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Artificial intelligence in chronic kidney disease, dialysis and kidney transplantation: Current evidence, clinical applications, implementation challenges, and future directions

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Abstract

Chronic kidney disease (CKD), dialysis-related complications, and kidney transplantation continue to impose a substantial global burden on morbidity, mortality, and healthcare utilization. In parallel, artificial intelligence (AI) has emerged as a potentially transformative tool for risk prediction, diagnostic support, treatment optimization, and longitudinal outcome assessment in nephrology. This review summarizes current evidence regarding AI applications in the early prediction of CKD and acute kidney injury, image-based diagnosis, dialysis decision support, mortality prediction in end-stage kidney disease and kidney transplantation, while also highlighting current limitations, clinical implementation challenges, and future directions for the responsible integration of AI into nephrology care. Available evidence suggests that machine-learning and deep-learning models can achieve promising predictive performance for CKD progression, acute kidney injury, and intradialytic complications. Convolutional neural network-based approaches have shown potential in kidney imaging, segmentation, and structural abnormality detection. Similarly, AI-based prognostic tools for dialysis and transplantation have demonstrated encouraging initial performance in estimating mortality, graft outcomes, and post-transplant complications. However, most published models remain limited by retrospective development, insufficient external validation, inadequate prospective testing, and substantial barriers to implementation, including dataset bias, limited interpretability, regulatory uncertainty, and workflow integration challenges. Overall, AI should be regarded as an adjunctive tool in modern nephrology rather than a replacement for clinical judgment. Robust validation, transparent reporting, and careful integration into healthcare systems will be required before routine clinical adoption can be justified.

Keywords: Artificial intelligence, chronic kidney disease, acute kidney injury, renal dialysis, kidney transplantation

Introduction

Chronic kidney disease (CKD) remains a major global health problem because of its high prevalence, progressive nature, and close association with cardiovascular events, kidney failure, and premature death [1,2]. The burden of CKD is expected to increase further as populations age and metabolic diseases become more prevalent [2,3]. Its pathophysiology is multifactorial and involves diabetes mellitus, hypertension, vascular injury, chronic inflammation, and other systemic processes that interact across the course of disease [4]. Since these determinants are heterogeneous and often dynamic, early identification of CKD and accurate prediction of

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progression remain challenging in routine clinical practice [5,6]. Meanwhile, interest in artificial intelligence (AI)-based tools has increased substantially because these approaches may improve risk stratification and support earlier, more individualized clinical decision-making [7].

AI encompasses a broad group of computational approaches, including machine learning and deep learning, that can extract patterns from large and complex clinical datasets [8,9]. In nephrology, these approaches have been applied to structured clinical data, laboratory results, medical imaging, and electronic health records to support diagnosis, predict complications, and optimize treatment strategies [10]. Published studies have reported promising performance for the prediction of CKD, acute kidney injury (AKI), and intradialytic hypotension, among other outcomes [10,11]. Nevertheless, the current evidence base remains constrained by several important limitations, including heavy reliance on retrospective datasets, limited external validation, data bias, and infrastructure barriers that may hinder deployment across diverse healthcare settings [10,12-14]. Therefore, a critical synthesis of the current role of AI in nephrology remains necessary. Such an appraisal is especially important because model performance in curated research datasets may not translate directly into real-world clinical practice, where patient heterogeneity, workflow complexity, and resource constraints are more pronounced [13,14].

This review summarizes the roles of AI in disease prediction, diagnosis, and management of CKD, dialysis-related care and kidney transplantation. In this review, the current evidence base, existing limitations, and the key requirements for clinically meaningful implementation are emphasized. Emerging technological developments and future research priorities are also discussed in order to clarify how AI may contribute to improved nephrology care while remaining aligned with safe, equitable, and evidence-based practice.

AI applications in early prediction and risk assessment of CKD and AKI

Advances in AI algorithms, including deep neural networks, gradient-boosting methods, random forests, and logistic regression-based models, have expanded the capacity for early prediction of CKD as well as AKI [10]. These methods can evaluate large volumes of clinical data, model nonlinear relationships, and capture complex interactions among demographic, laboratory, and longitudinal clinical variables that may be difficult to identify using conventional analytical approaches [15,16]. In nephrology, such models have been developed to estimate CKD risk, predict progression to kidney failure, and identify patients at heightened risk of AKI before overt clinical deterioration occurs [16,17]. Broadly, these approaches may be divided into traditional machine-learning methods and deep-learning architectures, each of which offers advantages that depend on the structure, dimensionality, and modality of the available data. Studies have reported high discrimination for CKD prediction, including deep learning-based models with strong area under the receiver operating characteristic curve values and ensemble approaches for prediction of end-stage kidney disease among high-risk populations such as sepsis survivors with underlying CKD [18,19].

AI-based predictive algorithms have also shown promise for identifying AKI up to 48 hours before clinical recognition, thereby creating an opportunity for earlier intervention [17,20,21]. However, high apparent discrimination has not always translated into seamless clinical utility. In some settings, elevated false-positive rates have been reported, particularly in complex inpatient populations, thereby increasing alert frequency and raising concerns regarding alert fatigue [22,23]. These observations emphasize that predictive performance should not be interpreted solely through discrimination metrics. Calibration, external validation, prospective evaluation, and the balance between sensitivity and specificity remain critical if AI models are to produce clinically meaningful benefit in real-world nephrology practice.

AI applications in image-based diagnosis and classification of CKD

Convolutional neural networks and related deep-learning architectures have increasingly been applied to image-based nephrology across computed tomography, magnetic resonance imaging, ultrasonography, and retinal imaging [24,25]. These models have been used for kidney segmentation, volumetric assessment, and automated detection of structural abnormalities, including renal masses, cysts, stones, and other morphologic changes [26,27]. Such approaches may improve efficiency and reproducibility in image interpretation and may also support quantitative phenotyping that is difficult to achieve consistently through manual review alone.

AI has also been applied to noninvasive CKD screening using retinal fundus photography combined with clinical variables [10,28,29]. A study found that CondenseNet-based and related models have demonstrated high discriminatory performance for CKD detection, with area under the receiver operating characteristic curve values exceeding 0.90 [10]. These findings suggest that AI-assisted analysis of retinal images may provide a scalable and noninvasive approach to CKD screening, particularly when integrated with routinely collected clinical data. However, broader clinical adoption will require careful validation across populations, imaging platforms, and healthcare environments before these methods can be considered robust screening tools.

AI applications in dialysis therapy optimization and intra-dialytic decision support

The application of AI in dialysis care has expanded substantially, particularly in the prediction of intradialytic hypotension (IDH) and other hemodynamic complications [30]. Machine-learning models, including XGBoost, random forest, and deep-learning architectures, have been developed using predialysis and intradialytic physiologic parameters such as blood pressure, ultrafiltration rate, cardiac variables, and other hemodynamic indicators [31,33]. Studies have reported high discriminatory performance, with some XGBoost-based models achieving very high area under the receiver operating characteristic curve values for early IDH prediction [30,33]. If validated prospectively, such tools could support earlier intervention through adjustment of ultrafiltration targets, dialysate composition, or dry-weight assessment, thereby improving hemodynamic stability during dialysis sessions. Nevertheless, performance estimates should be interpreted cautiously when derived from limited or highly selected datasets, and clinical utility must ultimately be demonstrated through implementation studies rather than retrospective accuracy metrics alone.

AI applications have also been explored for vascular access surveillance, including detection of arteriovenous fistula stenosis using multimodal architectures that combine convolutional neural networks with recurrent models such as long short-term memory or gated recurrent unit networks [34,35]. These approaches may enable more continuous and less invasive surveillance of vascular access function and may reduce dependence on repeated Doppler studies or delayed recognition of access dysfunction. However, evidence for routine clinical adoption remains preliminary, and further validation in real-world dialysis programs is required [36].

Beyond complication prediction, AI has been investigated for real-time estimation of clinically relevant dialysis parameters, including Kt/V, fluid removal requirements, heart rate, and blood pressure [37]. Such estimates may support more individualized dialysis prescriptions by informing ultrafiltration strategy, treatment duration, and dose adjustment. The potential value of these systems lies not only in prediction but also in their ability to provide dynamic decision support during treatment. However, the reliability, interpretability, and workflow compatibility of these tools must be established before they can be incorporated into routine dialysis care.

A growing number of studies have evaluated AI-enhanced clinical decision support systems in CKD and dialysis care, including tools that support anemia management, erythropoiesis-stimulating agent dosing, and patient education related to potassium and phosphate intake [38,39]. These applications illustrate that AI may function not only as a predictive technology, but also as an instructional and operational support tool within nephrology services. Even so, evidence for meaningful improvement in patient-centered outcomes remains limited, and future work should determine whether these systems improve safety, adherence, efficiency, or quality of care under real clinical conditions.

AI applications in predicting long-term outcomes and mortality in end-stage kidney disease

AI-based models have also been developed to estimate long-term outcomes in patients with end-stage kidney disease, including mortality risk after dialysis initiation [30,40]. These models typically integrate multiple predictors, such as residual kidney function, comorbid conditions, laboratory measures, and dialysis-related variables, to generate individualized risk estimates [40]. Such predictions may assist with prognostic stratification, advance care planning, and prioritization of transplant evaluation, provided that model performance is sufficiently robust and generalizable [40,41]. However, the clinical utility of these models depends on transparent reporting, external validation, and demonstration that their use improves decision-making rather than merely generating statistically accurate predictions.

Beyond mortality prediction, AI has been explored for forecasting long-term complications in end-stage kidney disease, including sarcopenia, persistent anemia, hospitalization, and other adverse outcomes, particularly among patients receiving peritoneal dialysis [42]. Integration of longitudinal clinical, inflammatory, nutritional, and laboratory data may facilitate earlier identification of vulnerable patients and may support more proactive management strategies. However, much of the current literature remains exploratory, and stronger evidence will be required before these systems can be recommended as part of routine longitudinal care pathways [43].

AI applications in kidney transplantation

AI applications in kidney transplantation have increasingly focused on risk stratification for long-term allograft loss and post-transplant complications [44]. One of the most prominent examples is the iBox system, which integrates clinical, histopathological, and immunological variables to estimate the risk of graft failure [45]. Such models may assist with tailoring follow-up intensity, refining immunosuppressive strategies, and identifying patients at heightened risk of chronic rejection. Their potential value lies in improving individualized post-transplant surveillance; however, broader clinical implementation requires careful attention to validation, recalibration, and the interpretability of model outputs.

AI has also been investigated for donor-recipient matching and organ allocation [46,47]. By integrating immunologic compatibility, donor and recipient characteristics, and other clinical variables, machine-learning models may support more data-driven allocation strategies and may improve the efficiency with which scarce donor organs are assigned [47]. In principle, such approaches could enhance post-transplant outcomes and reduce unwarranted variation in access to transplantation. Nonetheless, algorithmic fairness, transparency, and ethical oversight remain critical, particularly when AI is used in decisions that affect access to limited healthcare resources.

The summaries of the roles of AI in chronic kidney disease, acute kidney injury, dialysis care, end-stage kidney disease, and kidney transplantation are presented in **Table 1**.

Table 1. Summary of the roles of artificial intelligence in chronic kidney disease, acute kidney injury, dialysis care, end-stage kidney disease, and kidney transplantation

Application domain	Role of artificial intelligence	References
Early prediction and risk assessment of CKD and AKI	Predicts CKD risk and progression to kidney failure	[16,18,19]
	Identifies patients at high risk of AKI before overt clinical deterioration	[16,17,20,21]
	Analyzes large and complex clinical datasets, including demographic, laboratory, and longitudinal variables	[10,15,16]
	Supports earlier intervention by predicting AKI up to 48 hours before clinical recognition	[17,20,21]
Image-based diagnosis and classification of CKD	Performs kidney segmentation and volumetric assessment	[24-27]
	Detects structural abnormalities such as renal masses, cysts, stones, and other morphologic changes	[24,26,27]
	Supports quantitative phenotyping from imaging data	[24-27]
	Enables noninvasive CKD screening using retinal fundus photographs combined with clinical data	[10,28,29]

Application domain	Role of artificial intelligence	References
Dialysis therapy optimization and intra-dialytic decision support	Predicts intradialytic hypotension and other hemodynamic complications	[30,31,33]
	Supports early adjustment of ultrafiltration targets, dialysate composition, and dry-weight assessment	[30,33]
	Detects vascular access problems such as arteriovenous fistula stenosis	[34-36]
	Estimates dialysis-related parameters in real time, including Kt/V, fluid removal needs, heart rate, and blood pressure	[37]
	Assists clinical decision support for anemia management, erythropoiesis-stimulating agent dosing, and patient education	[38,39]
Predicting long-term outcomes and mortality in end-stage kidney disease	Estimates mortality risk after dialysis initiation	[30,40]
	Supports prognostic stratification and advance care planning	[40,41]
	Helps prioritize transplant evaluation	[40,41]
	Forecasts long-term complications such as sarcopenia, persistent anemia, and hospitalization	[42,43]
	Identifies vulnerable patients for more proactive management	[42,43]
Predicting long-term outcomes and mortality in end-stage kidney disease	Predicts risk of long-term allograft loss and post-transplant complications	[44,45]
	Supports individualized follow-up and surveillance after transplantation	[44,45]
	Helps refine immunosuppressive strategies	[44,45]
	Assists donor-recipient matching and organ allocation	[46,47]
	Supports more data-driven and efficient transplant decision-making	[46,47]

Recent advances and future directions

Recent developments suggest increasing interest in foundation models, transformer architectures, and multimodal AI systems that can integrate laboratory data, medical imaging, and clinical records within a unified analytical framework [10]. Such approaches may improve performance by capturing heterogeneous patterns that are not apparent when individual data modalities are analyzed in isolation. In nephrology, this may allow more personalized risk modeling and more comprehensive decision support for CKD, AKI, and dialysis-related complications. However, the complexity of these models also increases the need for rigorous validation, transparent reporting, and robust governance frameworks.

As AI moves closer to clinical deployment, explainability has become increasingly important for transparency, accountability, and clinician trust. Methods such as SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations) have been used to identify the features that contribute most strongly to model predictions and to provide a more interpretable representation of algorithmic reasoning [49]. Explainable AI may facilitate clinical acceptance, support error detection, and improve accountability in high-risk decisions. However, interpretability tools should complement, rather than substitute for, proper model validation and assessment of clinical impact [50].

Large language models and chatbot-based systems have also begun to enter nephrology, particularly in patient education, preliminary triage, and guideline summarization [51]. These tools may improve patient engagement and may reduce administrative burden by automating selected communication or documentation tasks [52]. Their potential is substantial, but so are the risks related to hallucination, misinformation, privacy, and overreliance on unverified recommendations. Accordingly, deployment in nephrology should remain cautious and should be accompanied by strong clinician oversight and clear safeguards.

Limitations and challenges in clinical implementation

Data limitations and restricted generalizability remain major barriers to the clinical translation of AI in nephrology. Many published models have been derived from single-center retrospective cohorts with limited demographic diversity, and their apparent performance may therefore not generalize to broader patient populations. The lack of external validation and prospective evaluation further weakens confidence in real-world performance. In addition, class imbalance, inadequate cross-validation, overfitting, and dataset shift may all lead to inflated estimates of accuracy during model development. These concerns are particularly important in low-resource settings, where digital infrastructure, data completeness, and local calibration capacity may be limited. Collectively, these issues highlight the need for multicenter validation, standardized evaluation methods, and careful assessment of transportability before clinical implementation is pursued.

Transparency and ethics represent additional challenges, particularly for high-performing deep-learning models that may function as opaque or so-called black-box systems. Limited interpretability may reduce clinician trust and may complicate the justification of AI-assisted recommendations in high-risk decisions. Moreover, biased training data, including inappropriate reliance on race-based variables or institution-specific practices, may perpetuate inequities and produce systematically poorer predictions in underrepresented groups. Ethical deployment therefore requires bias mitigation, secure data governance, privacy protection, informed consent processes where applicable, and continuing clinician oversight. These safeguards are essential if patient safety and fairness are to be maintained in AI-enabled nephrology practice.

Regulatory and operational barriers also remain substantial. Regulatory frameworks for medical AI continue to evolve and have not consistently kept pace with technological development. Questions regarding liability, post-deployment monitoring, and the allocation of responsibility between clinicians, institutions, and developers remain unresolved in many jurisdictions. At the operational level, integration into dialysis and nephrology workflows requires technical interoperability, reliable maintenance, and minimal disruption to clinical services. Without these prerequisites, even technically strong models may fail to deliver practical value.

Workforce readiness is another prerequisite for responsible implementation. Clinicians, nurses, and allied healthcare professionals require sufficient training to understand the capabilities, limitations, and appropriate use of AI systems. Effective implementation also depends on integration into clinical decision support systems and alignment with existing workflows. In this regard, a human-AI collaboration framework is essential, in which AI supports, rather than replaces, clinical judgment. Such a model is most consistent with safe deployment in nephrology, where contextual interpretation and patient-centered decision-making remain indispensable.

Conclusion

AI has shown considerable promise across nephrology, including in early risk prediction, diagnostic support, image analysis, dialysis decision support, and transplantation. However, the current literature remains weighted toward retrospective prediction models, whereas evidence for treatment optimization, workflow benefit, and patient-centered outcome improvement is still limited. A substantial gap therefore persists between experimental performance and routine clinical implementation. Future research should move beyond proof-of-concept studies and prioritize prospective multicenter validation, standardized reporting, implementation science, and rigorous assessment of safety, fairness, and clinical utility. At present, AI should be viewed as a complementary tool that may augment nephrology care when used within robust clinical, ethical, and regulatory frameworks. Its long-term value will depend not only on technical accuracy, but also on successful integration into real-world practice while preserving clinician oversight, patient safety, and human-centered care.

Ethics approval

Not required.

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Competing interests

The authors declare that there are no competing interests.

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Underlying data

Derived data supporting the findings of this study are available from the corresponding author on request.

Declaration of artificial intelligence use

Artificial intelligence tools, including ChatGPT and QuillBot, were used for language refinement. All AI-assisted output was critically reviewed and edited by the authors, and responsibility for the accuracy, interpretation, and final content of the manuscript was retained entirely by the authors.

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