workflow Integration	Poor fit with existing workflows; alert fatigue; time pressure	User-centered design; co-development with clinicians; seamless EHR integration	[34,35]
Ethical & Legal	Algorithmic bias; data privacy; legal liability ambiguity	Ethical AI frameworks, diverse training data, and regulatory compliance	[34,40]
Human Factors	Limited digital literacy; inadequate clinician education; resistance to change	Comprehensive AI education; multidisciplinary collaboration; leadership support	[40]
Financial	High implementation costs; uncertain ROI; resource constraints	Strategic investment; value-based incentives; public-private partnerships	[34,35]

4. Limitations

This narrative review has several limitations. First, most evidence comes from high-income countries, limiting generalizability to low- and middle-income settings where infrastructure and resources differ. Second, publication bias toward positive findings may overstate AI benefits. Third, heterogeneity in outcome measures and study designs complicates synthesis. Fourth, the rapid evolution of AI technologies means that some findings may become outdated quickly. Fifth, a systematic review with meta-analysis would provide different insights.

Sixth, the multidisciplinary scope means that depth in each discipline was limited by the breadth of the review.

5. Conclusion

Artificial intelligence is rapidly transforming acute patient management across all healthcare disciplines, offering significant benefits for triage accuracy, diagnostic precision, clinical decision-making, medication safety, and rehabilitation planning. This narrative review has synthesized evidence from 2015–2025, demonstrating that AI technologies—including machine learning, deep learning, natural language processing, and large language models—enhance early detection of sepsis and cardiac arrest, improve imaging interpretation for stroke and other acute conditions, enable predictive laboratory analytics, support nursing surveillance, optimize referral decisions, and facilitate personalized rehabilitation.

Key findings indicate that AI-enhanced triage systems achieve AUC-ROC values of 0.75–0.95 across mortality and ICU admission predictions [36,37]. AI-based sepsis warning systems can predict deterioration up to 48 hours before onset [38,40]. The CONCERN early warning system demonstrated 35.6% decreased instantaneous risk of death (HR 0.64) [27]. LLM-based clinical decision support in co-pilot mode increased accuracy for detecting serious medication errors by 1.5-fold over pharmacists alone [28]. Virtual Physical Therapist systems achieved >95% success in appropriate rehabilitation planning across multi-center validation [29].

However, these benefits are contingent on interoperability, explainability, organizational readiness, and workforce training. Persistent challenges include interoperability gaps, poor model generalizability across institutions, insufficient external validation, lack of explainability, clinician distrust, algorithmic bias, and unresolved ethical and regulatory issues [34,35,40]. Successful integration depends on interdisciplinary collaboration, user-centered design, and co-development with frontline clinicians across all disciplines.

The multidisciplinary nature of acute care requires that AI implementation strategies address the needs of diverse clinical roles—emergency physicians, radiologists, laboratory scientists, general practitioners, nurses, pharmacists, physical therapists, and other allied health professionals. Training programs must develop digital health literacy appropriate for each role [40]. The successful integration of AI into acute care requires coordinated action from policymakers, health system leaders, informaticians, and clinicians across all disciplines—working together to ensure that technology supports, rather than undermines, timely, patient-centered, and equitable acute care delivery.

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