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Artificial Intelligence in Acute Kidney Injury Prediction: Challenges and Opportunities in Low-Income Settings

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Abstract

Background: Acute kidney injury (AKI) remains a major cause of morbidity and mortality worldwide[1]. Most cases occur in low- and middle-income countries (LMICs), where delayed diagnosis and limited access to nephrology care worsen outcomes[2]. Artificial intelligence (AI) tools can predict AKI hours before serum creatinine rises, enabling earlier intervention[3,4]. However, most existing models are developed and validated in high-income settings, relying on continuous electronic data infrastructures that are rarely available in LMICs, raising concerns about generalizability and equity.

Methods: A narrative review of studies published between 2015 and 2025 identified AI-based AKI prediction models. Articles were assessed for study design, input variables, validation strategies, performance metrics, and applicability to low-resource environments. Contextual clinical insights from North African nephrology practice, including common AKI etiologies such as sepsis and obstetric complications, were incorporated to enhance relevance.

Results: Most AI models rely on large datasets, time-series analyses, and complex algorithms, achieving high predictive performance[3–5]. However, external validation in LMIC populations is lacking, and model performance may be affected by regional differences in AKI etiology and data availability. Simplified, interpretable models using routinely available clinical variables such as serum creatinine, urine output, blood pressure, age, and sepsis status may still provide clinically meaningful early warning signals in low-resource settings.

Conclusion: AI offers a promising opportunity for earlier AKI detection worldwide. To ensure equitable clinical benefit, models must be contextually adapted, ethically validated, and integrated into routine care through simplified, open-access approaches supported by regional collaborations led by nephrologists in LMICs.

Main Text

Introduction

Acute kidney injury (AKI) remains a significant contributor to global morbidity and mortality. Worldwide, AKI affects an estimated 13 million individuals annually and is responsible for nearly 1.7 million deaths[1]. The majority of these cases occur in low- and middle-income countries (LMICs), where diagnostic delays and limited access to nephrology care remain major barriers to improved outcomes[2]. In these settings, AKI is often driven by preventable and potentially modifiable factors, positioning it as a critical target for early intervention. Traditional detection methods based on rising serum creatinine or reduced urine output often identify kidney injury only after significant damage has occurred. The absence of continuous monitoring systems or electronic health records (EHRs) in many LMIC hospitals further delays recognition.

Recent advances in artificial intelligence (AI) have introduced new possibilities for early AKI prediction. By learning patterns from laboratory, physiological, and clinical data, AI algorithms can detect subtle trends that precede biochemical injury. Several high-income country studies have shown that AI models can predict AKI hours to days before creatinine rises, enabling timely intervention and improved patient outcomes[3,4]. However, these advances have largely been developed and validated in data-rich environments, raising concerns regarding their applicability, generalizability, and equity in low-resource settings. Understanding how AI can be adapted to such environments is essential to ensure equitable progress in global kidney care.

Current AI Models for AKI Prediction

AI models for AKI prediction generally rely on machine-learning algorithms trained on large EHR datasets. Common approaches include logistic regression, random forests, gradient boosting, and deep learning architectures such as recurrent neural networks[5,6]. These models analyze temporal changes in laboratory values especially serum creatinine, blood urea nitrogen, and electrolyte trends alongside vital signs and demographic information. Time-series analyses are particularly valuable, as they capture dynamic physiological changes rather than isolated measurements, allowing earlier risk stratification.

For example, the DeepMind AKI model developed for the UK National Health Service achieved an area under the receiver-operating curve (AUC) of 0.93, predicting AKI up to 48 hours before onset[7]. Similarly, the Mayo Clinic's study using the eICU database demonstrated that combining laboratory data with dynamic vital-sign trends improved predictive accuracy beyond 85%[8]. While performance metrics such as AUC reflect discrimination, clinical relevance also depends on sensitivity at actionable thresholds, calibration, and the ability to reduce adverse outcomes such as dialysis initiation or mortality.

However, nearly all these studies depend on high-quality, continuously updated EHR systems that automatically collect data from laboratory and bedside monitors. In LMICs, such digital infrastructure is uncommon. Laboratory results are often delayed, missing, or stored on paper, while patient monitoring is intermittent. Therefore, despite the technological maturity of AI models, their direct transfer to low-resource hospitals is rarely feasible without adaptation.

Barriers in Low-Resource Environments

The first challenge to AI deployment in LMICs is data availability and quality, as many hospitals rely on handwritten records, delayed laboratory results, and non-standardized data archiving practices that hinder effective model training or validation[9]. Missing data, irregular sampling intervals, and small sample sizes further limit the use of complex machine-learning architectures. Computational and financial limitations also restrict the ability to host AI systems, given limited IT support, unreliable electricity, and insufficient bandwidth.

Human resource shortages further complicate implementation, as AI deployment requires collaboration between clinicians, data scientists, and engineers expertise that remains scarce in these contexts. Ethical and regulatory challenges add another layer of complexity, including concerns about generalizability, algorithmic bias, and underdeveloped data protection frameworks[10]. These barriers collectively explain why AI models for AKI prediction, despite strong performance in high-income settings, remain largely untested in low-resource environments.

Adapting AI to Local Realities

To make AI meaningful in low-resource environments, innovation must prioritize simplicity, accessibility, and context-appropriate adaptation rather than technological sophistication. Simple, interpretable models such as logistic regression using routinely available variables (e.g., age, baseline creatinine, urine output, blood pressure, sepsis status, and obstetric context) may offer clinically useful early warnings with minimal infrastructure requirements.

Such models are particularly relevant in LMICs, where AKI etiologies frequently include sepsis, obstetric complications, dehydration, and exposure to nephrotoxic medications or traditional remedies, factors that may differ substantially from high-income settings and influence model performance. Mobile and offline tools can provide bedside decision support, while regional collaborations enabling shared anonymized datasets can facilitate the creation of locally relevant AI models. These efforts should be complemented by capacity-building initiatives that empower nephrologists to participate in algorithm design, validation, and deployment.

Ethical and Policy Considerations

Equitable AI development requires transparent governance to prevent algorithmic bias and ensure fair clinical outcomes, particularly since most AI models are trained on Western populations. Regional validation across diverse patient groups and AKI etiologies is therefore essential before clinical deployment. Robust approaches to patient privacy, informed consent, and secure data management must be established, while international organizations such as the ISN may contribute standardized ethical frameworks and support North–South collaboration to promote responsible and inclusive AI deployment in nephrology.

The Way Forward

Artificial intelligence is not a substitute for clinical expertise but a tool to enhance decision-making. In nephrology, where early recognition of AKI can mean the difference between recovery and dialysis, timely insights are invaluable. Practical integration scenarios may include early triage tools in emergency departments, continuous risk scoring in intensive care units, and alert-based surveillance systems in general wards using minimal input variables.

For LMICs, the path toward AI adoption will require infrastructure strengthening, collaborative research networks to develop and validate context-specific algorithms, and local leadership from nephrologists who understand both clinical challenges and data limitations. The role of clinicians from LMICs is essential. Their experiences working with delayed laboratories, paper-based records, and limited diagnostic tools can inform pragmatic, low-cost AI solutions tailored to their realities. By contributing to open datasets and pilot projects, these physicians can shift AI development toward inclusivity and global relevance. Ultimately, AI's promise in nephrology will only be realized when innovation reflects the diversity of the global patient population.

Conclusion

AI represents a transformative opportunity to improve early AKI detection worldwide. Yet its benefits remain concentrated in data-rich, high-income settings. Adapting AI for LMICs requires more than algorithm transfer; it demands collaborative, locally driven innovation grounded in real clinical practice. By prioritizing simplified models, contextual validation, and ethical deployment, AI can evolve from a technological advance into a practical tool for global kidney health equity.

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