Artificial Intelligence to Treat Acute Kidney Injury

Acute kidney injury (AKI) often complicates critical illness, with management focusing on supportive care per the Kidney Disease Improving Global Outcomes (KDIGO) guideline due to the lack of specific reversing therapies. Although timely implementation of these guidelines can reduce postoperative moderate and severe AKI, adherence in routine clinical practice remains low.

Artificial intelligence (AI), particularly machine learning (ML), enhances early AKI detection, personalises treatment, and supports clinical decision-making, improving compliance with guidelines. ML enables systems to learn from data and optimise task performance.

ML techniques can predict AKI 24–48 hours before serum creatinine changes occur. Ongoing validation and outcome-focused investigations are essential for their adoption in routine clinical practice.

The PrevAKI trial highlighted haemodynamic optimisation and avoidance of nephrotoxic drugs as key measures to prevent moderate or severe AKI after cardiac surgery. Nephrotoxic drugs, frequently used in combination and for extended periods, contribute to 19–26% of hospital-acquired AKI. A computer-based decision support system reduced AKI incidence in high-risk hospitalised children, with ongoing studies evaluating its effectiveness in adults and critically ill children.

Creatinine-based formulas for estimating glomerular filtration rate (GFR) are unreliable in patients with muscle wasting. A new ML tool predicts next-day creatinine clearance (CrCl) in ICU patients to improve drug dosing accuracy. Its effectiveness in AKI patients and its impact on renal recovery require further study. Real-time GFR measurement combined with AI could enhance early detection of GFR decline, enabling timely interventions.

Vancomycin dosing in AKI and during renal replacement therapy (RRT) often results in out-of-range trough levels. ML algorithms have been developed to estimate the risk of under- and overdosing, as well as to predict contrast-associated AKI, but these tools still require prospective validation.

Haemodynamic optimisation is crucial in AKI management, with individualised targets. Higher blood pressure may protect septic patients with chronic hypertension from severe AKI. Factors like mean arterial pressure, central venous pressure, cardiac output, and heart rate are strongly linked to AKI, highlighting the complexity of assessing perfusion pressure and cardiac output. AI could help identify ideal haemodynamic targets and treatments, while ML may predict fluid responsiveness in patients with oliguric AKI.

Stress-induced hyperglycaemia increases the risk of AKI. An AI tool for managing glucose levels improved glucose control, reduced AKI stage 3 incidence, and decreased the need for new RRT without raising hypoglycaemia risk compared to tolerating hyperglycaemia.

AKI is a complex syndrome with diverse causes and pathophysiological processes, and its current definition relies on late markers without identifying aetiology. AI tools can differentiate AKI sub-phenotypes, aiding in targeted prevention and treatment. Automatic sub-phenotyping could enhance future research by identifying patient subgroups that are more likely to benefit from specific interventions.

ML models may help improve adherence to preventive measures, reducing the risk of AKI progression and non-recovery. However, their potential to enable specific interventions or personalised treatments, such as tailored fluid management or initiating RRT, remains uncertain.

Researchers are exploring ML techniques to improve RRT management, including real-time monitoring, predicting complications like hypotension, and collecting data for bedside review. As AI advances, it could enhance the safety and effectiveness of RRT, leading to better patient outcomes.

The ultimate goal of using AI in critically ill patients is to reduce mortality, decrease organ dysfunction, and improve patient outcomes. AI should be seen as a tool to support clinical decision-making, not replace clinical judgment. Developing effective AI models requires access to high-quality electronic health records, which may not be available in all settings. Ethical, legal, and social implications must be considered to prevent algorithm bias and healthcare inequities. Additionally, promising diagnostics not routinely evaluated may improve accuracy but are often absent in large datasets.

Most studies on AI in AKI management are retrospective. There is an urgent need for prospective, multicentre, randomised-controlled trials to evaluate the effectiveness of AI-driven interventions on patient outcomes. Research should also focus on integrating AI tools into existing AKI management, alongside other diagnostics like biomarkers, imaging, and histology.

Source: Intensive Care Medicine
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