REVIEW ARTICLE

Enhancing Extracorporeal Membrane Oxygenation Care with Artificial Intelligence: A New Era in Critical Care Medicine

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Received on: 23 December 2025; *Accepted on*: 02 February 2026; *Published on*: xx xxxx xxxx

Abstract

Extracorporeal membrane oxygenation (ECMO) is a life-saving modality used in severe cardiac and respiratory failure. Despite its benefits, it is a labor-intensive therapy in which patients face high costs and significant mortality risks. Decision-making in ECMO is also complex regarding predicting outcomes and resource allocation. Artificial intelligence (AI) offers novel approaches to improve outcome prediction, patient monitoring, and complication detection. Relevant studies evaluating AI or machine learning (ML) applications in ECMO were identified, screened, and analyzed to provide a broad contextual narrative overview. AI-based models demonstrated improved accuracy for predicting ECMO initiation, mortality, complications, and weaning success compared with conventional clinical scores. The findings suggested that AI can enhance ECMO care by supporting complex clinical decisions. However, challenges remain regarding data heterogeneity, validation, and implementation. AI enhances ECMO decision-making but requires further validation. It has significant potential to augment ECMO management. Future research should emphasize multicenter validation and prospective trials.

Keywords: Artificial intelligence, Critical care, Extracorporeal membrane oxygenation, Machine learning.

Indian Journal of ECMO (2026): 10.5005/jaypee-journals-11011-0092

Introduction

Extracorporeal membrane oxygenation (ECMO) is one of the most demanding modalities in critical care medicine, providing life-saving cardiopulmonary support to patients with severe respiratory or cardiac failure.[1,2] The decision-making process surrounding ECMO—from patient selection and initiation timing to ongoing management and weaning—involves intricate clinical judgments that require the integration of multiple physiological parameters, patient characteristics, and dynamic clinical data.[1,3] With recent progress in artificial intelligence (AI) and machine learning (ML), new opportunities have emerged to strengthen clinical decision-making, enhance prognostic accuracy, and improve the allocation of ECMO resources. This review summarizes contemporary AI applications in ECMO care, critically analyzes current evidence, and highlights emerging directions for research and clinical translation.[4–6]

Method/Search Strategy

This article is presented as a narrative overview aimed at providing a broad analysis of the rapidly evolving literature on AI in ECMO.

Search Strategy

We conducted a comprehensive literature search using electronic databases (PubMed/MEDLINE, Embase, and Google Scholar) to identify relevant studies published up to June 2024.

Studies were selected if they applied AI or ML methodologies to ECMO datasets and addressed clinical domains such as patient selection, mortality prediction, or complication detection. Emphasis was placed on recent studies (2018–2024) demonstrating the transition from static scoring to dynamic prediction models.

Applications of AI in ECMO Management

Patient Selection and Initiation Prediction

One of the most critical decisions in ECMO management involves identifying which patients are likely to benefit from this resource-intensive therapy. Traditional patient selection relies on clinical criteria and scoring systems, such as the respiratory ECMO survival prediction (RESP) score and the predicting death for severe ARDS on VV-ECMO (PRESERVE) score, which have shown moderate discriminatory ability with area under the receiver operating characteristic curve (AUROC) values ranging from 0.65 to 0.81.[7–9] However, these tools often fail to consider complex nonlinear associations among clinical variables and may not perform uniformly across diverse patient groups.[4,7]

A recent meta-analysis evaluated 36 studies on AI-based ECMO prediction models published between January 1980 and June 2024, encompassing 212 initial records.[4] The pooled analysis demonstrated that AI models achieved an AUROC of 0.838 (95% CI: 0.804–0.873) for ECMO initiation prediction, demonstrating improved discriminatory ability compared with traditional clinical assessments.[4,5] Despite this advantage, variability between studies

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How to cite this article: Khandelwal V, Singh VK, Taneja S. Enhancing Extracorporeal Membrane Oxygenation Care with Artificial Intelligence: A New Era in Critical Care Medicine. Indian Journal of ECMO 2026;xx(xx):xx–xx.

Source of support: Nil

Conflict of interest: Dr Vinod K Singh and Saurabh Taneja are associated as the Editorial board members of this journal and this manuscript was subjected to this journal's standard review procedures, with this peer review handled independently of these Editorial board members and their research group.

was substantial ($I^2 = 96.5\%$), indicating differences in methodology, feature selection, and validation techniques.[4]

Machine learning models have also been developed to predict ECMO utilization with clinically actionable lead times.[10,11] Forecast ECMO, a gradient-boosting-based model trained on over 6,000 ICU patients from 15 hospitals, demonstrated high performance in predicting ECMO requirements 12–24 hours in advance, outperforming conventional indicators such as the PaO_2/FiO_2 ratio, the sequential organ failure assessment (SOFA) score, and the RESP score. This predictive lead time is clinically valuable for arranging patient transfers or preparing ECMO teams.

Another model, PreEMPT-ECMO (prediction, early monitoring, and proactive triage for ECMO), employed a hierarchical deep-learning architecture integrating both static variables and time-series data to generate continuous predictions of ECMO utilization through long short-term memory (LSTM) networks. It consistently outperformed classical ML models and logistic regression across 12, 24, and 48 hours prediction windows,[12] reflecting its ability to detect evolving physiological trends relevant to ECMO needs.[3,12]

Mortality and Outcome Prediction

Veno-arterial ECMO (VA-ECMO)

Artificial intelligence-assisted mortality prediction for VA-ECMO patients has advanced significantly. Extracorporeal membrane oxygenation predictive algorithm (ECMO PAL), the first AI-powered ECMO survival score model derived from the Extracorporeal Life Support Organization (ELSO) registry, was trained on more than 18,000 patients and validated in an additional 5,015 individuals. The model demonstrated superior accuracy and AUROC compared with established prognostic scores, maintaining performance across diverse geographic regions and ECMO centers.[2,6,13]

Similarly, eCMoML, an AI-powered random forest-based model, was developed to predict 28 days mortality risk after VA-ECMO decannulation using data from five hospitals in China. Ten different ML algorithms were evaluated, and random forest was identified as the optimal predictor.[5] Despite using only 25 routinely available clinical variables, including basic patient information, standard ICU scores, and routine blood test results the model achieved exceptionally high AUROC values (training: 1.00; validation: 0.93–1.00), highlighting its practicality and generalizability in virtually any hospital with a VA-ECMO program.[5,14]

Veno-venous ECMO (VV-ECMO)

For VV-ECMO patients, ML models such as extreme gradient boosting (XGBoost) and light gradient boosting (LightGBM) have shown clear advantages over RESP and PRESERVE scores. Both boosting models produced AUROC values above 0.80, compared with RESP (0.66) and PRESERVE (0.71).[7,15] Their accuracy persisted in external validation, with decision curve analysis confirming superior net clinical benefit.[15]

Complication Prediction

Hemorrhage and Thrombosis

Hemorrhage and thrombosis remain leading contributors to ECMO morbidity, with transfusion-requiring bleeding occurring in nearly half of patients in the EOLIA trial.[2] Machine learning approaches have been applied for the first time to predict ECMO complications, comparing five supervised classification algorithms: Random forest, recursive feature elimination, decision trees, *k*-nearest neighbors, and logistic regression. Using a dataset of 44 consecutive ECMO patients, the decision tree model predicted moderate accuracy for hemorrhage prediction and lower accuracy for thrombosis prediction.[16,17] Key predictive features included cannula characteristics, platelet counts, INR values, and heparin dosing.[16]

Later research involving 357 ECMO patients across 71 hospitals found that LightGBM and random forest models achieved ROC AUC values above 0.7 for bleeding prediction using RBC transfusion as a surrogate endpoint.[6] Shapley additive explanations (SHAP) interpretability methods identified blood volume, hemoglobin, and body weight as dominant predictors.[6–8] This approach demonstrates the potential of AI to support early identification of high-risk patients and optimize transfusion management strategies.[6]

Neurological Complications

Neurological injury prediction in ECMO patients is challenging due to the complex interplay of factors, including systemic inflammation, hemodynamic instability, and anticoagulation management. A multi-algorithm ML framework using random forest, CatBoost, LightGBM, and XGBoost identified circuit characteristics and laboratory variables associated with favorable neurological outcomes.[18]

However, ML has been found to perform suboptimally in predicting acute brain injury in VV-ECMO patients, likely due to a lack of data granularity.[18] This highlights the dependency of ML accuracy on data completeness and temporal richness.[3,4,18]

Weaning and Decannulation Decisions

Optimal timing for ECMO weaning and decannulation requires considerable expertise and clinical intuition. The continuous evaluation of VV-ECMO outcomes (CEVVO) deep learning model utilized both pre- and post-cannulation data from 118 VV-ECMO patients to predict decannulation success.

Continuous evaluation of VV-ECMO outcomes demonstrated the ability to stratify patients into high- and low-risk groups for successful decannulation. When measured at 72 hours, successful decannulation was achieved in 92% of low-risk patients but only 58% of high-risk patients; by 96 hours, the difference widened further.[14] Continuous evaluation of VV-ECMO outcomes outperformed logistic regression and standard neural networks by effectively modeling dynamic physiological fluctuations.[3,14]

Resource Allocation and Triage

The COVID-19 pandemic dramatically highlighted the critical importance of efficient ECMO resource allocation during periods of overwhelming demand.[19] AI-driven models such as ForecastECMO provide actionable forecasts up to 24 hours before ECMO initiation, allowing the reallocation of equipment, assembly of ECMO teams, or transfer of patients to higher-resourced centers.[10,11] Such tools could significantly improve system-level planning during surges of critical illness.

Technical Approaches and Methodological Considerations

Machine Learning Algorithms

The AI models developed for ECMO applications employ a vast array of algorithms, each with distinct strengths and limitations.[3,7]

Tree-based ensemble methods, including random forest, XGBoost, LightGBM, and CatBoost, have evolved as particularly effective for ECMO outcome prediction; these are widely used due to their ability to model nonlinear relationships and handle missing data.[5,6,15] Gradient-boosting approaches often outperform other ML methods through iterative refinement of prediction errors.[10,15]

Deep learning approaches, particularly neural networks including LSTM networks, excel in capturing temporal patterns inherent in critical illness and physiological changes that occur during ECMO support and capture the complex physiology of ECMO.[3,12,14]

Model Validation and Generalizability

Robust external validation remains a critical challenge in translating AI models from research settings to clinical practice.[3,4,15] The heterogeneity observed in meta-analytic summaries of ECMO AI studies reflects variable validation approaches across institutions.[4] Internal validation through cross-validation techniques, while computationally efficient, may overestimate generalizability compared with true external validation on independent institutions and patient populations.[7,15]

Several factors contribute to validation challenges in ECMO AI research.[3,4,15] First, the relatively low incidence of ECMO utilization at most institutions limits dataset sizes for training robust models. Second, temporal trends in ECMO practice, equipment evolution, and patient populations create distribution shifts between training and deployment environments.[4,15] Third, substantial variation in data collection standards, medical record systems, and clinical documentation practices across centers introduces heterogeneity that models must accommodate.[4,11,15]

Interpretability

Interpretability tools such as SHAP have been widely applied to ECMO AI models, providing transparent insights into feature contributions. For example, SHAP analysis of ECMO-PAL consistently identified age, vasopressor need, renal function, and hepatic parameters as important predictors.[7,13] However, feature importance does not imply causation and should not be interpreted as such.[7,8]

Limitations and Challenges

Data Constraints

The quality and availability of training data fundamentally limit AI model development for ECMO. For instance, small sample sizes, missing data, inconsistent documentation, and variations in ECMO protocols all constrain model reliability and complicate external validation.[3,4,18]

Data heterogeneity across institutions introduces additional challenges by creating a significant distribution shift when deploying models trained at single centers across the broader ECMO community.[4,11,15] These limitations underscore the need for improved data integration and standardized ECMO reporting across institutions.

Regulatory and Implementation Issues

Physician acceptance represents a major critical implementation barrier. Clinical adoption of AI tools remains limited due to regulatory uncertainties, IT integration challenges, and clinician skepticism. Building confidence requires not only superior predictive performance but also extensive prospective validation and demonstration of improved patient outcomes through randomized controlled trials.[3,4,11]

Privacy and Federated Learning

Privacy concerns restrict large-scale sharing of ECMO datasets for model development and validation. Federated learning offers a solution by enabling cross-institutional model training without transferring raw data. Applications specific to ECMO for critical care prediction remain limited. Transfer learning may also enhance small dataset performance by leveraging knowledge from broader critical-care models. Pre-training on general critical care mortality prediction followed by fine-tuning on ECMO-specific populations represents a promising strategy for improving model performance when ECMO-specific data is scarce.[4,11]

Proposed clinical integration framework: To operationalize these findings, we propose a stepwise "hybrid intelligence" framework for ECMO patient selection: Starting from screening phase: An automated calculation of traditional scores (e.g., RESP, PRESERVE) at the time of ICU admission to establish a baseline risk profile followed by dynamic monitoring phase: Using time-series AI models (e.g., PreEMPT-ECMO, Forecast ECMO) to continuously monitor physiological trends. An alert is triggered if the model predicts ECMO requirement with a >12 hours lead time. This alert triggers an automated notification to the ECMO team for early resource preparation. The multidisciplinary team reviews the AI prediction alongside the patient's clinical context and decides to support the final decision.

Future Directions and Perspectives

Prospective Clinical Validation

Randomized controlled trials comparing AI-guided ECMO decision-making with standard care are needed to evaluate true clinical benefit.[4] Such trials should randomize patients to receive either standard care with clinician-selected ECMO decisions or AI-augmented care in which prediction models provide decision support to the clinical team.[3,11]

Such trials must include outcome measures should include metrics beyond mortality alone, such as functional recovery and cost-effectiveness.[4] Also, the protocols should permit clinician override of algorithm recommendations while capturing the frequency and rationale for such overrides. It is recommended that trials should specifically examine heterogeneity of treatment effect, identifying patient subgroups most likely to benefit from algorithm-guided care.[3,11]

Personalized ECMO Care

Future AI systems may move beyond mortality prediction toward personalized support, identifying optimal anticoagulation targets, ventilation strategies, and complication-prevention pathways.[11] Multi-task learning architectures could simultaneously predict multiple outcomes (mortality, hemorrhage, and neurological injury) while sharing learned representations; hence, they may improve overall model performance by implementing norms that specifically address a patient's highest-risk complications.[3,4]

Explainability and Causal Modeling

Integrating causal inference into AI models could enable counterfactual predictions.

Explainability and Causal Inference

Future AI models should prioritize explainability through the incorporation of causal inference methods with modern ML architectures—an active area of methodological research. Rather than identifying predictive associations, causal models can estimate the effect of specific interventions (e.g., changing anticoagulation intensity) on patient outcomes.[7,8]

This capability will estimate how outcomes might change with alternative interventions—moving AI from predictive to prescriptive applications.

Conclusion

Artificial intelligence and ML have shown considerable confidence in enhancing ECMO care, with models demonstrating superior predictive accuracy for patient selection, mortality prediction, complications detection, and resource allocation.[4,5,13,15] Meta-analytic evidence indicates that AI models significantly outperform traditional clinical scores across multiple ECMO applications, with pooled AUROC values exceeding 0.80 for mortality prediction.[4,15] Deep learning approaches show particular promise for capturing temporal dynamics and complex feature interactions characteristic of critical illness.[12,14] Despite these advances, major challenges remain, including data limitations, regulatory barriers, and insufficient external validation.[3,4,11] Collaborative, multicenter efforts and rigorous clinical trials will be essential to ensure the effective and safe integration of AI into ECMO practice. Ultimately, AI should complement—not replace—expert clinical judgment in this high-stakes setting.

Declarations

Funding

No funding was received for this study.

Acknowledgment

Nil.

AI Use Declaration Statement

The authors declare that No AI tools were used for data generation, analysis, or interpretation. The authors take full responsibility for the content of the manuscript.

Authors' Contributions

All authors contributed to the conception, design, data collection, analysis, and manuscript preparation. All authors have read and approved the final version of the manuscript.

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