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AI-driven innovations in intensive care nephrology; bridging intensive care and kidney diseases

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ABSTRACT

This narrative review explores the transformative role of artificial intelligence (AI) in critical care nephrology, focusing on the early detection, risk prediction, and management of acute kidney injury (AKI) and the optimization of renal replacement therapies in intensive care settings. Drawing from recent valid-indexed studies, the review highlights AI's ability to enhance clinical decision-making through advanced machine learning models that predict AKI onset hours to days before traditional biomarkers indicate injury. The integration of explainable AI frameworks improves clinician trust and fosters personalized treatment strategies. Additionally, AI applications in continuous renal replacement therapy (CRRT) facilitate individualized dosing and timing, reducing complications and supporting better outcomes. Challenges in data quality, ethical considerations, and clinical implementation are discussed, alongside future directions such as multi-modal data integration and adaptive learning systems. The review underscores AI's potential to bridge intensive care and nephrology, ultimately aiming to improve patient prognosis in critically ill populations.

Keywords: Artificial intelligence, Machine learning, Deep learning, Critical care, Intensive care unit, ICU, Acute kidney injury, AKI, Chronic kidney disease, Kidney diseases, Renal replacement therapy, Dialysis

Implication for health policy/practice/research/medical education:
This study's clinical implications emphasize the transformative potential of artificial intelligence (AI)-driven tools in critical care nephrology, offering earlier and more accurate detection of acute kidney injury (AKI) that enables timely, targeted interventions to reduce patient morbidity and mortality. The incorporation of explainable AI models enhances clinician confidence and supports personalized treatment plans based on individual risk profiles. Additionally, AI facilitates optimization of continuous renal replacement therapy (CRRT), improving dosing precision and safety, which can reduce complications. Successful clinical application depends on overcoming challenges like data quality, ethical concerns, and integrating AI systems seamlessly into workflows. Multidisciplinary collaboration and education are essential to ensure AI augments clinicians' expertise effectively. Overall, AI promises to significantly improve critical care outcomes in kidney disease, advancing precision medicine and patient prognosis in intensive care settings.

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Introduction

Acute kidney injury (AKI) complicates up to 60% of intensive care unit (ICU) admissions and remains a major driver of in-hospital morbidity and mortality due to delayed detection by conventional markers such as serum creatinine and urine output (1). Recent advances in artificial intelligence (AI) offer promising avenues to overcome these limitations by leveraging machine learning and deep learning models trained on high-dimensional electronic health record data to predict AKI onset up to 48 hours in advance (2,3). Moreover, AI-enhanced continuous renal replacement therapy (CRRT) platforms dynamically adjust dose and timing based on real-time physiologic parameters, optimizing solute clearance while minimizing hemodynamic instability (4). Explainable AI frameworks, including Shapley additive explanations and integrated gradients, further facilitate clinician trust by elucidating key predictive features such as creatinine trajectories and vasopressor requirements (1,4). This narrative review synthesizes valid-indexed literature on AI-driven innovations in critical care nephrology, highlighting applications in early AKI detection,

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prognostication, CRRT optimization, and forthcoming directions for clinical integration and adaptive learning systems.

Search strategy

The literature search for this narrative review was conducted in the valid databases (Scopus, Web of Science, Embase, Cochrane Library, Science Direct, DOAJ [Directory of Open Access Journals], CINAHL [Cumulative Index to Nursing and Allied Health Literature], and Google Scholar search engine), focusing on articles published till October 2025, to capture the most recent advances in AI applications in critical care nephrology. The search combined keywords and MeSH terms related to AI techniques (artificial intelligence, machine learning, deep learning, neural networks), intensive care settings (critical care, intensive care unit, ICU), and nephrology-specific conditions and interventions (acute kidney injury, AKI, chronic kidney disease, kidney diseases, renal replacement therapy, dialysis). Boolean operators (AND, OR) were used to link these terms. Limitations included the use of human studies only and the exclusion of animal studies.

Background on critical care nephrology

Critical care nephrology has emerged as a specialized discipline addressing the complex interplay between AKI and multiorgan dysfunction in critically ill patients, with AKI affecting up to 50% of ICU admissions and significantly increasing mortality and length of stay (5). Early recognition and management of AKI are paramount, as delayed intervention correlates with poorer renal recovery and higher healthcare costs (6). The CRRT represents the cornerstone of renal support in hemodynamically unstable patients, offering hemodynamic stability and precise fluid removal, yet its optimal prescription remains challenging due to variable patient responses (5,7). Innovations in biomarker research and predictive modeling have facilitated risk stratification, while multidisciplinary collaboration among nephrologists, intensivists, and nursing staff is critical for tailoring therapies to individual physiological needs (1). Moreover, pediatric critical care nephrology underscores unique anatomical and developmental considerations, necessitating age-specific protocols to improve outcomes in younger populations (8). Together, these advances underline the evolving role of critical care nephrology in delivering precision-based renal support within the ICU (5).

AI for early AKI detection and prediction

Using AI has significantly advanced the early detection and prediction of AKI, addressing a critical challenge in clinical care where traditional biomarkers, such as serum creatinine, lag behind kidney damage. Machine learning models leveraging large, multimodal electronic health record (EHR) datasets demonstrate promising sensitivity and specificity in forecasting AKI hours to days before clinical diagnosis, enabling earlier intervention (9). Deep learning architectures like Long Short-Term Memory networks enhance temporal prediction by modeling dynamic patient data streams such as urine output and blood pressure trends (10). Recent meta-analyses report AI prediction models achieving pooled sensitivities around 77% and specificities near 75%, reflecting clinically meaningful diagnostic accuracy (9). Explainability frameworks integrated into models help build clinician trust, supporting real-time decision-making in intensive care units (11). Despite promising retrospective validations, prospective studies are limited, and challenges remain in standardizing datasets, overcoming algorithmic bias, and ensuring model generalizability across diverse populations (12,13). Pediatric-specific AI applications show potential for tailored AKI prediction in vulnerable neonatal groups, underscoring the importance of age-specific data incorporation (14,15). Overall, AI-enabled early AKI detection represents a transformative approach toward proactive kidney care, with ongoing research needed for bedside implementation and evaluation of impact on patient outcomes.

Static versus dynamic models

- Static risk scores: Traditional models using baseline clinical data (e.g., preoperative variables) demonstrate moderate predictive performance (area under the curve [AUC] ~0.70) (16).
- Dynamic machine learning (ML) models: Incorporating time-updated variables from EHRs, dynamic models using recurrent neural networks and gradient boosting achieve AUCs up to 0.97 for AKI severity staging (3).
- Ensemble methods: Boosted decision trees and random forests achieve early AKI prediction up to 48 hours in advance with AUCs of 0.85–0.90 (17).

Comprehensive reviews and meta-analyses studies

A systematic review and meta-analysis of 95 ML models for AKI risk classification reported pooled AUCs of 0.82 for internal validation and 0.78 for external validation, highlighting logistic regression, neural networks, and XGBoost as prevalent approaches (18). Meta-analysis of novel biomarkers combined with ML further improved early detection, with urinary neutrophil gelatinase-associated lipocalin and tissue inhibitor of metalloproteinases-2 × insulin-like growth factor-binding protein-7 (TIMP-2×IGFBP7) integrated into AI algorithms, yielding diagnostic odds ratios >13 (19).

Pediatric and specialized cohorts

Explainable ML models in critically ill pediatric cohorts achieved robust AKI prediction while providing interpretability through feature importance, facilitating clinician trust (20). In liver transplantation, serum cystatin C-based ML models predicted postoperative AKI onset with high discrimination (21).

AI in prognostication and mortality prediction

Several AI-driven mortality prediction models trained on AKI cohorts report superior performance compared to traditional scoring systems. Broad learning system and elastic net final models both achieved pooled AUCs of 0.852 for in-hospital mortality prediction (22). In acute pancreatitis–associated AKI, XGBoost outperformed logistic regression (AUC 0.941 vs. 0.85), indicating applicability across subpopulations (23).

AI-enhanced RRT optimization

Timing and modality selection

- Early versus late CRRT initiation: Reinforcement learning algorithms analyze real-time hemodynamic trends and biochemical markers to propose optimal windows for initiating CRRT, which may reduce both the duration of renal replacement therapy and ICU length of stay (24).
- Dose titration: Reinforcement learning models dynamically adjust CRRT dosing by continuously evaluating solute clearance and hemodynamic stability, enabling precise maintenance of targeted fluid balance while minimizing risks such as hypotension. This approach provides adaptive, personalized therapy that responds to the patient's evolving physiological state, surpassing traditional static dosing regimens. Such AI-driven dose titration could improve treatment efficacy, reduce complications, and enhance overall outcomes in the intensive care setting by guiding clinical decision-making with real-time data analysis (25-27).

Continuous versus intermittent therapies

Deep learning systems leveraging multimodal ICU data suggest when to transition between continuous and intermittent RRT, balancing solute clearance against cardiovascular tolerance (1).

Explainable AI and clinical integration

Interpretability frameworks

- Integrated Gradients: Applied to recurrent neural networks, this method attributes risk predictions to specific variables, enabling clinicians to understand model drivers (3).
- Shapley additive explanations: Used in tree-based models to quantify individual feature contributions, highlighting predictors like serum creatinine trajectory, vasopressor dose, and inflammatory markers (23).

Implementation challenges

- Data quality and standardization: Heterogeneity in EHR systems and missing data impede model generalizability (13).
- Workflow integration: Embedding AI tools into ICU dashboards requires seamless interoperability, user training, and real-time computational resources (28).
- Regulatory and ethical considerations: European conformity (CE) marking of the NAVOY AKI algorithm exemplifies progress toward clinical deployment, yet wider regulatory frameworks and bias mitigation remain priorities (28).

Future directions and research gaps

- Multi-modal data integration: Fusion of imaging, genomics, and continuous physiologic signals promises richer phenotyping and personalized intervention strategies.
- Adaptive learning systems: Online learning algorithms that update with new data can maintain performance despite evolving clinical practices and patient populations.
- Ethical frameworks: Development of standardized guidelines for AI transparency, accountability, and patient consent to ensure trust and equity.
- Multi-institutional validation: Large-scale prospective trials are needed to confirm efficacy and safety in diverse ICU settings, including resource-limited environments (13).

Conclusion

AI-driven innovations are transforming critical care nephrology by enabling earlier AKI detection, accurate prognostication, and optimized RRT. Despite promising performance demonstrated in retrospective and proof-of-concept studies, translation into routine clinical practice necessitates robust validation, explainable frameworks, and integrated workflows. Collaborative efforts among clinicians, data scientists, and regulators will bridge intensive care and nephrology, improving patient outcomes in critically ill populations.

Authors' contribution

Conceptualization: Malihe Abniki and Masood Zangi.
Data curation: Mahdi Amirdosara and Masood Zangi.
Investigation: Masood Zangi and Mahdi Amirdosara.
Supervision: All authors.
Validation: Malihe Abniki and Mahdi Amirdosara.
Visualization: Malihe Abniki and Masood Zangi.
Writing–original draft: All authors.
Writing–review and editing: All authors.

Conflicts of interest

The authors declare that they have no competing interests.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors utilized Perplexity to refine grammar points and language style in writing. Subsequently, the authors thoroughly reviewed

and edited the content as necessary, assuming full responsibility for the publication's content.

Ethical issues

Ethical issues (including plagiarism, data fabrication, double publication) have been completely observed by the authors.

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