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Applications of Artificial Intelligence in nephrology nursing: an integrative review of predictive and clinical management tools

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ABSTRACT

Introduction: The introduction of artificial intelligence (AI) into the field of nephrology offers a new perspective for analysing technology-mediated real-time data.

Objectives: To determine the applications of artificial intelligence in nephrology nursing practice and to characterise predictive, diagnostic, and clinical management tools aimed at patients with kidney disease.

Methodology: We conducted an integrative literature review in accordance with the PRISMA statement. Original articles with no time restriction were searched in MEDLINE, EBSCO, Cochrane, and LILACS using combinations of terms related to artificial intelligence, nursing, and nephrology. Observational studies, experimental studies, and clinical trials in adult populations published in English, Spanish, or Portuguese were included. Excluded were robotic developments, gynaecological–obstetric patients, and previous reviews. Two reviewers independently extracted data on study design, sample, interventions, comparators, and main outcomes, applying CASPe guidelines to assess methodological quality.

Results: From 279 initial records, 30 studies met the inclusion criteria. They were grouped into 2 categories: 16 studies on predictive and diagnostic tools, and 14 on improved care and clinical management (patient classification systems, early warning systems, dialysis optimisation, and readmission prevention). Most demonstrated the superiority of machine learning and deep learning models compared with traditional approaches.

Conclusions: AI applied to nephrology nursing shows promising performance in prediction and diagnosis, as well as in the optimisation of care processes. Clinical implementation studies and cost-effectiveness evaluations are needed to consolidate its integration into daily practice and maximise its benefits.

Keywords: artificial intelligence; machine learning; kidney diseases; nephrology nursing; computerised clinical decision support systems; literature review.

RESUMEN

Aplicaciones de la inteligencia artificial en la enfermería nefrológica: revisión integrativa de las herramientas predictivas y de gestión clínica

Introducción: La introducción de la inteligencia artificial, en el área de la nefrología, proporciona una nueva perspectiva para analizar datos en tiempo real mediados por tecnología.

Objetivos: Determinar las aplicaciones de la inteligencia artificial en la práctica de la enfermería nefrológica y caracterizar herramientas predictivas, diagnósticas y de gestión clínica dirigidas a pacientes con enfermedad renal.

Cuacialpud-Marin KS, et al. https://doi.org/10.37551/S2254-28842025021

Metodología: Se realizó una revisión integrativa de literatura siguiendo la declaración PRISMA. Se buscaron artículos originales sin límite temporal en MEDLINE, EBSCO, Cochrane y LILACS, usando combinaciones de términos relacionados con inteligencia artificial, enfermería y nefrología. Se incluyeron estudios observacionales, experimentales y ensayos clínicos en población adulta, publicados en inglés, español o portugués. Se excluyeron desarrollos robóticos, pacientes gineco-obstétricas y revisiones previas. Dos revisores extrajeron de forma independiente datos sobre diseño, muestra, intervenciones, comparadores y resultados principales, aplicando guías CASPe para evaluar la calidad metodológica.

Resultados: De 279 registros iniciales, 30 estudios cumplieron los criterios de inclusión. Se agruparon en dos categorías: 16 trabajos en herramientas predictivas y diagnósticas, y 14 en mejora de atención y gestión clínica (sistemas de clasificación de pacientes, alertas tempranas, optimización de diálisis y prevención de readmisiones). La mayoría mostró superioridad de modelos de aprendizaje automático y deep learning frente a enfoques tradicionales.

Conclusiones: La inteligencia artificial aplicada en enfermería nefrológica demuestra un rendimiento prometedor en predicción y diagnóstico, así como en la optimización de procesos asistenciales. Se requieren estudios de implementación clínica y evaluaciones costo-efectivas para consolidar su integración en la práctica diaria y maximizar sus beneficios.

Palabras clave: inteligencia artificial; aprendizaje automático; enfermedades renales; enfermería nefrológica; sistemas de apoyo a la decisión clínica computarizados; revisión de literatura.

INTRODUCTION

Artificial intelligence (AI) refers to the capacity of algorithms encoded in technological media to learn in order to perform automated tasks that do not require human interaction at each stage of the process[1]. AI is a branch of engineering and computer science dedicated to the design and programming of tools that imitate neuronal synapses using a binary command code to approach human abilities such as learning, reasoning, and self-correction[2].

Currently, the search for tools and processes that facilitate and improve quality of life has permeated all fields, including health sciences, which continue to undergo transformation[3]. Among the advantages offered by the application of AI are its ability to enhance the competencies of healthcare providers by supporting diagnosis, optimizing treatment plans through personalized approaches, and assisting financial processes within health systems. This contributes to improving services offered to the population[1,2].

Chronic kidney disease (CKD) is the 6th leading cause of death worldwide. It affects approximately 10% of the population—an estimated 850 million people globally—and is responsible for at least 2.4 million deaths per year, while acute kidney injury, a precursor of CKD, affects more than 13 million individuals worldwide[4]. In Latin America, the average incidence is 162 patients per million inhabitants[5]. Latin America has the highest global mortality rate from CKD and is the second leading cause of years of life lost[4]. CKD represents a substantial burden for the affected individual, their family, society, and the healthcare system[4].

In nephrology, the application of AI-based tools is still emerging but has already achieved impact across the entire continuum of care (prevention, diagnosis, treatment, and follow-up) for individuals with kidney disease. This review identified the applications of AI in the field of nephrology nursing. The importance of AI lies in its ability to analyze large quantities of data and extract useful information that can help healthcare professionals make more precise and informed decisions[2].

For the discipline of Nephrology Nursing (NN), understanding AI applications will allow more optimal planning of effective and individualized care plans by identifying risks and needs, and by freeing time from administrative tasks that can instead be invested in direct nursing care[6].

This study aimed to determine the applications of AI in NN practice and to characterize predictive, diagnostic, and clinical-management tools directed toward the care of people with kidney disease. Accordingly, the following review question was posed: What are the applications of AI for NN practice, and what AI-based tools have been developed for the care of people with kidney disease?

METHODOLOGY

Design

We conducted an integrative literature review was conducted to guide the search for the most up-to-date publications and research, based on the PRISMA 2020 guidelines[7].

Eligibility Criteria

Studies addressing the application of AI in the health sciences, with observational or experimental designs in adult populations and including aspects of nursing care, were selected. No time restriction was applied. Publications in English, Spanish, or Portuguese were included. Studies focused on robotics or mechatronics, research conducted on gynecologic–obstetric patients, and previous literature reviews were excluded.

Information Sources

A bibliographic search of original articles indexed in EBSCO, MEDLINE, the Cochrane Library, and LILACS was carried out in February 2024.

Search Strategy

The research question was developed using the PICO strate-

Cuacialpud-Marin KS, et al. https://doi.org/10.37551/S2254-28842025021

gy, which supported the construction of the following search equations: English: "Artificial Intelligence" AND "Nursing Care", "Artificial Intelligence" AND "Kidney Disease", "Artificial Intelligence" AND "Nephrology"; Spanish: "Inteligencia artificial" AND "Cuidado de Enfermería", "Inteligencia artificial" AND "Enfermedad Renal", "Inteligencia artificial" AND "Nefrología". Search equations included DeCS/MeSH terms: ("Artificial Intelligence"[Mesh]) AND "Nursing Care"[Mesh], ("Artificial Intelligence") AND "Nursing Care", "artificial intelligence" AND "nursing", ("Artificial Intelligence") AND "kidney", "artificial intelligence" AND "kidney disease", ("Kidney Diseases"[Mesh]) AND "Artificial Intelligence"[Mesh]. Filters applied: human studies and original research. Preprints were excluded. No date limits were applied.

Quality Assessment

Articles were independently evaluated by the authors using the appropriate methodological appraisal tools according to study design, specifically the Critical Appraisal Skills Programme Español (CASPe). Articles achieving less than 50% compliance with CASPe criteria were excluded. Discrepancies were resolved through discussion until unanimous consensus was reached.

Data Extraction

Data were extracted systematically and structured into two thematic groups: 1) AI applications as predictive and diagnostic tools in nephrology. 2) AI applications in patient-care optimization and clinical management For each article, the title, authors, methodological design, sample characteristics, main objective, and a summary of key findings were recorded. A narrative synthesis was then performed to integrate and contrast findings across both categories.

RESULTS

Study Selection

Electronic searches yielded a total of 279 titles. Three records were removed for being duplicates. After screening titles and abstracts, 236 records were excluded for not meeting the established criteria. Forty publications were read in full. Ten articles were excluded after being evaluated with the CASPe tool because they did not meet the methodological validity criteria. Finally, 30 records were included in the review (**figure 1**).

Characteristics of the Studies

Of the 30 selected articles, 12 were from Asia (40%), 8 from North America (27%), 9 from Europe (30%), and 1 from Africa (3%). The study designs included 9 observational studies (30%), 7 randomized clinical trials (23%), 6 multicenter studies (20%), 4 comparative studies (13%), 3 quasi-experimental studies (10%), and 1 multicohort observational study (3%).

Results of Individual Studies

Table 1 illustrates the characteristics of the 16 studies included under the category of AI applications as a predictive and diagnostic tool in nephrology. The characteristics of the

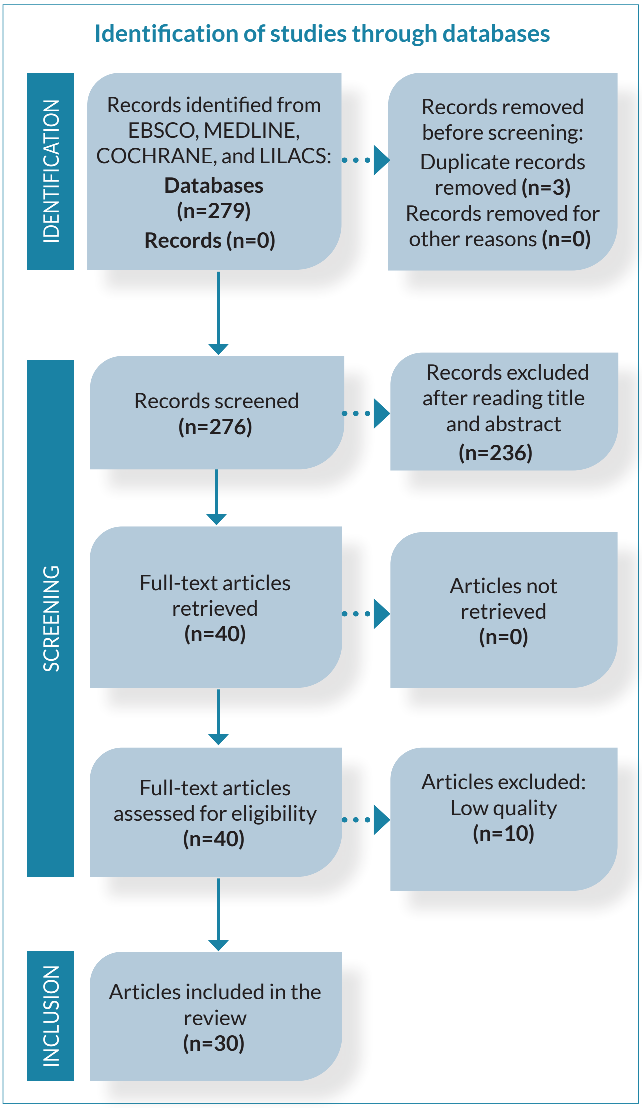

Figure 1. Flow diagram of article search based on PRISMA statement recommendations.

14 articles included in the category of AI applications for improving patient care and clinical management are shown in **table 2.**

Synthesis Results

Application of AI as a Predictive and Diagnostic Tool in Nephrology

In this category, 16 studies were identified investigating the potential of AI-based technologies for both prediction and early diagnosis of kidney diseases. Flechet et al.[8]. evaluated a predictive model for acute kidney injury (AKI) in the intensive care unit (ICU), comparing the predictive capability of expert physicians with an AI algorithm (AKIpredictor). At ICU admission, both AI and experts showed similar performance, with an area under the receiver operating characteristic

Cuacialpud-Marin KS, et al. https://doi.org/10.37551/S2254-28842025021

curve (AUROC) of 0.80 *vs* 0.75, respectively[8]. However, on the first morning, AKIpredictor outperformed experts with an AUROC of 0.94 *vs* 0.89, and during the first 24 hours exceeded physicians with an AUROC of 0.95 *vs* 0.89, achieving a net benefit of 67% *vs* 50%[8]. Martínez et al.[9] analyzed emergency department data and developed a predictive model capable of early identification of individuals at high risk for AKI, demonstrating strong predictive performance up to 72 hours before traditional diagnostic criteria were met[9]. These findings align with those described by Ozrazgat-Baslanti et al.[10], who noted that deep learning (DL) tools can generate continuous, accurate, and early predictive data.

According to Chaudhuri et al.[11], AI is capable of processing and analyzing large volumes of data that enable prediction of future events related to kidney disease and support clinical decision-making regarding therapeutic measures[11]. Wu et al.[12] compared a machine learning (ML)-based approach with traditional models (Framingham risk scale) for cardiovascular risk stratification in young adults with hypertension,

Table 1. Characteristics and qualitative analysis of the articles included regarding the application of artificial intelligence as a predictive and diagnostic tool in nephrology.

Author (Year)	Country	Study Type	Participants	Intervention	Comparison	Main Outcome	CASPe
Wu X. et al.[12] (2020)	China	Observational study.	508 young adults with hypertension.	Evaluate cardio-vascular risk in young hypertensive patients using two new ML methods (RFE and XGBoost).	Performance compared with a traditional statistical model (Cox regression) and the available clinical Framin-gham Risk Score (FRS).	ML identified 11 valuable variables for predicting clinical outcomes. ML model C-statistic: 0.757, outperforming Cox regression (0.723) and recalibrated FRS (0.529) in identifying composite endpoints.	100%
Roth J. et al.[13] (2021)	Switzer-land	Multicenter study.	12,761 people with HIV in the Swiss HIV Cohort Study.	Evaluate various ML algorithms and modeling strategies for individualized CKD prediction in a high-dimensional cohort.	Logistic regres-sion (“short models”) using well-established predictors.	64 static variables+502 time-varying variables used. ML models outperfor-med expert-based models with AUC 0.926–0.996 and precision-recall 0.631–0.956, demonstrating state-of-the-art predictive performance.	100%
Martínez D. et al.[9] (2020)	USA	Multicenter study.	59.792 patiens.	Early identification of high-risk acute kidney injury (AKI) patients using an ML-based prediction model in the emergency department.	N/A	AKI incidence at 72 hours: 7.9% for stage≥1 and 1.0% for stage≥2. Predictive performance AUC=0.74–0.81. Median time from ED arrival to prediction: 1.7 hours.	100%
De Gonza-lo- Calvo D. et al.[30] (2020)	USA	Clinical trial.	810 patients with end-stage renal disease receiving hemodialysis (AURORA trial).	Evaluate whether plasma miRNAs im-prove cardiovascu-lar-risk prediction in ESRD patients on HD	Predictive models without miRNAs.	Adding miRNAs improved discrimina-tion accuracy at baseline (integrated AUC = 0.71) compared with models lacking miRNAs.	90%
Raynaud M. et al.[19] (2021)	France, United Kingdom, Italy, Belgium, Canada, South America	Multicohort observational study.	13,608 adult kidney transplant recipients from 18 academic centers	Develop a dynamic artificial-intelli-gence approach for continuously refined survival predictions using updated clinical data	N/A	Bayesian joint models identified inde-pendent predictors of graft survival (recipient immunologic profile, inters-titial fibrosis, tubular atrophy, graft inflammation, repeated eGFR and proteinuria). The final model showed high accuracy and predictive ability in the development cohort and was validated in Europe, the U.S., South America, and RCT cohorts.	100%

Cuacialpud-Marin KS, et al. https://doi.org/10.37551/S2254-28842025021

Author (Year)	Country	Study Type	Participants	Intervention	Comparison	Main Outcome	CASPe
Churpek M. et al.[34] (2020)	USA	Multicenter study.	495,971 hospitalized patients (2008–2016).	Internal and external validation of a machine-learning risk score to detect AKI in hospitalized patients.	N/A	Variable AKI rates observed; predictive capabilities assessed via AUC. A probability threshold of 0.057 anticipated stage-2 AKI before increases in serum creatinine across cohorts.	100%
Chan L. et al.[29] (2021)	USA	Observational study.	1,146 patients with type 2 diabetes and CKD.	Develop/validate KidneyIntelX combining EHR data and biomarkers.	N/A	High accuracy with AUC 0.77 in both cohorts, outperforming the clinical model (AUC 0.62). In the high-risk group, PPV was 61% (*vs* KDIGO 40%); low-risk identification showed NPV 90%.	90%
Roblot V. et al.[35] (2022)	France	Observational study.	124 patients with metastatic renal cell carcinoma (2007–2019).	Validate a deep-learning algorithm for skeletal muscle index (SMI) measurement and survival prediction.	N/A	Both methods classified 56% as sarcopenic. Sarcopenic groups showed significantly lower survival: 6.0 *vs* 12.5 months (manual), 6.0 *vs* 13.9 months (DL). In an independent population, DL-defined sarcopenia predicted poorer survival (10.7 *vs* 17.3 months).	75%
Xiao J. et al.[36] (2019)	China	Comparative study.	551 CKD patients.	Rapid prediction of CKD severity using demographic and biochemical blood features, comparing statistical, ML, and neural network models.	N/A	Logistic regression performed best (AUC 0.873, sensitivity 0.83, specificity 0.82). Albumin, serum creatinine, TG, LDL, and GFR were significant predictors.	80%
Azar AT. et al.[28] (2011)	Egypt	Egypt Comparative study.	156 hemodialysis patients.	Evaluate artificial neural networks to predict urea rebound and identify optimal input parameter combinations.	Compared with Smye and Daugirdas models.	ANN obtained correlation 0.97 (*p*<0.0001). Smye and Daugirdas methods had R=0.81 and 0.93. Smye method showed larger errors and substantial bias; predictive accuracy for eqKt/V was similar between ANN and Daugirdas.	75%
Xi IL. et al.[15] (2020)	China	Multicenter study.	1,162 renal lesions diagnosed by pathology or imaging.	Develop a deep-learning model (ResNet) to distinguish benign renal tumors from RCC on routine MRI.	N/A	DL model achieved higher test accuracy vs. baseline (0.70 *vs* 0.56), and comparable to experts (0.70 *vs* 0.60). Sensitivity (0.92 *vs* 0.80) and specificity (0.41 *vs* 0.35) also outperformed experts.	50%
Liu Y. et al.[37] (2022)	China	Randomized clinical trial.	120 patients with renal dysplasia.	Assess EM-based low-dose CT imaging for detection and diagnosis of renal dysplasia.	N/A	EM algorithm improved PSNR, reduced processing time, and enhanced diagnostic accuracy across dysplasia subtypes, suggesting clinical usefulness.	60%
Byun S. et al.[16] (2021)	Korea	Clinical trial.	2,139 patients with non-metastatic clear-cell RCC.	Evaluate prognosis of nm-ccRCC using DeepSurv model, compared with Cox and RSF.	RSF and CPH models	DeepSurv showed superior prediction of RFS and CSS compared to CPH and RSF. Deep learning appears useful for survival prediction in RCC.	50%

Cuacialpud-Marin KS, et al. https://doi.org/10.37551/S2254-28842025021

Author (Year)	Country	Study Type	Participants	Intervention	Comparison	Main Outcome	CASPe
Purkayastha S. et al.[17] (2020)	USA	Multicenter study.	82 RCC lesions confirmed pathologically.	Differentiate low-grade (Fuhrman I–II) from high-grade (III–IV) RCC using MRI radiomic features.	N/A	Automated TPOT pipeline achieved ROC AUC 0.60 with 81% accuracy. Manual pipeline AUC 0.59 with 77% accuracy. Automated pipelines may be equally or more effective for non-invasive Fuhrman grade prediction.	60%
Jacob A. et al.[14] (2010)	USA	Comparative study.	1,126,495 USRDS dialysis records.	Build predictive survival models for ESRD patients using USRDS data.	Compared with Cox proportional hazards model.	Predictive models showed C-statistics ~0.78–0.80. Cox model performed better at some time points, but USRDS-based models enabled accurate long-term survival prediction after dialysis initiation.	63%
Toda N. et al.[18] (2022)	Japan	Multicenter study.	585 contrast-enhanced CT images from patients with histologically confirmed RCC.	Develop a deep-learning algorithm for fully automated detection of small renal tumors (≤4 cm).	N/A	High performance: accuracy 88.3%/87.5%, sensitivity 84.3%/84.8%, specificity 92.3%/90.2% (datasets A/B). AUC 0.930 and 0.933 (internal/external validation). Useful for early detection of small RCC.	50%

Table 2. Characteristics and Qualitative Analysis of Included Articles on the Application of Artificial Intelligence to Improve Patient Care and Clinical Management.

Author (Year)	Country	Study Type	Participants	Intervention	Comparison	Main Outcome	CASPe
Hong L. et al.[21] (2021)	China	Randomized clinical trial.	447 people with COPD.	Identify how AI-based technology improves quality of life in COPD patients seen in Emergency Services.	Medical intervention without AI tools.	Improved quality of life at 12 months; reduced hospitalization rate and length of stay for COPD. Preliminary results confirm effectiveness of the AI-based treatment.	90%
Brom H. et al.[26] (2020)	USA	Observational study.	2,165 EHR records.	Identify patients at risk of readmission using machine-learning CART applied to hospital EHRs.	N/A	30-day readmission rate was 11.2%. CART showed highest risk among ER visitors, ≥9 comorbidities, Medicaid insurance, and age ≥65. Findings support improved nursing care for high-risk patients.	
Barbieri C. et al.[38] (2015)	Germany, Spain, France, Portugal, Czech Republic	Observational study.	752 hemodialysis patients from 3 NephroCare clinics.	Assess impact of Anemia Control Model (ACM) decision-support system in routine anemia management.	Standard anemia management (expert nephrologists following best practice).	Darbepoetin dose decreased (0.63→0.46 mg/kg/month). Hb in target range rose from 70.6%→76.6%→83.2% with ACM. Hb variability decreased (SD 0.95→0.83 g/dL).	81%
Zhao C. et al.[22] (2022)	China	Randomized clinical trial.	44 people with diabetic kidney disease.	Evaluate ultrasound imaging and comprehensive nursing scheme based on AI algorithms.	N/A	Group B showed improved resistance index, fewer complications, and better quality of life. Intelligent ultrasound monitoring provides clinically relevant renal function tracking.	82%

Cuacialpud-Marin KS, et al. https://doi.org/10.37551/S2254-28842025021

Author (Year)	Country	Study Type	Participants	Intervention	Comparison	Main Outcome	CASPe
Yin P. et al.[33] (2022)	China	Randomized clinical trial.	60 postpartum women with mild–moderate pelvic organ prolapse.	Apply AI-based ultrasound technology and rehabilitation training for postpartum recovery.	N/A	Experimental group showed greater levator ani thickness, reduced perineal diameter, and stronger pelvic floor muscle strength vs. control. AI algorithm outperformed traditional imaging in Dice coefficient, PPV, sensitivity, and Hausdorff distance.	75%
Chen X. et al.[32] (2022)	China	Randomized clinical trial.	120 CKD patients (stages 3–5).	Evaluate "Internet + Hospital-to-Home (H2H)" nutritional care model using improved wavelet transform algorithm for CT imaging.	N/A	Improved arm muscle circumference, triceps skinfold, biochemical markers, nutritional screening scores, and patient satisfaction. Enhanced renal blood flow and vascular efficiency. AI-enhanced CT imaging performed better, supporting clinical use.	75%
Bagnasco A. et al.[27] (2015)	Italy	Observational study.	840 nurses.	Apply artificial neural networks to predict communication failures in emergency departments.	N/A	Variables such as terminology, listening, attention, and clarity predicted communication failure. Multilayer perceptron model correctly predicted >80% of failures based on personnel characteristics.	80%
Barrera A. et al.[23] (2020)	United Kingdom	Randomized clinical trial.	41 psychiatric inpatients (755 nights) and 18 nurses.	Apply AI-assisted digital nursing observations to minimize sleep disruption while maintaining safety.	Comparison with usual observations without AI.	AI-assisted observations matched manual ones; no adverse events in >755 nights. Qualitative data show improved patient and night-staff experience.	80%
Smith BP. et al.[39] (1998)	USA	Clinical trial.	Heparin dosing and coagulation data from 89 patients.	Evaluate ability of population statistics vs. ANN (MLP) to predict heparin pharmacodynamics during hemodialysis.	Two models: traditional NONMEM *vs* neural network.	Neural network showed greater accuracy and fewer outliers. Distribution volume and clearance increased after dialysis started; baseline coagulation time influenced results. ANN suitable as alternative for dosing predictions.	90%
An R. et al.[24] (2021)	China	Observational study.	300 ICU patients.	Develop classification system stratifying ICU patients by severity and care needs.	N/A	Three clinical subgroups identified with different trajectories and nursing workloads. Regression model predicted classes with good fit and satisfactory performance after 200 permutations.	80%
Du Q. et al.[25] (2022)	China	Randomized clinical trial.	64 patients with diabetic nephropathy.	Develop unsupervised-learning patient classification system; evaluate improved FCM algorithm with PDCA home nursing.	N/A	Experimental group had higher satisfaction and nursing service quality. Improved FCM algorithm aided diagnosis. PDCA home-nursing improved quality of life in diabetic nephropathy.	75%
Flechet M. et al.[18] (2019)	Italy	Observational study.	252 critically ill patients without end-stage renal disease or AKI at ICU admission.	Evaluate the AKIpredictor model to predict AKI-23 within the first week of ICU stay; prospective evaluation.	Compared with ICU physicians' predictions.	At admission, AKIpredictor and physicians showed similar performance (AUROC 0.80 *vs* 0.75). After 24 h, AKIpredictor outperformed clinicians (AUROC 0.95 *vs* 0.89). Net benefit favored AKIpredictor across broader threshold ranges.	80%

Author (Year)	Country	Study Type	Participants	Intervention	Comparison	Main Outcome	CASPe
Tangri N. et al.[20] (2011)	United Kingdom	Comparative study.	3,269 adults initiating peritoneal dialysis (PD) between 1999–2004.	Compare predictive factors for PD technique survival using ANN vs. logistic regression vs. Cox regression.	N/A	PD center had a major impact on technique survival. Other predictors showed marginal/variable effects. Comorbid conditions and high BMI were not consistently associated with increased technique failure.	90%
Barbieri C. et al.[31] (2016)	Portugal, Italy, Spain (Fresenius Medical Care clinics).	Observational study.	4,135 hemodialysis patients.	Develop an ML model to predict anemia-treatment response in ESRD patients on dialysis.	Compared with linear model and MLP; in Italy & Spain also compared with a previously published MLP.	Proposed model outperformed linear and previous MLP models. Success rates for Hb prediction error <1 g/dl: 93% (Portugal), 91% (Italy), 90% (Spain). Low error rates indicate no systematic Hb-estimation bias. MLP showed strong performance and validation in training, validation, and external test sets.	90%

demonstrating that the ML model surpassed the predictive capacity of traditional models[12]. Roth et al.[13] demonstrated the utility of AI in predicting the incidence of chronic kidney disease (CKD) in persons living with HIV. Their evaluation of multiple ML algorithms and modeling strategies showed that ML models outperformed expert-based models, with AUROC values ranging from 0.926 to 0.996 and PR values from 0.631 to 0.956, demonstrating state-of-the-art predictive performance[13]. Jacob et al.[14] developed models based on United States Renal Data System (USRDS) data to accurately predict survival in individuals with end-stage renal disease receiving kidney replacement therapy, showing strong model performance and supporting their usefulness in long-term survival assessment[14].

Five articles highlighted that advances in AI have improved image-analysis capabilities, increasing diagnostic precision in nephrology[18-21]. Toda et al.[18] developed an ML algorithm to detect renal tumors in contrast-enhanced CT images using a multicenter database. The algorithm achieved 84.3% sensitivity and 92.3% specificity, demonstrating utility for early detection of small renal tumors[18]. Other authors have tested the efficiency of AI-based predictive models compared with conventional statistical models. Byun et al.[16] evaluated the survival-predictive capacity of a DL model and concluded it outperformed linear regression models due to its ability to process large heterogeneous datasets (CT images, genetic data, histology), offering the potential to identify new biomarkers and generate hypotheses from large data volumes[16].

In the area of kidney transplantation, one study identified that the application of AI improved risk stratification for kidney transplant recipients. Raynaud et al.[19] used an AI-based tool to predict outcomes following kidney transplantation. The model incorporated histological, immunological, and functional characteristics of the grafts, which were combined with repeated measurements of proteinuria and glomerular filtration rate. This resulted in a global dynamic AUC of 0.857 (95% CI: 0.847–0.866), which improved with successive repeated measurements, increasing from 0.780 (0.768–0.794) to 0.926 (0.917–0.932), demonstrating its high predictive performance ($p<0.0001$)[19].

Application of AI in improving patient care and clinical management

AI has had a significant impact on improving patient care and clinical management. Tangri et al.20 compared predictors of peritoneal dialysis (PD) technique survival using an artificial neural network (ANN) vs Cox regression. Both analyses identified technique failure—defined as switching modality to hemodialysis for more than 30 days—with similar outcomes[20].

Six studies were identified that, while not strictly nephrology-nursing–specific, provided relevant insights from a broader care-delivery perspective.

Hong et al.[21] described that AI-based technology improves the quality of life of patients diagnosed with chronic obstructive pulmonary disease (COPD). A significant improvement in quality of life was demonstrated over a 12-month period, accompanied by a reduction in hospitalization rates and length of hospital stay due to COPD, when nursing interventions were guided by AI. However, in the single-factor analysis, the AI-supported medical intervention did not show significant changes, and the experimental results preliminarily confirmed the effectiveness of AI-assisted medical treatment. In contrast, Zhao et al.[22] explored the effect of AI-based ultrasound image evaluation in patients with diabetic kidney disease, determining that nursing interventions can help control renal function and that intelligent ultrasound imaging systems can monitor these changes[22].

Some AI-based tools focus on early-warning systems. Barrera et al.[23] suggest that digitally assisted nursing observations could maintain patient safety and improve the experience of both patients and staff during night shifts, aiming to minimize sleep disruption—thus proposing new utilities for AI-enabled technology[23].

In efforts to improve clinical care, An R et al.[24] developed a patient-classification system that stratifies individuals upon ICU admission according to severity and care needs, reducing workload burden in nursing teams and demonstrating strong predictive efficiency[24]. Du et al.[25] also developed a self-learning–based patient-classification system to identify subgroups of critically ill patients and build classifiers capable of predicting patient categories, thereby benefiting diagnosis and patient quality of life[25]. Brom et al.[26] identified patients at risk of readmission using a machine-learning technique—classification and regression trees (CART). The findings generated by this algorithm can be used to improve the quality of nursing care delivery for patients with a higher likelihood of readmission.

Regarding nursing care and the risk of communication-related errors, Bagnasco et al.[27] developed artificial neural networks to predict the risk of communication failures. They achieved successful prediction of more than 80% of communication errors based on the characteristics of the receiving operator. The aim is to prevent such failures and ultimately avoid errors in patient care.

Regarding dialysis adequacy parameters, Azar et al.[28] found that the use of AI improves efficiency and reduces complication risk[28]. Their study evaluated the use of artificial neural networks to predict urea rebound and examined different combinations of input parameters to determine the most predictive set, thereby improving the quality of dialysis treatment.

DISCUSSION

Based on the findings of this integrative review, the transformative potential of AI-based tools in the clinical approach and care practices for people with kidney disease—both in hospital and outpatient settings—is evident. The results show that AI enables the prediction of adverse events[27], the early diagnosis of kidney diseases[15,17,18], risk stratification[14,19,29,30], and the optimization of clinical interventions[20,21,23,26,28,30-33], all through the analysis of large volumes of data. These capabilities demonstrate AI's usefulness not only for diagnostic precision and clinical decision-making support, but also as a tool to promote more timely and personalized care. For example, the review highlights how, in critical scenarios, the complementarity between clinical judgment and AI enhances the ability to identify subtle patterns within large datasets, reducing human error and improving diagnostic accuracy[8]. It was also observed that multimodal clinical data analysis has the potential for clinical implementation to optimize risk-prevention strategies and early therapeutic management for individuals at risk of developing kidney diseases[10], through AI-based predictive models[11-13,35].

The advantages offered by AI-based technologies benefit not only patients but also clinical staff. Various interventions demonstrated that AI can personalize treatments, automate repetitive tasks, and prioritize interventions[23,24], with the goal of improving healthcare team efficiency and, most importantly, increasing human interaction time. Likewise, AI has proven useful in out-of-hospital environments: through remote patient monitoring it is possible to identify those at risk of hospital readmission, enabling personalized planning, improved care quality, and reduced financial burden for the health system[26].

AI-driven imaging analysis has also improved diagnostic precision in nephrology, opening new possibilities for clinical outcomes in individuals with kidney disease through more accurate and timely diagnoses[18]. Its application extends to clinical management as a tool for monitoring, treatment planning, and follow-up[19], supporting decision-making and the design of individualized interventions based on predictive risk.

It is clear that AI has an impact not only as a tool for prevention, prediction, and diagnosis in nephrology, but also as a valuable resource to improve patient care and clinical management. Studies validated in various clinical contexts highlight AI's ability to identify complex data patterns invisible to traditional statistical models[20-22]. By recognizing risk patterns early, clinical teams can plan timely interventions to prevent complications associated with renal replacement therapy[28] or kidney-related diseases[21,22].

The benefits of AI-based technologies extend beyond patient well-being and support clinical teams. As demonstrated, AI can personalize care, automate routine activities, and help prioritize nursing interventions[23,24]. Its usefulness has also been shown in outpatient follow-up contexts, identifying patients at risk of rehospitalization and allowing better planning, improved care quality, and lowered care costs[26].

In nephrology nursing practice specifically, AI has the potential to significantly improve care for individuals with kidney disease. Automation of certain clinical tasks allows more time for direct patient care, positively impacting the overall quality of nursing care.

In research, AI can help identify patterns and correlations among risk factors, symptoms, and outcomes, contributing to a deeper understanding of kidney diseases and the development of new therapies. AI should be regarded as a complementary tool to clinical care, supporting but never replacing professional clinical judgment or the empathy that characterizes human-centered care.

Comparatively, the findings of this review align with those reported by authors such as Bagnasco et al.[27] and Zhao et al.[22], who demonstrated AI's impact on clinical settings and nursing practice, including improvements in patient safety, reductions in adverse events, and optimization of nurse-patient care time. However, specific scientific evidence focused on nephrology nursing remains limited. This review helps fill that gap by offering a broad perspective on how integrating these technologies into routine nursing practice can enhance clinical decision-making in kidney health care. For nephrology nursing, AI implementation represents a path toward the future of care through strengthened clinical vigilance, individualized care planning, and continuous quality improvement—supported by predictive models that anticipate health deterioration and guide early therapeutic interventions.

Despite the promising findings, several limitations were identified. Sample sizes varied greatly across studies, demonstrating substantial heterogeneity in population characteristics, AI algorithms used (from logistic regression to artificial neural networks), and clinical environments. These discrepancies hinder direct comparisons and reduce the generalizability of findings. Additionally, many models were validated only on local datasets with no external testing, limiting their broader applicability and potentially introducing bias when used with populations of different clinical or sociodemographic characteristics. Furthermore, several included studies were not exclusively focused on nephrology nursing, a limitation often encountered due to limited scientific literature in the field. Nevertheless, including broader interdisciplinary studies enriched the review by offering complementary perspectives relevant to nursing practice.

Challenges and opportunities for AI implementation were also identified. There is a need for multicenter validation studies to ensure reliability across diverse clinical settings. Intervention strategies are required to progressively integrate AI into kidney care processes and rigorously evaluate model performance in real-world environments. Future research should explore cost-effectiveness, usability among nursing staff, and the impact of AI on clinically meaningful outcomes for people with kidney disease. Ethical and legal considerations are also crucial, including data privacy, transparency of AI tools, equity and nondiscrimination, and equitable access to such technologies.

In conclusion, the synthesis of findings supports AI as a complementary tool in the care of individuals with kidney disease—particularly for prediction, risk stratification, and clinical decision-making support. Although several well-designed studies demonstrate clinically relevant outcomes, caution is advised when generalizing the findings due to limited external validation and study heterogeneity. The integration of AI into renal care must rely on solid evidence while respecting the clinical judgment and human-centered approach fundamental to nursing practice.

Authors' contributions

All authors participated in literature search, review protocol development, data collection, analysis, interpretation, and writing.

Conflicts of interest

The authors declare no financial, personal, or institutional conflicts of interest that could have influenced the development of this research.

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