Integrating Artificial Intelligence into Chronic Kidney Disease Care: Enhancing Hemodialysis Scheduling, Comorbidity Management, and Diagnostic Capabilities

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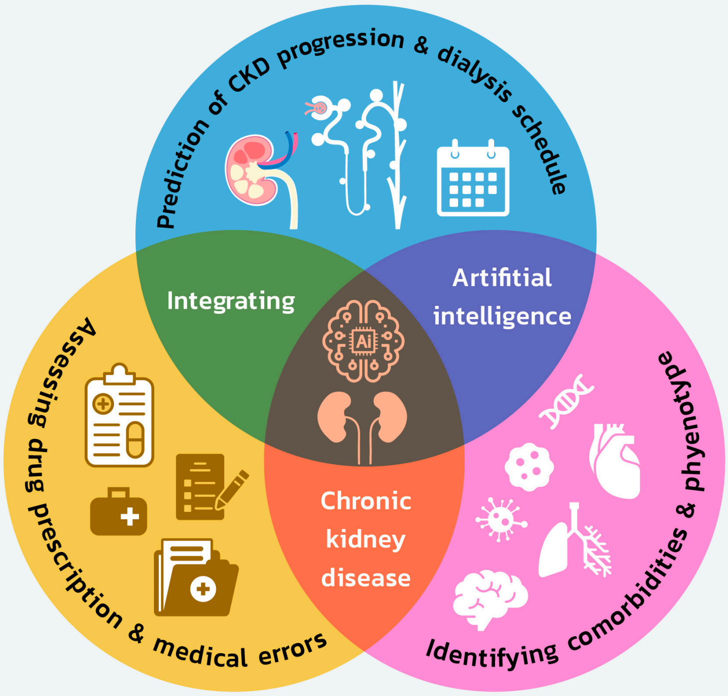

Objective: To reduce the need for frequent dialysis and to explore the future potential of AI in the field of nephrology.

systematically search

Google Scholar PubMed

CKD, hemodialysis, AI

Conclusion: Integrating AI in nephrology holds promise for reducing kidney dialysis frequency through its applications in the management plans of patients with CKD

- AI (Artificial Intelligence)
- CKD (Chronic Kidney Disease)

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ABSTRACT

Chronic kidney disease (CKD) is one of the most common and serious illnesses affecting individuals worldwide, potentially leading to kidney failure. Various strategies exist to manage CKD, with hemodialysis being the most effective. However, this treatment comes with numerous limitations that can significantly affect patients' quality of life. Therefore, it is crucial to explore new approaches to address these challenges. Recently, artificial intelligence (AI) has emerged as a promising tool in nephrology. This review aims to reduce the need for frequent dialysis and to explore the future potential of AI in the field of nephrology. The frequency of hemodialysis refers to the regular, scheduled dialysis sessions mainly prescribed for patients with CKD, in addition to the unplanned or premature initiation of hemodialysis through predictive and preventive interventions. This narrative review systematically searched Google Scholar and PubMed using keywords related to CKD, hemodialysis, and AI. AI is used in kidney disease to predict CKD progression, evaluate drug prescriptions, detect medical errors, adjust dialysis schedules, and identify unknown comorbidities and phenotypes. Integrating AI in nephrology holds promise for reducing kidney dialysis frequency through its applications in the management plans of patients with CKD.

Keywords: Chronic kidney disease; hemodialysis; artificial intelligence (Siriraj Med J 2025; 77: 543-552)

INTRODUCTION

Chronic kidney disease (CKD) is one of the most common and fatal disorders that affect individuals globally and it is expected to be the fifth leading cause of death worldwide by 2040.[1] It is characterized by a gradual decline in kidney function, which results from several causes including diabetes, hypertension, obesity, polycystic kidney disease, glomerulonephritis, and chronic obstruction of the urinary tract.[2] CKD is classified into five stages based on the estimated glomerular filtration rate (eGFR), where the fifth stage is referred to as end-stage kidney disease (ESKD) or kidney failure in which the eGFR is less than 15 milliliters per minute. This stage could progress to multiple overlapping complications and usually needs kidney dialysis or kidney transplantation.[3] Hemodialysis is the most effective treatment modality for CKD patients, and it has a role in the longevity of the patient's life. However, this treatment has several modifications and restrictions impacting the quality of life for patients with kidney failure. Particularly, hemodialysis impacts the social and economic status of these patients as well as their psychological standing leading to a large number of psychological illnesses.[4] Moreover, numerous complications such as cardiovascular issues, infections, and problems related to the dialysis access sites. Frequent hemodialysis sessions could be associated with cardiovascular strain, due to rapid shifts in the fluids and electrolytes.[5] This may exacerbate left ventricular hypertrophy and augments the risk of arrhythmias. Likewise, repeated access to the ventricle increases the tendency of infections, thrombosis and stenosis.[6] Accordingly, it is important to implement a new strategy to adjust the impact and frequency of hemodialysis to improve the quality of patients' life and to overcome the aforementioned challenges.[7]

Artificial intelligence (AI) is recently implemented as an interesting strategy in various fields of medicine, including nephrology. It could be applied to monitor hemodialysis, improve clinical care, and follow-up transplant recipients.[8] The potential of AI in nephrology aims to improve kidney dialysis for CKD patients by reducing frequency and enhancing quality of life. This review discusses the role of AI in dialysis treatment, addressing challenges and limitations while exploring future applications in nephrology.

1. Current strategies in chronic kidney disease treatment

The management of CKD involves several approaches aimed at reducing symptoms, slowing progression, and improving quality of life.[9]

1.1 Management of the coexistent diseases

1.1.1 Reducing the risk of cardiovascular disease

Cardiovascular disease is more prevalent in patients with CKD than in those without, often leading to life-threatening outcomes.[10] Therefore, it is important to reduce the risk of cardiovascular diseases by encouraging patients to stop smoking, intensive blood pressure control (target blood pressure is less than 120 millimeters of mercury (mmHg)), and treating elderly patients who have CKD with low to moderate doses of statin regardless of the levels of low-density lipoprotein cholesterol.[11]

1.1.2 Management of hypertension

Antihypertensive drugs such as angiotensin II receptor blockers (ARBs) and angiotensin-converting enzyme inhibitors (ACEIs) are valuable in patients with CKD.[12] Renin-angiotensin-aldosterone system blockade can reduce systolic blood pressure by approximately 20 mmHg in patients with hypertension and CKD, the same as calcium channel blockers (CCBs) and diuretics.[13] However, in patients with diabetes and proteinuria, ARBs and ACEIs show superiority in comparison to other groups.[14]

Diuretic therapy can alleviate volume overload in CKD patients, helping reduce left ventricular mass and arterial stiffness. For non-proteinuric CKD, thiazide (e.g., bendroflumethiazide) or thiazide-like diuretics (e.g., indapamide) may be first-line treatments. While loop diuretics (e.g., furosemide) are useful, they require higher doses for patients with lower eGFR rates.[15] CCBs, particularly dihydropyridines like amlodipine, are effective for managing hypertension in non-proteinuric CKD patients. For proteinuric CKD, a combination of ACEIs and CCBs is recommended, while non-dihydropyridines like verapamil can reduce proteinuria and control blood pressure.[16]

Beta-blockers can be safely used in all stages of renal impairment with potential dosage adjustments. Carvedilol, a liver-excreted beta-blocker with vasodilatory effects, is especially beneficial for CKD patients.[17,18]

1.1.3 Management of diabetes mellitus

Controlling blood sugar delays the progression of CKD with a goal of 7% hemoglobin A1c as recommended by most studies.[19-21] Moreover, adjusting the dose of oral antidiabetics will also be helpful. For instance, the dose of drugs that are metabolized by the liver and partially excreted by the kidney (such as metformin and some sodium-glucose cotransporter 2 inhibitors (SGLT2) and dipeptidyl peptidase inhibitors) may require adjustment or cessation, especially when eGFR falls below 30 mL/min/1.73 m^2.[22,23] Drugs cleared by the kidney, like glyburide, should be avoided. SGLT2 inhibitors are recommended for patients with severe albuminuria.[24,25]

The nephrology and clinical evaluation (CREDENCE) trial found that patients with type 2 diabetes and CKD taking canagliflozin had a 30% lower risk of primary renal complications compared to placebo, indicating cardiovascular benefits.[26,27]

1.1.4 Nephrotoxins

Nephrotoxic medications should be avoided for patients with CKD for example, non-steroidal anti-inflammatory drugs, especially among patients who are on ARBs or ACEIs therapy.[28,29] Phosphate-based bowel preparations can cause acute phosphate nephropathy, so it's important to advise caution. Herbal remedies are concerning as they lack FDA standardization; some, particularly those with anthraquinones and aristolochic acid, can lead to kidney issues like acute and chronic interstitial nephritis, nephrolithiasis, acute tubular necrosis, Fanconi syndrome, rhabdomyolysis, and hypokalemia.[30-32] Proton pump inhibitors have been linked to acute interstitial nephropathy in individuals with CKD. Their use in this population should be evaluated in primary care units.[33,34]

1.1.5 Drug dosing

Patients with CKD require dose adjustment of certain drugs due to the high risk of adverse drug reactions.[35] These drugs include antibiotics, opiates, and anticoagulants.[36] Furthermore, contrast agents such as gadolinium-based agents are contraindicated in patients with acute kidney injury with an eGFR rate of less than 30 mL/min/1.73m^2 or ESKD due to the potential of nephrogenic systemic fibrosis.[37] New macrocyclic chelate formulations like gadobutrol, gadoteritol, and gadoterate have a lower risk of fibrosis. However, avoiding gadolinium entirely is the best way to prevent this complication. Patients should be informed of the fibrosis risk if it must be used, and a nephrologist may be consulted for post-exposure hemodialysis.[38]

1.2 Monitoring and treating of chronic kidney disease complications

The Kidney Disease Improving Global Outcomes (KDIGO) guidelines recommend annual monitoring of kidney function, eGFR, and albuminuria. High-risk patients should be monitored twice a year, while very high-risk patients require thrice a year.[39,40] Patients with moderate to severe CKD are at an increased risk of minerals, electrolytes, bone abnormalities, and anemia. Laboratory abnormalities are assessed according to the stage of CKD and include evaluations of blood count, lipid panel, phosphate, serum albumin, 25-hydroxyvitamin D, parathyroid hormone, and metabolic panel.[39]

1.2.1 Anemia

It is important to monitor anemia in CKD patients by assessing iron stores, and in case of iron deficiency; oral or intravenous replacement therapy might be assisted.[41] However, patients with very low levels of hemoglobin less than 10 g/dL might need additional therapy, such as erythropoietin-stimulating agents after weighing the potential benefits of such therapy against the risks that include stroke, venous thromboembolism, and death.[42]

1.2.2 Electrolytes, minerals, and bone abnormalities

Electrolyte abnormalities occur in 3-11% of CKD patients. Early management includes dietary restrictions for hyperphosphatemia and hyperkalemia. Oral bicarbonate supplementation is recommended for serum bicarbonate levels below 22 mmol/L to reduce the risk of metabolic acidosis and slower CKD progression.[43]

In addition, mineral and bone disorders are also common, and many nephrologists have agreed to address the concomitant hypocalcemia, hyperphosphatemia, and vitamin D deficiency by elemental calcium intake, a low-phosphate diet and/or phosphate binders, and vitamin D supplementation.[44]

2. Limitations of the current strategies in chronic kidney disease treatment

Managing CKD with traditional strategies addresses several challenges including, economic and healthcare burdens in which significant costs associated with medications, dialysis, and hospitalization limit the access to optimal care for some patients.[45] The side effects of certain medications that are used to manage CKD such as ARBs and ACEIs which can lead to hyperkalemia and kidney dysfunction, will complicate the treatment and require further monitoring and medical interventions.[46] Patients with CKD may struggle to maintain medication adherence, lifestyle changes, regular dialysis sessions, and dietary restrictions which can impact the overall health and the effectiveness of treatment.[47] Finally, the quality of life will be reduced due to the physical and emotional burdens of CKD and its management through which patients experience depression, fatigue, and social isolation that would complicate their treatment adherence.[48]

The limitations highlight the need to integrate advanced technologies like AI into traditional CKD management strategies, potentially enhancing patient care and quality of life.

3. The applications of artificial intelligence in chronic kidney disease treatment

The use of AI in nephrology is crucial for improving management plans, aiding clinician decision-making, and reducing the need for hemodialysis and hospital visits. AI applications in kidney disease include predicting CKD progression, assisting treatment, identifying medical errors, adjusting dialysis schedules, and detecting unknown comorbidities as illustrated in Fig 1.[49]

3.1 Prediction of chronic kidney disease progression

Patients with ESKD have high hospitalization and mortality rates. Therefore, early detection of CKD and controlling its progression are essential for better patient outcomes. Several machine learning techniques in AI generally exist, including logistic regression, linear regression, ensembles like random forest and XGBoost, Lasso, Ridge, support vector machines, k-means clustering, k-nearest neighbors, decision trees, and principal component analysis.[50]

The development of AI techniques nowadays makes them effective choices for CKD prediction.[51] A traditional regression model for predicting kidney failure has been developed by Tangri et al. This model uses clinical and

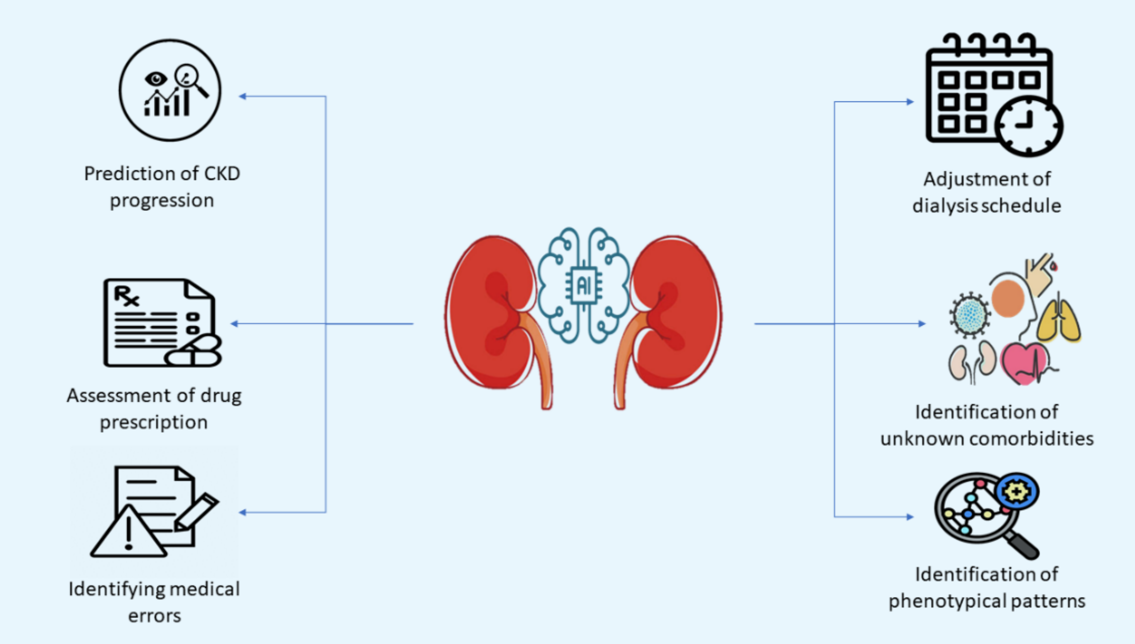

Fig 1. Artificial intelligence (AI) applications in chronic kidney disease (CKD).

demographic data from two independent groups of patients with stages 3 to 5 of CKD.[52] In two recent studies, random forest models have been developed to create a prognostic risk score. These models combine data from electronic medical records and circulating biomarkers, such as kidney injury molecule-1 and tumor necrosis factors, to predict the progression of CKD.[53,54]

Predictive interventions using hospitalization and mortality models based on traditional statistical techniques have been performed; utilizing several features including machine learning models. Machine learning is a branch of AI that allows computers to learn from data and make predictions and decisions that might be missed by humans.[55]

Advanced machine learning methods involve developing complex models to enhance the efficacy of machine learning and include several models.[56] The most common model used in nephrology is the random forest, a collaborative method that builds several decision trees using a random set of data to get a more accurate prediction of CKD progression. An early example of employing the random forest models in nephrology was the prediction of sudden cardiac death among elderly hemodialysis patients.[57] Another example was the use of support vector machine model for the prediction of ischemic heart disease in patient with dialysis.[58] The support vector machine is a supervised machine learning algorithm used for the classification and regression of CKD stages.[59]

Xiao et al. compared several machine learning methods to predict the risk of proteinuria in CKD patients using blood biochemical features and demographic data.[60] Moreover, Jamshid Norouzzi et al. established an artificial neural network (ANN) model to predict the progression of kidney failure through the assessment of glomerular filtration rate in patients with CKD, ANN is organized in layers and serves as the foundation for supervised or unsupervised machine learning systems that can replicate complex tasks involved in categorization or prediction procedures.[61]

The Renal Research Institute utilized AI models to predict the progression of CKD, and the results of the models were included in the CKD Forecaster Tool to be used by nephrologists to support clinical decisions. Accordingly, the nephrologists that used this Tool had fewer transitioning patients to hemodialysis providing better care planning for patients with ESKD.[62]

3.2 Treatment assessment

AI models provided interesting aid in the prescription of drugs for patients with CKD and identified several medical errors. For example, the erythropoietin prescription could be automated in patients with ESKD to increase its efficacy and enhance patient care. Several approaches have been to reduce the erythropoietin dose and improve patient care.[63] For instance, the use of ANN for the treatment of anemia has minimized the variability of hemoglobin levels and reduced the dose of erythropoietin.[64] Moreover, the historical data of patients is another area of understanding the appropriate drug for specific patient categories, which can guide clinicians in the decision-making process. In this regard, Fresenius Medical Care, is a major dialysis organization that specializes in providing integrated care for kidney disease, has provided nephrologists the option to recommend cinacalcet off-label for in-center administration three times a week, with direct observation.[65] Following observations for the indication of three times per week in-center administration of cinacalcet indicated that it is not superior to the daily administered cinacalcet in regulating the levels of parathyroid hormone, supporting the results of a virtual clinical trial.[66] Despite being theoretical, attempts such as these could improve and customize secondary hyperparathyroidism treatment and increase understanding of the debatable impact of drugs in mineral bone medications on real outcomes.[67]

3.3 Identifying medical errors

Medical errors are the third leading cause of death in the United States thus, identifying medical errors is another important strategy to improve patient care which can be ensured by using AI approaches.[68] Several causes of medical errors are available, such as human factors and ergonomics, healthcare system complexity, education, competency, and training. Correcting medical errors using traditional approaches could be accomplished by creating new rules that need to be used in a healthcare system.[69] Nonetheless, the application of AI approaches can be implemented when historical data exist; guiding the clinicians to identify what therapeutic approach is ideal for patients.[70]

Additionally, machine learning algorithms can aid in decision-making when the susceptibility of complex and uncommon medical interactions is expected such as therapeutic duplication and drug-allergy or drug-drug interactions.[71] Several technological companies have facilities that assist in reducing medical errors by supporting physicians in interacting with patients' data. Therefore, integrating the technology with AI models could assist in the decision support system. The prediction of algorithms developed at the University of Stanford has established the best examples of such applications where researchers have created a network to study drug interactions with over 19,000 proteins in the body. They used deep learning approach of AI to identify patterns in side effects based on drug-targeting proteins. The system supposed patterns about drug interaction side effects and predicted unexpected consequences from taking two drugs together.[72]

3.4 Adjustment of dialysis schedule

Fascinatingly, AI algorithms adjust dialysis settings and schedules based on patient-specific data, such as electrolyte balance and fluid retention. This would help in individualization of the dialysis frequency according to the patient's need, which may involve increasing, decreasing or rescheduling sessions, aiding in replacing the standard fixed hemodialysis schedule, reducing the potential complications and customizing treatment regimens and leading to optimizing dialysis treatments and improving quality of life.[73]

3.5 Identification of unknown comorbidities

Patients' comorbidities are another area of concern in which the rate of survival will decrease among patients with ESKD and multiple comorbidities. Additionally, the health picture of patients could be complicated by the presence of comorbidities as highlighted by prognostic comorbidity indexes which demonstrate the mortality risk of patients with renal replacement therapy.[74] Moreover, comorbidity information is an important element participating in medical billing. In which patients suffering from ESKD, who have complex health pictures, receive multiple payment coverage for medical services.[75] Therefore, comorbidities must be properly recorded in medical documents in order to appropriate the payment procedures for extra levels of services and support tied to these populations.[76]

In nephrology, one long dialysis organization integrated with a kidney disease care organization has used the machine learning model to identify potentially undocumented comorbidities and to eliminate the expected comorbidities, by finding the patterns in physicians' notes regarding the diseases.[76]

3.6 Identification of phenotypical patterns

On the topic of mortality rate, it increases nearly six-fold with the presence of concomitant pathophysiological risk factors including malnutrition, inflammation, and atherosclerosis, which have been detected by traditional statistical methods in patients with ESKD.[77] Additionally, fluid overload has been included in recent studies' pathophysiological patterns. In nephrology, the detection of patterns is based on an unsupervised learning technique, a category of machine learning that teaches a computer to use unlabeled data and allows the program to work without human oversight.[78,79] For example, three distinct phenotypic patterns were found using agglomerative hierarchical clustering, an unsupervised learning technique, in patients with heart failure who had retained ejection fraction. These patterns were based on echocardiographic, laboratory, and clinical characteristics. The mortality risk varied significantly among these groupings. The authors referred to the application of unsupervised learning methods in cardiology to identify phenotypical patterns as "phenomapping", thus monitoring the progress of cardiovascular disease among CKD patients.[80]

In the field of infection medicine, researchers applied k-means clustering, a type of unsupervised learning, to analyze a group of sepsis patients, identifying four distinct phenotypes that exhibited significant differences in outcomes. One of these was the β phenotype, which consisted of older patients with more chronic illnesses and renal failure. Another phenotype, the δ phenotype, included patients experiencing liver dysfunction and septic shock, and it had the highest mortality rate at 40%. In comparison, the β phenotype had a mortality rate of 13%, while the low-risk α phenotype had a rate of just 5%.[81] Additional research is necessary to identify phenotypic patterns in patients with CKD to personalize treatment.

4. Clinical applications of artificial intelligence in kidney dialysis

In 2001, Akl and his colleagues addressed the application of AI to the urea kinetic of hemodialysis patients, aiming to predict the adequate dialysis time to reach target urea removal, as a result, they concluded that AI can provide valuable insights for tailoring intradialysis protocols to meet individual clinical needs. This method improved the customization of hemodialysis session prescriptions, especially for patients with varying weight and dietary habits. Instead of using a standard prescription, their dialysis sessions should be tailored to meet their unique needs.[82]

In 2004, Gabutti and his colleagues explored the role of the AI approach to assist nephrologists in accurately recognizing the trend in the evolution of the protein nutritional status and they concluded that the predicted protein catabolic rate is more accurate than the protein catabolic rate established by clinicians, hence enabling the implementation of preventative interventions.[83]

In 2016, an Anemia Control Model (ACM) using artificial intelligence decision support system, was conducted in an aim to improve anemia outcomes for patients undergoing hemodialysis. The ACM was developed based on patient profiles and was used to recommend appropriate doses of erythropoietic-stimulating agents such as darbepoetin. The study included 752 patients receiving hemodialysis treatment across three NephroCare clinics located in different countries. The primary outcomes measure was the percentage of hemoglobin values that fell within the target range, the individual fluctuations in hemoglobin levels, and the median dose of darbepoetin administered. The results indicated that care guided by the ACM led to a decrease in hemoglobin variability, a significant reduction in darbepoetin usage, and an increase in the percentage of hemoglobin values on target. These findings suggest that the ACM can enhance anemia management, reduce the need for erythropoietic-stimulating agents, and significantly lower treatment costs.[64]

In 2018, Neil and Bastard utilized AI a study to increase the precision of dry weight measurements in hemodialysis patients. Dry weight refers to the minimum weight that patients on hemodialysis can safely tolerate. Accurate estimation of dry weight is essential to reduce morbidity and mortality but can be challenging to achieve. A neural network was created using blood pressure readings, blood volume monitoring, and bio-impedancemetry. Fourteen children were moved from nephrologists to dry-weight AI patients. According to the findings, the dry weight of AI was 28.6%, 50%, or the same as that of nephrologists. Systolic blood pressure was considerably lower and antihypertensive medications were successfully stopped in patients with higher artificial intelligence dry weight. Finally, the study concluded that AI is a powerful tool for predicting dry weight among patients with hemodialysis.[84]

5. Future promising issues of AI in CKD and potential limitations

Nephrologists are increasingly collaborating with AI researchers to enhance kidney disease diagnosis and treatment. AI has great promise for CKD research regarding early and precise kidney disease prediction, enabling individualized risk assessments for CKD patients.[50]

AI can analyze vast patient data and identify complex relationships that traditional prediction models often miss. AI can create detailed risk profiles by integrating additional information such as biomarkers, socioeconomic factors, medical images, genetic markers, and comorbidities. This enables the personalization of treatment plans for patients.[50] For example, deep learning models can detect early kidney disease in patients with type 2 diabetes mellitus by analyzing retinal fundus photographs and clinical metadata, including sex, age, weight, height, blood pressure, and body mass index.[85] Furthermore, external photographs of the eyes can help identify poor blood glucose control, serving as a warning for the progression of diabetic complications, including kidney failure.[86]

In a significant project, Google DeepMind collaborated with the United States Department of Veterans Affairs to develop an AI system capable of predicting acute kidney injury up to 2 days before it becomes clinically apparent. This system demonstrates how data science can be applied to nephrology to develop effective tools for the prevention and early detection of kidney disease, optimizing the use of medical resources, and potentially saving lives.[87]

Using AI-based approaches in clinical practice presents significant challenges, particularly because deep learning models operate as “black boxes”, due to their complexity, it is often impossible to trace the path from input to output, making it difficult for doctors to assess and understand the predictions made by these models and complicating the understanding of how decisions are made.[88]

Researchers are increasingly focusing on Explainable AI (ExAI) to address important issues in artificial intelligence. ExAI aims to enhance the transparency of AI models by providing clear explanations for their decisions. Techniques such as attention mechanisms, feature importance analysis, and model-agnostic approaches are used to identify the factors that influence AI predictions. By improving transparency, ExAI helps clinicians assess the reliability of AI systems, trust their outputs, and integrate them into clinical decision-making processes with greater confidence. Addressing the “black box” problem is essential for complying with regulatory standards, ensuring accountability, and addressing concerns related to patient privacy, safety, and ethical implications.[89] A new reporting approach for medical models is needed to improve healthcare outcomes, focusing on ethical considerations and data-sharing policies.

CONCLUSION

Despite the challenges regarding data privacy and ethical considerations that need more clinical validation, the integration of AI in nephrology provides a potential value in reducing the frequency of kidney dialysis. This could be obtained through early disease prediction, treatment assessment, and identification of expected comorbidities. Besides, AI approaches could personalize patient care and improve the quality of life by customizing dialysis schedules and settings.

Data Availability Statement

The data supporting the findings of this review article are available from the cited primary literature sources. No new data were generated or analyzed for this study.

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Conflict of Interest

The authors declare no competing conflicts of interest.

Registration Number of Clinical Trial

There is no clinical trial number because this study is not a clinical trial/experimental study.

Author Contributions

Conceptualization and methodology, RIA, MNA, FAA; Investigation, MNA, FAA, and MHA. Visualization and writing – original draft, RIA; Writing-review and editing, MNA, FAA; Supervision, MNA, FAA, and MHA.; All authors have read and agreed to the final version of the manuscript.

Use of Artificial Intelligence

This study did not use artificial intelligence.

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