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AI-Enabled Critical Care: Advancing Diagnosis, Triage, and Treatment Decision-Making

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Abstract- Background: Intensive care units generate high-frequency, multimodal data suited to artificial intelligence (AI)-enabled clinical decision support systems (CDSS), yet clinical translation remains inconsistent. Objectives: To synthesise evidence on AI-CDSS in adult critical care, appraise methodological maturity against AI reporting standards, and identify implementation barriers. Methods: Narrative synthesis following the SANRA framework. Literature was appraised against TRIPOD+AI, PROBAST+AI, DECIDE-AI, and CONSORT-AI standards across six dimensions: validation tier, data generalisability, metric completeness, human-AI workflow integration, equity reporting, and deployment status. Results: Diagnostic AI models report high internal discrimination but inconsistent calibration and limited prospective validation. Triage systems outperform static scoring retrospectively, yet alert fatigue and clinician override rates remain underreported. Treatment decision support models often conflate observational prediction with causal intervention effects. Cross-cutting gaps include single-centre training data, heterogeneous equity reporting, and absence of standardised post-deployment monitoring. Conclusions: AI-CDSS in critical care exhibits strong algorithmic promise but fragmented clinical validation. Priorities include prospective multi-centre evaluation, human-centred workflow integration, causal treatment framing, and standards-compliant reporting.

Keywords: Artificial intelligence; critical care; clinical decision support; triage; sepsis; machine learning; external validation.

I. INTRODUCTION

Adult intensive care units operate under conditions of physiological complexity, time-sensitive decision windows, and constrained resources. The proliferation of electronic health records (EHRs) and continuous monitoring has created unprecedented data density, positioning AI-enabled CDSS as potential catalysts for precision critical care.[1,2] Machine learning (ML), deep learning (DL), and natural language processing (NLP) models have been developed to detect deterioration, optimise resource allocation, and recommend therapeutic titrations.[2]

Despite algorithmic advances, translation from retrospective validation to prospective clinical impact remains uneven. Many studies report high discrimination on internal cohorts without external validation, calibration assessment, or linkage to patient-centred outcomes.[3] Triage tools frequently lack workflow integration testing, while treatment recommendation models rely on observational associations rather than causal inference.[4] Inconsistent adoption of AI-specific reporting guidelines—TRIPOD+AI for predictive model development, PROBAST+AI for risk-of-bias assessment, DECIDE-AI for early-stage clinical evaluation, and CONSORT-AI for interventional trials—limits reproducibility and regulatory readiness.[5-8]

This narrative synthesis addresses three clinical decision nodes: diagnosis, triage, and treatment optimisation. It appraises methodological maturity using established AI reporting standards and identifies cross-cutting implementation challenges, providing a structured framework aligning algorithmic development with clinical utility.

II. METHODS

Design and Reporting Framework

This narrative synthesis was designed and reported in accordance with the Scale for the Assessment of Narrative Review Articles (SANRA) framework, which

mandates transparent scoping, explicit selection criteria, structured appraisal, and thematic synthesis.[9]

Search Strategy

A scoping search was conducted across PubMed/MEDLINE, Embase, Scopus, and IEEE Xplore from January 2018 to December 2025. Search terms combined controlled vocabulary and free-text keywords spanning: (1) AI methodologies (machine learning, deep learning, natural language processing, clinical decision support); (2) critical care settings (intensive care unit, adult ICU, high-dependency unit); and (3) clinical functions (diagnosis, risk stratification, triage, treatment recommendation). Boolean operators were applied to refine retrieval.

Selection Criteria

Inclusion criteria: peer-reviewed empirical studies reporting AI-CDSS validation or deployment in adult ICU populations (age ≥18 years), with a clinical or methodological comparator, published in English. Exclusion criteria: paediatric cohorts, purely algorithmic papers without clinical validation, conference abstracts, editorials, letters, and non-English publications. Reference lists of included studies and AI evaluation guidelines were hand-searched for additional eligible literature.

Appraisal Framework

Included studies were appraised against AI-specific reporting frameworks aligned with the EQUATOR Network. Predictive and diagnostic models were evaluated using TRIPOD+AI and PROBAST+AI criteria, focusing on validation tier, calibration, and risk of bias.[5,6] Early-stage clinical AI studies were assessed using DECIDE-AI domains, including safety monitoring, interpretability, and human-AI workflow integration.[7] Interventional or prospective deployment studies were mapped to CONSORT-AI standards.[8] Each study was coded across six dimensions: validation tier, data generalisability, metric completeness, human-AI interaction, equity/bias reporting, and implementation status.

Synthesis Approach

Findings were synthesised thematically by clinical domain. Studies were grouped by methodological maturity, clinical outcome linkage, and deployment readiness rather than chronologically. Discrepancies between retrospective algorithmic performance and prospective utility were explicitly contextualised. Limitations of narrative synthesis design are addressed in the Discussion.

III. DIAGNOSTIC AI IN CRITICAL CARE

Medical Imaging

Deep learning models have achieved radiologist-level performance in chest X-ray interpretation. CheXNet, a 121-layer convolutional neural network, detected pneumonia with AUROC 0.763 on the ChestX-ray14 dataset, exceeding average radiologist performance.[10] Self-supervised models have since matched or exceeded expert performance across multiple thoracic pathologies.[11] In the ICU, AI can triage portable chest radiographs for pneumothorax, pleural effusion, and line malposition, reducing time-to-intervention.[12] Deep learning for intracranial haemorrhage detection on head CT has shown sensitivities exceeding 95% in multicentre validation.[13]

However, external validation often degrades performance due to dataset shift, particularly in ICU populations with tube lines, atypical positioning, and suboptimal image quality.[14] A systematic review and meta-analysis of externally validated ML-based ICU scoring systems found that external validation performance was on average 0.037 AUROC lower than internal validation, with decreases of up to 50% in some cases.[15] This underscores the fragility of internally validated diagnostic models and the imperative for multi-centre external validation.

Electroencephalography

Continuous EEG monitoring is used for seizure detection and prognostication after cardiac arrest. Deep learning models detect non-convulsive seizures with sensitivity and specificity outperforming conventional algorithms.[16] AI also quantifies burst-suppression ratios and reactivity, providing objective prognostic markers.[17]

However, false alarms in patients with artefact limit clinical trust and contribute to alarm fatigue.

Laboratory and Multi-Modal Data

Gradient-boosted models integrating lactate trends, white-cell counts, and procalcitonin improve early infection detection compared with qSOFA alone.[18] A deep learning approach for continuous prediction of acute kidney injury (AKI), developed on over 700,000 patients across multiple sites, predicted a substantial proportion of inpatient AKI episodes and dialysis-requiring AKI with lead times of up to 48 hours, providing confidence assessments and salient feature lists.[19] Despite these advances, calibration reporting remains inconsistent, temporal validation is absent in most single-centre cohorts, and label leakage frequently inflates performance metrics.

IV. AI-ENABLED TRIAGE AND RISK STRATIFICATION

Early Warning Scores and Deterioration Prediction

Traditional scores (NEWS2, MEWS, SOFA, APACHE II) rely on linear thresholds and suffer from alarm fatigue. ML-enhanced early warning scores incorporate interaction terms and temporal trends, reducing false-alarm rates while maintaining high sensitivity in retrospective analyses.[20] Recurrent neural networks and transformer architectures predict cardiac arrest, unplanned ICU admission, and septic shock hours before clinical onset.[21,22] Dynamic risk stratification shows promise in prioritising haemodynamic instability and optimising step-down transitions, though static scoring systems remain widely used due to implementation simplicity.

Sepsis Triage: The Epic Sepsis Model

The Epic Sepsis Model (ESM) illustrates the translational gap between algorithmic promise and clinical reality. An independent external validation at Michigan Medicine found an AUROC of only 0.63 (95% CI 0.62–0.64), substantially worse than the developer-reported performance.[23] The model failed to identify a majority of patients with sepsis while generating alerts for a large proportion of hospitalised patients, creating significant alert fatigue. A subsequent prospective multicentre validation of ESM version 2 across four US health systems found AUROCs between 0.82 and 0.92 but with high institutional variability, low positive predictive value, and high alert burden.[24] This case demonstrates that proprietary models require independent validation, time-horizon-based AUROCs can be misleading, and local recalibration is essential.

Resource Allocation

During surges such as the COVID-19 pandemic, AI has been proposed for optimising ventilator and bed allocation by forecasting demand curves.[25] Reinforcement-learning agents suggest dynamic staffing schedules.[26] However, ethical considerations regarding resource allocation during surge events and demographic fairness in risk scoring complicate deployment. Alert fatigue, clinician override rates, and dashboard usability are infrequently evaluated, leaving DECIDE-AI criteria for human-AI collaboration underreported.

V. TREATMENT DECISION SUPPORT

Sepsis Management

AI models dynamically reassess sepsis likelihood using time-varying features.[27] The AI-Clinician, a reinforcement learning model using data from over 100,000 admissions, learned optimal fluid and vasopressor dosing strategies, suggesting mortality reduction in simulated environments.[26] However, this model has not been prospectively tested in randomised trials. A subsequent randomised trial of an RL-guided fluid protocol showed reduced cumulative fluid balance but no mortality difference,[28] highlighting the critical distinction between observational prediction and causal intervention effects.

Mechanical Ventilation

Deep learning models predict optimal PEEP and FiO2 settings using respiratory mechanics data, outperforming ARDSNet tables in retrospective cohorts.[29] Closed-loop ventilation systems use rule-based algorithms to automatically adjust pressure support and PEEP, reducing clinician workload while maintaining comparable outcomes

to manual ventilation in randomised evaluations.[30,31] However, these systems employ rule-based rather than adaptive AI logic, and the transition to fully AI-driven closed-loop control requires prospective safety evaluation.

Fluid Resuscitation and Weaning

Bayesian networks and RL agents personalise fluid bolus volumes by integrating haemodynamics, urine output, and capillary refill. AI models predict fluid responsiveness using non-invasive pulse wave analysis. Transfer-learning approaches adapt models across ICUs with minimal retraining.[32] Treatment decision support represents the most complex AI application in critical care, as recommendation systems must distinguish observational associations from actionable intervention policies. Safety constraint enforcement, rollback protocols, and CONSORT-AI-compliant prospective trials measuring patient-centred outcomes remain scarce.

VI. CROSS-CUTTING IMPLEMENTATION CHALLENGES

The literature reveals a persistent validation gap: the majority of AI-CDSS studies rely on internal retrospective cohorts. A systematic review of ML-based ICU scoring studies found that fewer than one-quarter had undergone external validation by 2023, with MIMIC and eICU accounting for over 80% of validation datasets, raising concerns about generalisability.[15] Dataset shift, EHR heterogeneity, and temporal drift degrade performance upon deployment, yet drift monitoring and recalibration protocols are rarely reported.

Human-AI integration remains a critical determinant of clinical impact. Equity and fairness reporting are heterogeneous, with subgroup performance stratification by age, sex, race, or comorbidity burden absent in many studies.[3] Regulatory pathways, including FDA Software as a Medical Device (SaMD) classifications and EU AI Act compliance, emphasise the need for post-market surveillance and continuous performance auditing.[33]

Table 1. Cross-cutting implementation challenges and mitigation strategies for AI-CDSS in critical care

Challenge	Description	Mitigation Strategies
Data heterogeneity	Variable EHR systems, coding practices, missingness	Federated learning, common data models (OMOP)
Poor generalisability	Performance drops on external cohorts; US-centric datasets	Multi-centre training, domain adaptation, diverse validation
Algorithmic bias	Under-representation of subgroups	Bias audits, fairness constraints, STANDING Together standards
Explainability deficit	Black-box models erode clinician trust	SHAP, attention maps, concept-based explanations
Workflow integration gaps	Alert fatigue, high override rates	Human-centred design, EHR embedding, co-design with clinicians
Regulatory uncertainty	Unclear FDA/EMA pathways for adaptive AI	SaMD classification, pre-certification, post-market surveillance
Validation gap	Minority of models prospectively validated	CONSORT-AI compliance, pragmatic trials, implementation science

VII. FUTURE DIRECTIONS

Federated and privacy-preserving learning enables multi-institutional model training without data sharing, improving generalisability while preserving privacy.[34] Explainable AI (XAI) techniques such as SHAP and LIME provide feature-level explanations that improve adoption when integrated into clinical dashboards.[35] Adaptive decision support involves reinforcement-learning agents that continuously update policies as new data arrive, combined with

online learning to maintain performance against temporal drift.[36] Digital twins—patient-specific physiological simulators—offer a pathway to personalise therapy without exposing patients to untested AI recommendations.[37] Prospective RCTs and implementation science remain the ultimate arbiters of clinical utility.[8]

VIII. DISCUSSION

This synthesis demonstrates that AI-CDSS in adult critical care exhibits strong retrospective algorithmic performance but fragmented clinical translation. Diagnostic models require prospective calibration and decision-curve validation. Triage systems must prioritise workflow integration, alert fatigue mitigation, and equitable risk communication. Treatment decision support necessitates causal framing, safety constraint reporting, and prospective outcome trials.

Figure 1. Proposed standardised evaluation pipeline for AI-enabled clinical decision support systems in critical care. The pipeline progresses from model development with TRIPOD+AI compliance through DECIDE-AI feasibility testing, CONSORT-AI prospective randomised trials, to continuous post-market equity and drift auditing.

The Epic Sepsis Model case study illustrates how widespread deployment of inadequately validated proprietary models can create national-level concerns about sepsis management.[23,24] This underscores the imperative for independent, multi-centre validation before clinical deployment. A standardised evaluation pipeline is proposed (Figure 1): (1) multi-centre temporal validation with TRIPOD+AI compliance;[5] (2) DECIDE-AI feasibility testing with clinician co-design;[7] (3) CONSORT-AI prospective trials measuring patient-centred outcomes;[8] and (4) continuous post-market equity and drift auditing. The STANDING Together initiative provides a framework for addressing bias in AI health datasets.[38]

Table 2. Proposed standardised evaluation pipeline for AI-CDSS in critical care

Evaluation Stage	Standard	Key Requirements	Outcome Measures
Development	TRIPOD+AI	Multi-centre training, full reporting, PROBAST+AI risk-of-bias assessment	Discrimination, calibration, decision-curve analysis
Feasibility	DECIDE-AI	Safety monitoring, interpretability, human-AI workflow integration	Usability, alert burden, clinician trust
Prospective trial	CONSORT-AI	Randomised design, pre-specified endpoints, intention-to-treat analysis	Patient-centred outcomes, adverse events
Post-market	FDA SaMD / EU AI Act	Drift monitoring, equity auditing, performance transparency	Sustained accuracy, subgroup fairness, incident reporting

Clinical implications:
Clinicians and health systems should approach AI-CDSS as decision-augmentation tools requiring rigorous local validation, transparent uncertainty reporting, and embedded override mechanisms. Implementation should proceed only after

prospective feasibility testing and alignment with institutional governance frameworks.

Limitations:

This narrative synthesis prioritises thematic coherence over exhaustive aggregation; publication bias and non-English literature were not systematically quantified. Heterogeneity in AI reporting practices limited direct methodological comparison. Nevertheless, the explicit appraisal framework and alignment with SANRA and EQUATOR Network standards mitigate selection bias.

IX. CONCLUSION

AI-enabled clinical decision support holds substantial promise for optimising diagnosis, triage, and treatment in adult critical care. Realising this potential requires shifting focus from algorithmic novelty to clinical utility, human-centred workflow integration, causal treatment evaluation, and standards-compliant reporting. Prospective, multi-centre trials embedding safety monitoring, equity auditing, and clinician-AI collaboration are essential to ensure safe, scalable, and evidence-based deployment in high-acuity care settings.

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