

Artificial Intelligence in The Care of Kidney Failure Patients Undergoing Dialysis: A Narrative Review

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NARRATIVE REVIEW

Artificial intelligence (AI) is increasingly transforming the care of patients with kidney failure undergoing dialysis, driven by advances in machine learning (ML) and deep learning (DL), alongside the availability of large, structured, and longitudinal clinical datasets and advances in computational resources. Dialysis practice is uniquely suited to AI applications due to its data-dense environment, characterised by repetitive treatments, continuous physiological monitoring, and integration with electronic health records and global registries. Early rule-based systems from the 1980s have evolved into sophisticated data-driven models capable of capturing complex, non-linear clinical relationships.

This review examines contemporary and emerging AI applications across the dialysis care continuum, including dialysis initiation, vascular access planning and surveillance, dialysis adequacy assessment, peritoneal dialysis peritonitis management, nutritional optimisation, intradialytic haemodynamic stability, anaemia management, and prediction of cardiovascular events and mortality. Across these domains, AI models—ranging from artificial neural networks to ensemble and reinforcement learning approaches—have consistently demonstrated superior predictive performance compared with traditional statistical methods, with potential to enable real-time, individualised clinical decision-making capable of continuous performance improvement.

AI-driven tools are increasingly transitioning from retrospective risk prediction to prospective, actionable decision support, including integration into dialysis machines and clinical dashboards. These developments support a shift toward proactive, personalised, and adaptive dialysis care. However, significant challenges remain, including data heterogeneity, limited external validation, model interpretability, workflow integration barriers, and concerns regarding data governance, privacy, and medico-legal accountability.

Future progress will depend on multicentre validation, harmonisation of registry data, and development of explainable, clinician-in-the-loop systems. With these advances, AI has the potential to redefine dialysis care through continuously learning, patient-centred clinical ecosystems.

Key Words: Artificial intelligence, Machine learning, Deep learning, Ensemble models, Haemodialysis, Peritoneal dialysis, Vascular access, Renal anaemia management, Cardiovascular mortality

INTRODUCTION

Artificial intelligence (AI) is a broad discipline focused on developing computational systems capable of performing tasks that traditionally require human intelligence, such as pattern recognition, reasoning, judgment, decision-making, and prediction.(1, 2) Machine learning (ML) constitutes the core methodological engine of contemporary AI, particularly in medicine, as it enables systems to learn patterns and generate predictions directly from data rather than relying on explicitly programmed rules.(2, 3) While algorithmic robustness and computational capacity are important, the reliability of medical AI models is determined primarily by the quality, representativeness, and clinical relevance of the data used for training, rather than by model complexity alone.(3, 4)

The rapid advancement of AI, particularly deep learning (DL)-based methods, has the potential to transform AI-assisted healthcare at an unprecedented pace.(5, 6) AI-based tools are already playing increasingly important roles across multiple medical specialties, including nephrology, where they are being applied to improve the care of patients with kidney disease, dialysis patients, and transplant recipients.(7) The core concepts, perspectives, broad clinical applications, and challenges of AI in nephrology have been reviewed previously.(7, 8)

Building on this foundation, the present review focuses in greater depth on the current and emerging applications of AI-based tools in the care of patients with kidney failure undergoing dialysis.

Why AI-based tools are suited for dialysis practice

The typical dialysis patient journey—from advanced stage 5 chronic kidney disease through dialysis planning, dialysis access creation, treatment initiation, maintenance therapy, and complication management—generates a wealth of data, much of it numerical, structured, and highly reproducible. The frequent and repeated interactions between dialysis patients and healthcare systems produce large volumes of longitudinal data at the individual patient level, many of which are directly relevant to their clinical outcomes and well suited for training AI models. Modern dialysis equipment, including haemodialysis (HD) and peritoneal dialysis (PD) cyclers machines, continuously generate high-resolution treatment and physiological data during therapy delivery. Although the volume and granularity of these data often exceed what can be comprehensively reviewed and judged by the clinicians in routine practice, they can be systematically captured through electronic systems and incorporated into AI training pipelines. Large volumes of geographically diverse, clinically rich, and standardized real-world data on kidney failure patients are captured across up to 79 registries spanning 77 countries, including the United States Renal Data System (USRDS), Australia and New Zealand Dialysis and Transplant Registry (ANZDATA), and European Renal Association (ERA-EDTA) Registry.(9) Harmonisation and accessibility of these datasets could enable the development of robust AI models, supporting

widely generalisable clinical decision tools with global applicability. Collectively, the data-dense and highly standardised nature of dialysis care makes it an ideal clinical domain for the development, testing, and implementation of medical AI tools.

RULE-BASED ALGORITHMIC PRECURSORS TO MODERN AI IN DIALYSIS

The earliest applications of computer-assisted, algorithm-based approaches in dialysis date back to the 1980s and early 1990s, when clinical and biochemical data were used to support the generation of individualised dialysis prescriptions. (10) These tools were predominantly rule-based expert systems, similar to those being explored contemporaneously in other areas of medicine and reflected early aspirations toward artificial intelligence-assisted clinical decision-making.(11, 12) They relied on explicitly encoded clinician rules rather than data-driven learning and were constrained by limited computational resources and the absence of large, digitised clinical datasets.(13) Despite these limitations, these early systems established the foundational concept that dialysis decision-making can be augmented through computational assistance, paving the way for subsequent data-driven AI approaches.(14, 15)

The transition from rule-based systems to data-driven ML occurred in the 1990s, when artificial neural networks (ANNs) and non-linear regression models were first applied to dialysis patients.(16, 17) At a fundamental level, many contemporary AI systems are built using ANNs, which are computational models composed of interconnected nodes, often referred to as “neurons”.(18) These neurons are not physical structures, but software-implemented mathematical constructs defined by weighted inputs, bias terms, and activation functions that perform customised arithmetic operations. This terminology reflects the historical origin of ANNs in simplified mathematical abstractions of biological neural activity, beginning with McCulloch and Pitts’ threshold neuron model,(19) and Rosenblatt’s perceptron.(20) Neural networks are computational systems inspired by the brain’s ability to learn internal representations from experience, although these models remain highly simplified abstractions of biological neurons.(21)

Early studies from the 1990s demonstrated that ANNs trained on patient-level data outperformed traditional regression-based formulas, such as Syme’s and Daugirdas’ equations, in predicting equilibrated Kt/V,(16) and achieved greater accuracy than non-linear mixed-effects models for anticoagulation modelling.(17) These findings highlighted the ability of neural networks to capture complex, non-linear relationships and to remain relatively robust in the presence of noisy or incomplete clinical data when appropriately trained.(22)

Early ANNs, which had limited capacity to model highly complex data, subsequently evolved into convolutional neural networks (CNNs) through the incorporation of convolutional and pooling layers, enabling efficient learning from high-dimensional,

spatially structured inputs.(23) The rapid progress of AI in medicine over the past decade has been largely driven by advances in DL - particularly the development of CNN architectures - together with the convergence of large-scale clinical datasets, substantial gains in computational power, and the availability of scalable digital infrastructure.(23, 24) DL-based computer vision (CV) methods have been influential particularly in medical imaging and other spatially structured data, while the advances in natural language processing (NLP), especially transformer based language models enabled AI systems to process unstructured clinical text.(18, 23) Together, these developments have expanded medical AI beyond structured prediction tasks to imaging, signal analysis, clinical documentation, and decision support.

The following sections examine the specific domains of dialysis care—ranging from dialysis initiation, vascular access planning, surveillance and complications, dialysis prescription optimisation, intradialytic complications and outcome predictions - in which AI-based tools have demonstrated practical clinical value. Studies such as the prediction of the development of COVID infection in the HD population (25, 26)— topics not directly related to the dialysis process are not covered in this review.

DIALYSIS INITIATION:

The question of when to start dialysis for kidney failure is not fully resolved.(27) Despite a focus on the e-GFR based thresholds in routine clinical practice, the decision is far more complex and influenced by many factors, including symptoms and signs related to kidney failure.(28, 29) Such a multidimensional approach is reflected in the KDOQI haemodialysis clinical practice guidelines, which recommend that dialysis initiation should be based on clinical signs and symptoms in conjunction with kidney function rather than kidney function alone.(30) Emerging AI models try to integrate multidimensional clinical information and may, following prospective validation, inform future guideline development and support more individualised decision-making.

Early applications of AI to dialysis initiation have focused on addressing the long-standing limitation of eGFR-based thresholds by integrating multidimensional clinical information into decision-support tools. A retrospective study developed and externally validated a neural network model across large multicentre cohorts, demonstrating superior discrimination for predicting 3-year survival after dialysis initiation compared with eGFR alone (AUROC ~0.70 vs ~0.54), underscoring the inadequacy of eGFR as the sole guiding tool.(31) Using a similar 'Dialysis Initiation Fuzzy Equation (DIFE)' that combines biochemical parameters, symptoms, and clinical context, has been proposed and planned to be examined in a multicentre randomised controlled trial designed to test whether AI-guided initiation improves 3-year mortality and clinical outcomes compared with conventional initiation strategies.(32)

Collectively, these studies suggest that AI-based, integrative frameworks may better capture the physiological complexity surrounding dialysis initiation than traditional thresholds and subjective assessments, which can be highly varied in clinical practice. Looking ahead, successful translation of such models into routine practice will depend on the demonstration of patient-centred benefit, seamless integration into clinical workflows, and evolution toward adaptive, continuously learning systems that personalise dialysis initiation timing rather than relying on rigid biochemical cut-offs.

DIALYSIS ACCESS: ARTERIO-VEIN FISTULA AND GRAFTS

Arterio-venous fistulas (AVF) are considered the gold standard vascular access for haemodialysis because of their low infection rates, prolonged patency, and improved durability.(33) However, the creation and long-term maintenance of AVF remain challenging, with a substantial burden of primary non-function, ongoing access dysfunction, and frequent need for repeated reinterventions.(34) The standard approach to overcome these barriers include target vessel mapping prior to AVF creation, active ultrasound surveillance and proactive interventions to maintain assisted patency.(33)

AI applications have been assessed in the domain of AVF planning and longitudinal outcome prediction. Simplified staging systems such as Arterio-venous access stage (AVAS) system, incorporating clinical history, examination, and limited measurements, and augmented by ML, approached the diagnostic performance of comprehensive ultrasound mapping while being more feasible for routine clinical use.(35) ML models using preoperative clinical data have shown strong performance for predicting AVF maturation approaching 97% accuracy in estimating postoperative flows. (36) Analysis of large, RCT-derived datasets using ML-supported Cox models has enabled robust prediction of long-term arteriovenous fistula patency and re-intervention burden incorporating early postoperative ultrasound data, and demonstrated the feasibility of individualized prediction via clinician-facing web applications.(37)

Most of the published AI applications in the field of AV access have focused on AVF surveillance and dysfunction. Although auscultation of an AVF can offer valuable clues about access health and maturation, its inherently subjective nature limits reliability, often necessitating reliance on ultrasound surveillance, which is more costly and less accessible. AI applications for AV access using 'AVF sounds' in dialysis have shown promise in enhancing the reliability of AVF surveillance by leveraging acoustic signal analysis to overcome the inherent subjectivity of clinical auscultation.

Early rule-based AI systems using fuzzy Petri nets demonstrated that phonoangiographic spectral features could classify AV shunt stenosis more accurately than human assessment.(38) Subsequent

proof-of-concept ML approaches analysing AVF sound patterns enabled low-cost, non-invasive surveillance strategies (39) while CNN-based models achieved accuracies exceeding 90% for grading stenosis-related AVF sounds.(40) More recent DL studies have reported near-perfect diagnostic performance, with discrimination against angiographic reference standards reaching an AUC of 0.99 for detecting $\geq 50\%$ AVF stenosis.(41) Similarly, contrastive learning-based DL models using smartphone-recorded AVG sounds from arterial and venous sides, transformed to spectrograms, demonstrated $>90\%$ accuracy for detecting AVG stenosis.(42) Lightweight CNNs have further demonstrated the feasibility of translating these technologies to the bedside through deployment on local, resource-limited devices, achieving near-perfect classification with minimal computational burden.(43)

AI has also been applied to the field of AVF complications, including thrombosis and high-flow states. ML models demonstrated excellent discriminative performance (AUROC 0.86–0.90) for predicting AVF thrombosis.(44) Larger retrospective studies demonstrated very high discrimination (AUROC > 0.95), SHAP analysis provided quantitative insight into how predictors influenced model outputs, enhancing the potential for personalised and evidence-based clinical interventions.(45)

While a mature, functioning AVF is essential for effective haemodialysis delivery, a proportion of AVF patients develop high-flow fistulas, with flows reaching up to 4000 mL/min, with potential adverse cardiovascular health impact.(46) In a cohort of 366 patients, bootstrap forest-based ML models predicted the development of high-flow AVFs (>2000 mL/min) with excellent discriminative performance (AUC ≈ 0.94), with approximately 30% of prevalent HD patients affected.(47) Finally, implementation of a real-time ML analytics platform within routine care was associated with improved vascular access management and lower predicted costs, supporting greater efficiency and highlighting the potential for AI-driven approaches to inform future standards of care in dialysis therapy. (48)

Overall, many of these AI tools in this context are best viewed as decision-support adjuncts rather than autonomous clinical replacements. Models with multi-centre data, external validation, interpretable outputs, and deployable dashboards appear most ready for individual patient care, whereas highly accurate single-centre acoustic or retrospective models still require broader validation.

DIALYSIS ADEQUACY

Urea kinetic modelling (UKM) has long provided the mathematical framework for quantifying dialysis adequacy, though reliance on small-solute urea clearance alone fails to fully capture the broader clinical impact of dialysis, including mortality, patient-centred outcomes, and quality of life.(49) However, dialysis adequacy is distinct from the broader quality of

dialysis patient management, and Kt/V (urea), derived from UKM, remains the predominant metric widely used to quantify delivered dialysis dose.(30)

The estimation of Kt/V (urea) in clinical settings most commonly relies on single-pool kinetics, which are susceptible to error due to post-dialysis urea rebound. While variable-volume, double-pool models provide more accurate estimates of urea generation and clearance,(50) their technical requirements - particularly the need for delayed post-dialysis blood sampling - limit their feasibility for routine clinical use.

AI based approaches to estimating dialysis adequacy have been investigated for more than two decades, with early efforts centred on ANNs to address the limitations of formula-based Kt/V calculations and the impracticality of repeated blood sampling. Initial studies demonstrated that ANNs could accurately predict Kt/V and equilibrated urea kinetics using dialysate-side measurements and routinely available treatment data, often matching or outperforming experienced nephrologists and conventional urea reduction-based methods.(51, 52) Subsequent validation studies confirmed that ANN-based models achieved comparable or superior diagnostic performance to established Kt/V formulas, with lower false-positive rates and strong correlations with measured equilibrated urea concentrations. (53) Notably, ANN models were able to estimate equilibrated Kt/V without post-dialysis blood sampling, achieving very high correlations (up to $r = 0.97$) and more accurate estimation of urea rebound than traditional methods.(54) Together, these early studies provided proof-of-concept that AI could deliver reliable, clinically meaningful assessments of dialysis adequacy and potentially substitute conventional kinetic approaches in routine practice.

More recent studies have expanded this concept using modern ML and data-driven techniques applied to large-scale, routinely collected dialysis data. Fuzzy logic systems and graph-based Takagi–Sugeno–Kang models have demonstrated that dialysis adequacy can be approximated using non-invasive clinical and intradialytic variables, achieving low prediction errors.(55) ML ensemble models, including XGBoost and Random Forests, trained on continuously captured HD machine data, have consistently outperformed conventional regression approaches, demonstrating strong correlations and low prediction errors across thousands of dialysis sessions.(56) These approaches belong to a broader class of tree-based ensemble methods, which make predictions by combining many simple prediction pathways rather than relying on a single statistical equation. Random Forests generate multiple such prediction pathways in parallel and combine their outputs, making the final prediction less dependent on any one unstable pattern in the dataset.(57) XGBoost uses a sequential strategy, where, instead of building many prediction pathways independently, it builds them step by step, with each new component focusing on the errors left by the previous ones.(58) This allows the model to progressively

improve its predictions in complex datasets where relationships are nonlinear or difficult to capture using conventional techniques. This may also explain why ensemble methods such as Random Forests and XGBoost perform well with dialysis data where the outcome is influenced by several overlapping complex factors such as blood flow, dialysate flow, treatment duration, membrane characteristics, blood chemistry levels, patient physiological parameters and so on.

Contemporary studies have further shown robust discrimination for clinically relevant adequacy thresholds, with AU-ROC values around 0.86–0.88 and preserved performance even in simplified, non-invasive models relying solely on general patient characteristics and dialysis-related parameters.(59, 60) Collectively, these findings suggest a trajectory toward real-time, individualized assessment of dialysis adequacy, with less reliance on blood tests and the potential for tools integratable with dialysis machines and clinical decision-support systems. This could enable us to personalize prescriptions, improve efficiency, and facilitate more adaptive, patient-centred dialysis care.

PD PERITONITIS AND TECHNIQUE FAILURE (HD TRANSFER)

PD peritonitis is a common serious complication of long-term PD which is currently managed using criteria-based diagnostic frameworks, with definitive confirmation pending formal culture results, and initial treatment using rule-based empiric antibiotic protocols. (61) This approach, while effective, may in the future be refined or supplanted by adaptive, AI-driven decision systems capable of real-time individualised prediction and therapy optimisation.

ML approaches can provide new insights by analysing peritoneal effluent immune cell populations together with inflammatory and regulatory cytokines and chemokines. ML-based methods can identify pathogen-specific immune “fingerprints,” enabling discrimination between different classes of causative organisms based on distinct cellular and cytokine signatures.(62) On the treatment front, model-free ML approaches have accurately predicted intraperitoneal antibiotic concentrations and clinically relevant exposure thresholds, outperforming traditional compartment-based pharmacokinetic models following intraperitoneal antibiotic administration.(63) While the implementation of these approaches could be several years away, they provide a potential for individualized therapy of PD peritonitis which could be more effective and favourably impact the risk of mortality, morbidity and HD transfer, in this population.(61)

Artificial intelligence-based approaches to predicting PD technique failure (HD transfer) have been explored for more than a decade. Early work demonstrated ANNs outperformed logistic regression in predicting early PD technique failure.(64) More recent studies have expanded predictive capacity by integrating mesothelial–mesenchymal transition biomarkers with clinical and

longitudinal data, enabling more granular prediction of peritoneal dialysis endurance and downstream complications, with month-level accuracy in forecasting PD technique survival.(65)

DIET IN KIDNEY FAILURE

AI has been applied to nutritional assessment and dietary management in kidney failure for over two decades, addressing long-standing challenges in accurately estimating dietary intake and identifying patients at nutritional risk. Early studies demonstrated that ANNs could predict short-term dietary protein intake in haemodialysis patients more accurately than experienced nephrologists, highlighting the capacity of data-driven models to capture complex dietary patterns, with performance closely linked to the size and heterogeneity of the training population. (52) More recently, explainable ML models have shown value in identifying patients at risk of protein–energy wasting, achieving good discrimination ($AUC \approx 0.83$) while providing interpretable predictors that support earlier and more objective nutritional intervention.(66) AI applications have also been extended into nutritional decision support, with a Generative Pre-trained Transformer (GPT)-based dietary recommendation system using real-time food image analysis improving the accuracy of dietary potassium estimation and achieving clinically meaningful reductions in pre-dialysis hyperkalaemia.(67) This highlights the potential of AI-assisted tools to deliver individualized dietary guidance.

VOLUME AND INTRA-DIALYTIC HYPOTENSION

Initial application of AI in managing dialysis related haemodynamic challenges focused on improving the prediction of intra-dialytic hypotension (IDH) and streamlining volume status assessment. Early studies demonstrated that ANNs could outperform experienced nephrologists in predicting IDH, as well as estimate key physiological parameters such as total body water and dry weight with greater accuracy than traditional anthropometric or equation-based approaches.(52, 68) By integrating real-time blood pressure (BP) and ultrafiltration rate (UFR) inputs, fuzzy logic systems progressed from prediction to active control, showing that AI-embedded ultrafiltration modulation within dialysis machines significantly reduces severe IDH while preserving fluid removal goals.(69) As data density and computational capacity expanded, ML models became increasingly capable of capturing the non-linear physiological dynamics of haemodialysis. Support vector regression, followed by ensemble and DL approaches, outperformed linear methods in modelling blood volume, heart rate responses, and dry weight using routinely collected clinical and bioimpedance data,(70-72) marking a shift from rule-based control toward more flexible, high-dimensional physiological modelling. Recurrent neural networks and gradient-boosting models leveraging high-frequency dialysis machine data and time-stamped vital signs have enabled near real-time prediction of rapid blood volume contraction and IDH, demonstrating excellent

discriminative performance (AU-ROC ≥ 0.89) across large and diverse dialysis cohorts.(73-75) These advances have shifted AI systems from retrospective risk modelling techniques toward actionable, real-time point-of-care tools capable of supporting timely and targeted clinical actions.

Personalized dashboards that integrate historical and real-time dialysis data have further enhanced the ability to predict IDH - up to an hour in advance and have been associated with measurable reductions in hypotension rates following implementation in routine clinical practice. (76)

Explainable ML frameworks and techniques such as generative adversarial networks (GAN) based data balancing and temporal knowledge graphs have further improved robustness, interpretability, and longitudinal risk prediction, enabling early warning of both hypotensive and hypertensive events across diverse patient trajectories.(77-80)

Collectively, these studies point toward a future in which AI-driven, continuously learning systems are embedded within dialysis machines and clinical workflows, enabling adaptive ultrafiltration, and pre-emptive prevention of haemodynamic instability—moving haemodialysis care from reactive management to proactive patient-specific therapy.

RENAL ANAEMIA / ERYTHROPOIETIN (EPO) THERAPY:

Renal anaemia management is inherently complex, requiring regular monitoring of haemoglobin and iron indices, ongoing individualized titration of erythropoietin dosing, and haematonic supplementation as clinically indicated, as well as careful identification and management of non-renal contributors to anaemia when present.(81)

AI-based tools could inform optimal dosing strategies and improve treatment efficiency. ML models, including support vector regression and ANNs, could predict individual EPO dosing more accurately than experienced nephrologists, substantially improving sensitivity for identifying under-treated patients while maintaining high specificity.(82, 83) Training ANNs on large multicentre datasets yielded robust and generalisable haemoglobin prediction models, with residual errors predominantly reflecting intercurrent clinical events rather than limitations in the models themselves.(84, 85) Hybrid systems combining ANNs with model predictive control frameworks reduced haemoglobin variability and improved time within target ranges compared with standard anaemia protocols, in both simulation and clinical settings, albeit in small patient cohorts.(86)

Expert-trained AI systems have demonstrated high clinical appropriateness in recommending ESA and iron therapy, which are required for safe clinical deployment.(87) Reinforcement-learning-based personalized dosing policies and explainable ML models have consistently improved haemoglobin

target attainment while reducing ESA dose and variability, underscoring their efficiency and implementation readiness.(88, 89) Decision support systems powered by AI can lower costs and improve quality of life even when applied at a population level, as demonstrated in health-economic modelling studies.(90)

MORTALITY / SURVIVAL / CV EVENTS:

Cardiovascular and non-cardiovascular mortality are 10-20 times higher in dialysis patients compared to general population.(91) Though the secular trends in cardiovascular mortality indicate a gradual reduction over the years in some dialysis patients, the excess cardiovascular risk when compared to the general population is in fact increasing.(92) Early identification of at-risk individuals using AI-based approaches, which have the ability to discern complex non-linear relationship between variables,(93) might permit aggressive interventions with the potential for outcome benefits.

ML models using random forests, non-linear support vector machines and ensemble models accurately predicted ischaemic heart disease, and mortality including sudden cardiac death in in the US, European and Japanese patients by leveraging pre- and post-dialysis electronic health information.(94-96). A simplified interpretable ML model predicted all-cause mortality and time to death utilizing only clinical data without laboratory results, with greater accuracy compared to regression models.(97) ML predictive models in general have been shown to be highly reliable in early identification of high-risk subjects, potentially enabling early interventions.(93)

AI-models retain the ability to predict mortality across multiple time horizons after dialysis initiation. XGBoost-based ML model discriminated risk of mortality within 90 days with excellent calibration, among 1 million subjects from USRDS data over 10 years.(98) Similar models have demonstrated impressive AUC-ROC values ranging from 0.933-0.979 in predicting 1-year, 4-year and 7-year mortality.(99) An autoencoder-driven DL framework that leverages short-term HD data (93) (61) predicted near- and medium-term mortality with high accuracy despite substantial missing data, (22) which is a common problem with health information databases.

There is a strong relationship between high BP and cardiovascular death in the general population, as well as dialysis patients, and BP lowering significantly improves all-cause and cardiovascular mortality in dialysis patients.(100) DL models based on CNNs using data from multiple HD sessions identified clinically meaningful longitudinal blood pressure patterns during haemodialysis and substantially improved prediction of 1-year mortality compared with single-session analyses, demonstrating the value of accrued treatment information.(101) ML models in PD patients also has demonstrated BP patterns, namely visit-to-visit BP variability to be an important predictor of CV mortality and outcomes.(102)

A fuzzy logic-based clinical decision support system provided risk stratification aligned with clinician judgement regarding cardiovascular disease risk in diabetic HD patients.(103) ML models incorporating bio-markers such as circulating microRNA profiles and interleukin IL12p70, significantly improved cardiovascular risk prediction in HD patients beyond conventional clinical variables.(104, 105)

DL models, have improved mortality prediction in peritoneal dialysis patients as much as in haemodialysis patients, especially in capturing the complex non-linear relation with greater accuracy.(106-108) ML models are superior to conventional Cox regression models in predicting CV events.(109) With respect to surrogate CV markers, pulse wave-driven ML models predicted coronary calcification with an average accuracy of 84% in HD patients. (65, 110) Collectively, AI-based approaches appear to identify cardiovascular risk with greater precision and consistency, potentially enabling more targeted interventions in the dialysis population—a group that has historically shown limited benefit from therapies proven effective in RCTs in the general population. (111)

END-TO-END AI-ENABLED DIALYSIS PATIENT JOURNEY – WHAT THE FUTURE MIGHT LOOK LIKE:

AI based technologies appear to hold tremendous future potential in kidney failure therapies. AI-enabled dashboards embedded within electronic health records could integrate longitudinal primary and specialist care data—including laboratory, imaging, and potentially genomic information—to predict disease trajectories and enable timely interventions. Live systems could incorporate emerging clinical trial evidence and real-world patient experience into training datasets, supporting progressively refined decision-making. Planning and implementation of vascular and peritoneal access could likewise be optimised through AI-enabled decision support, maximising the likelihood of successful outcomes. At the point of dialysis initiation, AI systems within electronic records and dialysis platforms may be able to process multidimensional data to personalise initiation strategies. During maintenance haemodialysis or peritoneal dialysis, real-time integration of high-density machine data, physiological signals, and prior treatment responses can enable dynamic adjustment of ultrafiltration, dialysate composition, and session duration, individualising each treatment and minimising complication risks. Continuous monitoring via wearable devices and patient-reported outcomes may extend this ecosystem beyond the dialysis unit, facilitating early detection of complications such as volume overload, infection, or cardiovascular instability. AI-driven decision support can further refine longitudinal management—including anaemia therapy, nutritional optimisation, and vascular access surveillance—through integration of multimodal, time-series data. Ultimately, such systems would function as continuously learning, closed-loop

clinical environments that augment clinician judgement while delivering personalised, anticipatory, and adaptive dialysis care.

LIMITATIONS AND CHALLENGES

Despite rapid advances, the implementation of AI in dialysis care remains constrained by challenges related to data quality, heterogeneity, interoperability across healthcare systems, and concerns regarding privacy, data governance and usage. The majority of published studies remain retrospective, and single-centre with limited external validation or prospective implementation. It should also be appreciated that improvements in predictive performance do not necessarily guarantee improved patient outcomes.

The complexity and relative opacity of advanced ML and DL models could affect clinician trust, and regulatory acceptance, particularly in high-stakes clinical decision-making contexts. Implementation can be challenging due to clinician cognitive overload, and unresolved medico-legal questions around accountability and liability. In addition, performance drift over time necessitates continuous model monitoring, recalibration, and robust governance frameworks. Algorithmic bias from non-representative dataset, fairness across ethnic and socio-economic groups and transportability across diverse healthcare systems and populations are also major concerns in medical AI and should be considered in the development and adoption of these technologies to routine clinical practice. Training based on geographically diverse datasets, multi-centre external validation and continuous model monitoring and recalibration are essential for these technologies to add value to healthcare. Future efforts should prioritise prospective multicentre validation, harmonisation of large-scale registry data, development of explainable and clinician-in-the-loop systems, and adoption of privacy-preserving consensus approaches to enable robust, equitable, and globally applicable AI tools in the care of dialysis patients.

REFERENCES

1. Rajpurkar P, Chen E, Banerjee O, Topol EJ. AI in health and medicine. *Nat Med*. 2022;28(1):31–8.
2. Al Kuwaiti A, Nazer K, Al-Reedy A, Al-Shehri S, Al-Muhanna A, Subbarayalu AV, et al. A Review of the Role of Artificial Intelligence in Healthcare. *J Pers Med*. 2023;13(6).
3. Haug CJ, Drazen JM. Artificial Intelligence and Machine Learning in Clinical Medicine, 2023. *N Engl J Med*. 2023;388(13):1201–8.
4. Cross JL, Choma MA, Onofrey JA. Bias in medical AI: Implications for clinical decision-making. *PLOS Digit Health*. 2024;3(11):e0000651.
5. Huo Y, Deng R, Liu Q, Fogo AB, Yang H. AI applications in renal pathology. *Kidney Int*. 2021;99(6):1309–20.
6. Obermeyer Z, Emanuel EJ. Predicting the Future - Big Data, Machine Learning, and Clinical Medicine. *N Engl J Med*. 2016;375(13):1216–9.

7. Niel O, Bastard P. Artificial Intelligence in Nephrology: Core Concepts, Clinical Applications, and Perspectives. *Am J Kidney Dis.* 2019;74(6):803–10.
8. Singh P, Goyal L, Mallick DC, Surani SR, Kaushik N, Chandramohan D, et al. Artificial Intelligence in Nephrology: Clinical Applications and Challenges. *Kidney Med.* 2025;7(1):100927.
9. Ng MSY, Charu V, Johnson DW, O'Shaughnessy MM, Mallett AJ. National and international kidney failure registries: characteristics, commonalities, and contrasts. *Kidney Int.* 2022;101(1):23–35.
10. Kovarik J, Graf H, Irschik H, Pohanka E, Stummvoll HK. [Individual dialysis using computer-controlled prescription]. *Wien Klin Wochenschr.* 1985;97(21):809–12.
11. Shortliffe EH. The computer as clinical consultant. *Arch Intern Med.* 1980;140(3):313–4.
12. Shortliffe EH, Buchanan BG. Artificial intelligence. *N Engl J Med.* 1980;302(26):1482.
13. Shortliffe EH, Sepúlveda MJ. Clinical Decision Support in the Era of Artificial Intelligence. *Jama.* 2018;320(21):2199–200.
14. Graf H, Irschik H, Kovarik J, Stummvoll HK. A new algorithm for individual dialysis prescription based on urea kinetics. *Med Prog Technol.* 1986;11(4):191–6.
15. Peek N, Combi C, Marin R, Bellazzi R. Thirty years of artificial intelligence in medicine (AIME) conferences: A review of research themes. *Artif Intell Med.* 2015;65(1):61–73.
16. Guh JY, Yang CY, Yang JM, Chen LM, Lai YH. Prediction of equilibrated postdialysis BUN by an artificial neural network in high-efficiency hemodialysis. *American Journal of Kidney Diseases.* 1998;31(4):638–46.
17. Smith BP, Ward RA, Brier ME. Prediction of anticoagulation during hemodialysis by population kinetics and an artificial neural network. *Artif Organs.* 1998;22(9):731–9.
18. Hornik K. Approximation capabilities of multilayer feedforward networks. *Neural Networks.* 1991;4(2):251–7.
19. McCulloch WS, Pitts W. A logical calculus of the ideas immanent in nervous activity. 1943. *Bull Math Biol.* 1990;52(1-2):99–115; discussion 73–97.
20. Rosenblatt F. The perceptron: a probabilistic model for information storage and organization in the brain. *Psychol Rev.* 1958;65(6):386–408.
21. Hinton GE. How neural networks learn from experience. *Sci Am.* 1992;267(3):144–51.
22. Su S, Gao J, Dong J, Guo Q, Ma H, Luan S, et al. Prediction of mortality in hemodialysis patients based on autoencoders. *Int J Med Inf.* 2025;195:105744.
23. Davenport T, Kalakota R. The potential for artificial intelligence in healthcare. *Future Healthc J.* 2019;6(2):94–8.
24. Topol EJ. High-performance medicine: the convergence of human and artificial intelligence. *Nat Med.* 2019;25(1):44–56.
25. Xiao L, Zhang H, Duan J, Ma X, Usvyat LA, Kotanko P, et al. Predicting SARS-CoV-2 infection among hemodialysis patients using deep neural network methods. *Sci.* 2024;14(1):23588.
26. Monaghan CK, Larkin JW, Chaudhuri S, Han H, Jiao Y, Bermudez KM, et al. Machine Learning for Prediction of Patients on Hemodialysis with an Undetected SARS-CoV-2 Infection. *Kidney360.* 2021;2(3):456–68.
27. Jia X, Tang X, Li Y, Xu D, Moreira P. Update of dialysis initiation timing in end stage kidney disease patients: is it a resolved question? A systematic literature review. *BMC Nephrol.* 2023;24(1):162.
28. Cooper BA, Branley P, Bulfone L, Collins JF, Craig JC, Fraenkel MB, et al. A randomized, controlled trial of early versus late initiation of dialysis. *N Engl J Med.* 2010;363(7):609–19.
29. Chen T, Lee VW, Harris DC. When to initiate dialysis for end-stage kidney disease: evidence and challenges. *Med J Aust.* 2018;209(6):275–9.
30. National Kidney F, Daugirdas JT, Depner TA, Inrig J, Mehrotra R, Rocco MV, et al. KDOQI Clinical Practice Guideline for Hemodialysis Adequacy: 2015 Update. *American Journal of Kidney Diseases.* 2015;66(5):884–930.
31. Liu Y, Wang D, Chen X, Sun X, Song W, Jiang H, et al. An Equation Based on Fuzzy Mathematics to Assess the Timing of Haemodialysis Initiation. *Sci.* 2019;9(1):5871.
32. Chen J, Liu Y, Chen X, Sun X, Li W, Yang W, et al. Assessment of dialysis initiation by a fuzzy mathematics equation (ADIFE): a study protocol for a randomised controlled trial. *BMJ Open.* 2019;9(9):e023162.
33. Bylsma LC, Gage SM, Reichert H, Dahl SLM, Lawson JH. Arteriovenous Fistulae for Haemodialysis: A Systematic Review and Meta-analysis of Efficacy and Safety Outcomes. *European Journal of Vascular and Endovascular Surgery.* 2017;54(4):513–22.
34. Udawadia FR, Cohen D, Gu N, Mordhorst A, Skala T, Hsiang YN, et al. Practical and ethical challenges of maintaining vascular access in chronic kidney disease: A qualitative interview study. *JVS-Vascular Insights.* 2024;2:100050.
35. Lawrie K, Waldauf P, Balaz P, Bortel R, Lacerda R, Aitken E, et al. Machine learning validation of the AVAS classification compared to ultrasound mapping in a multicentre study. *Sci.* 2025;15(1):2538.
36. Doneda M, Poloni S, Bozzetto M, Remuzzi A, Lanzarone E. Surgical planning of arteriovenous fistulae in routine clinical practice: A machine learning predictive tool. *J.* 2024;25(4):1170–9.
37. Fitzgibbon JJ, Ruan M, Heindel P, Appah-Sampong A, Dey T, Khan A, et al. Predicting long-term patency of radiocephalic arteriovenous fistulas with machine learning and the PREDICT-AVF web app. *Sci.* 2025;15(1):19203.
38. Chen WL, Kan CD, Lin CH, Chen T. A rule-based decision-making diagnosis system to evaluate arteriovenous shunt stenosis for hemodialysis treatment of patients using fuzzy petri nets. *IEEE j.* 2014;18(2):703–13.

39. Grochowina M, Leniowska L, Gala-Bladzinska A. The prototype device for non-invasive diagnosis of arteriovenous fistula condition using machine learning methods. *Sci.* 2020;10(1):16387.
40. Ota K, Nishiura Y, Ishihara S, Adachi H, Yamamoto T, Hamano T. Evaluation of Hemodialysis Arteriovenous Bruit by Deep Learning. *Sensors (Basel)*. 2020;20(17):27.
41. Park JH, Park I, Han K, Yoon J, Sim Y, Kim SJ, et al. Feasibility of Deep Learning-Based Analysis of Auscultation for Screening Significant Stenosis of Native Arteriovenous Fistula for Hemodialysis Requiring Angioplasty. *Korean J Radiol.* 2022;23(10):949–58.
42. Lin HY, Shien T, Xu JW, Kuo YJ, Chen PL, Niu SW, et al. The application of blood flow sound contrastive learning to predict arteriovenous graft stenosis of patients with hemodialysis. *PLoS ONE*. 2024;19(8):e0308385.
43. Wang JJ, Sharma AK, Liu SH, Zhang H, Chen W, Lee TL. Prediction of Vascular Access Stenosis by Lightweight Convolutional Neural Network Using Blood Flow Sound Signals. *Sensors (Basel)*. 2024;24(18):12.
44. Jin X, Fan Y, Li J, Qi X, Li X, Li H. Construction of Risk-Prediction Models for Autogenous Arteriovenous Fistula Thrombosis in Patients on Maintenance Hemodialysis. *Blood Purif.* 2024;53(10):813–23.
45. Shu P, Huang L, Wang X, Wen Z, Luo Y, Xu F. Machine learning-based prediction model for arteriovenous fistula thrombosis risk: a retrospective cohort study from 2017 to 2024. *BMC Nephrol.* 2025;26(1):304.
46. Rao NN, Dundon BK, Worthley MI, Faull RJ. The Impact of Arteriovenous Fistulae for Hemodialysis on the Cardiovascular System. *Seminars in Dialysis*. 2016;29(3):214–21.
47. Shah NA, Byrne P, Endre ZH, Cochran BJ, Barber TJ, Erlich JH. Predicting high-flow arteriovenous fistulas and cardiac outcomes in hemodialysis patients. *J Vasc Surg.* 2025;81(3):751–8.e8.
48. Balamuthusamy S, Dhanabalsamy N, Thankavel B, Bala MS, Pfaffle A. Utility of a ML analytics on real time risk stratification and re-intervention risk prediction on AV access outcomes and cost. *J.* 2024;25(4):1224–8.
49. Perl J, Dember LM, Bargman JM, Browne T, Charytan DM, Flythe JE, et al. The Use of a Multidimensional Measure of Dialysis Adequacy-Moving beyond Small Solute Kinetics. *Clin J Am Soc Nephrol.* 2017;12(5):839–47.
50. Santoro A. Confounding factors in the assessment of delivered hemodialysis dose. *Kidney International.* 2000;58:S19–S27.
51. Fernandez EA, Valtuille R, Willshaw P, Perazzo CA. Dialysate-side urea kinetics. Neural network predicts dialysis dose during dialysis. *Med Biol Eng Comput.* 2003;41(4):392–6.
52. Gabutti L, Vadalonga D, Mombelli G, Burnier M, Marone C. Artificial neural networks improve the prediction of Kt/V, follow-up dietary protein intake and hypotension risk in haemodialysis patients. *Nephrol Dial Transplant.* 2004;19(5):1204–11.
53. Fernandez EA, Valtuille R, Presedo JM, Willshaw P. Comparison of different methods for hemodialysis evaluation by means of ROC curves: from artificial intelligence to current methods. *Clin Nephrol.* 2005;64(3):205–13.
54. Azar AT, Wahba KM. Artificial neural network for prediction of equilibrated dialysis dose without intradialytic sample. *Saudi J Kidney Dis Transpl.* 2011;22(4):705–11.
55. Du A, Shi X, Guo X, Pei Q, Ding Y, Zhou W, et al. Assessing the Adequacy of Hemodialysis Patients via the Graph-Based Takagi-Sugeno-Kang Fuzzy System. *Comput.* 2021;2021:9036322.
56. Kim HW, Heo SJ, Kim JY, Kim A, Nam CM, Kim BS. Dialysis adequacy predictions using a machine learning method. *Sci.* 2021;11(1):15417.
57. Breiman L. Random forests. *Machine learning.* 2001;45(1):5–32.
58. Friedman JH. Greedy function approximation: A gradient boosting machine. *The Annals of Statistics.* 2001;29(5):1189–232, 44.
59. Liu YC, Qing JP, Li R, Chang J, Xu LX. Prediction of dialysis adequacy using data-driven machine learning algorithms. *Ren Fail.* 2024;46(2):2420826.
60. Zhou J, Wu H, Zhang L, Zhang Q, Wang J, Zhao H, et al. Development and validation of machine learning predictive models for assessing dialysis adequacy in dialysis patients. *Int J Artif Organs.* 2025;48(8):557–65.
61. Li PK, Chow KM, Cho Y, Fan S, Figueiredo AE, Harris T, et al. ISPD peritonitis guideline recommendations: 2022 update on prevention and treatment. *Perit Dial Int.* 2022;42(2):110–53.
62. Zhang J, Friberg IM, Kift-Morgan A, Parekh G, Morgan MP, Liuzzi AR, et al. Machine-learning algorithms define pathogen-specific local immune fingerprints in peritoneal dialysis patients with bacterial infections. *Kidney Int.* 2017;92(1):179–91.
63. Lv B, Liu W, Lu Y, Wang Z, Shi A. Machine learning-based prediction of vancomycin concentration after abdominal administration in patients with peritoneal dialysis-related peritonitis. *Therap Apher Dial.* 2025;29(1):106–13.
64. Tangri N, Ansell D, Naimark D. Predicting technique survival in peritoneal dialysis patients: comparing artificial neural networks and logistic regression. *Nephrol Dial Transplant.* 2008;23(9):2972–81.
65. Arriero-Pais EM, Bajo-Rubio MA, Arrojo-Garcia R, Sandoval P, Gonzalez-Mateo GT, Albar-Vizcaino P, et al. Biomarker and clinical data-based predictor tool (MAUXI) for ultrafiltration failure and cardiovascular outcome in peritoneal dialysis patients: a retrospective and longitudinal study. *BMJ Health Care Inform.* 2025;32(1):27.
66. Cai G, Zhang Y, Pan M, Zhou S, Xiang X, Ying J. Explainable machine learning models for predicting of protein-energy wasting in patients on maintenance haemodialysis. *BMC Nephrol.* 2025;26(1):562.
67. Jin H, Lin Q, Lu J, Hu C, Lu B, Jiang N, et al. Evaluating the Effectiveness of a Generative Pretrained Transformer-Based

- Dietary Recommendation System in Managing Potassium Intake for Hemodialysis Patients. *J Ren Nutr*. 2024;34(6):539–45.
68. Chiu JS, Chong CF, Lin YF, Wu CC, Wang YF, Li YC. Applying an artificial neural network to predict total body water in hemodialysis patients. *Am J Nephrol*. 2005;25(5):507–13.
 69. Mancini E, Mambelli E, Irpinia M, Gabrielli D, Cascone C, Conte F, et al. Prevention of dialysis hypotension episodes using fuzzy logic control system. *Nephrol Dial Transplant*. 2007;22(5):1420–7.
 70. Javed F, Chan GS, Savkin AV, Middleton PM, Malouf P, Steel E, et al. RBF kernel based support vector regression to estimate the blood volume and heart rate responses during hemodialysis. *Annu Int Conf IEEE Eng Med Biol Soc*. 2009;2009:4352–5.
 71. Guo X, Zhou W, Lu Q, Du A, Cai Y, Ding Y. Assessing Dry Weight of Hemodialysis Patients via Sparse Laplacian Regularized RVFL Neural Network with $L_{2,1}$ -Norm. *Biomed Res Int*. 2021;2021:6627650.
 72. Kim HR, Bae HJ, Jeon JW, Ham YR, Na KR, Lee KW, et al. A novel approach to dry weight adjustments for dialysis patients using machine learning. *PLoS ONE*. 2021;16(4):e0250467.
 73. Chaudhuri S, Han H, Monaghan C, Larkin J, Waguespack P, Shulman B, et al. Real-time prediction of intradialytic relative blood volume: a proof-of-concept for integrated cloud computing infrastructure. *BMC Nephrol*. 2021;22(1):274.
 74. Lee H, Yun D, Yoo J, Yoo K, Kim YC, Kim DK, et al. Deep Learning Model for Real-Time Prediction of Intradialytic Hypotension. *Clinical Journal of The American Society of Nephrology: CJASN*. 2021;16(3):396–406.
 75. Dong J, Wang K, He J, Guo Q, Min H, Tang D, et al. Machine learning-based intradialytic hypotension prediction of patients undergoing hemodialysis: A multicenter retrospective study. *Comput Methods Programs Biomed*. 2023;240:107698.
 76. Yang IN, Liu CF, Chien CC, Wang HY, Wang JJ, Shen YT, et al. Personalized prediction of intradialytic hypotension in clinical practice: Development and evaluation of a novel AI dashboard incorporating risk factors from previous and current dialysis sessions. *Int J Med Inf*. 2024;190:105538.
 77. Li Z, Hao S, Shi S, Li L, Tao Z. An explainable machine learning model for early warning of hypertensive and hypotensive anomalies in maintenance hemodialysis patients. *BMC Nephrol*. 2025;26(1):318.
 78. Lin HM, Lyu J. A holistic framework for intradialytic hypotension prediction using generative adversarial networks-based data balancing. *BMC Med Inf Decis Mak*. 2025;25(1):257.
 79. Zhou G, E H, Kuang Z, Tan L, Yao T, Song M. Intradialytic Hypotension Frequency Prediction Using Generalizable Neighborhood Reasoning on Temporal Patient Knowledge Graph. *IEEE j*. 2025;29(3):2233–45.
 80. Ren Z, Zhang M, Wang P, Chen K, Wang J, Wu L, et al. Research on the development of an intelligent prediction model for blood pressure variability during hemodialysis. *BMC Nephrol*. 2025;26(1):82.
 81. Mikhail A, Brown C, Williams JA, Mathrani V, Shrivastava R, Evans J, et al. Renal association clinical practice guideline on Anaemia of Chronic Kidney Disease. *BMC Nephrol*. 2017;18(1):345.
 82. Martin-Guerrero JD, Camps-Valls G, Soria-Olivas E, Serrano-Lopez AJ, Perez-Ruixo JJ, Jimenez-Torres NV. Dosage individualization of erythropoietin using a profile-dependent support vector regression. *IEEE Trans Biomed Eng*. 2003;50(10):1136–42.
 83. Gabutti L, Lotscher N, Bianda J, Marone C, Mombelli G, Burnier M. Would artificial neural networks implemented in clinical wards help nephrologists in predicting epoetin responsiveness? *BMC Nephrol*. 2006;7:13.
 84. Barbieri C, Bolzoni E, Mari F, Cattinelli I, Bellocchio F, Martin JD, et al. Performance of a Predictive Model for Long-Term Hemoglobin Response to Darbepoetin and Iron Administration in a Large Cohort of Hemodialysis Patients. *PLoS ONE*. 2016;11(3):e0148938.
 85. Martinez-Martinez JM, Escandell-Montero P, Barbieri C, Soria-Olivas E, Mari F, Martinez-Sober M, et al. Prediction of the hemoglobin level in hemodialysis patients using machine learning techniques. *Comput Methods Programs Biomed*. 2014;117(2):208–17.
 86. Gaweda AE, Jacobs AA, Aronoff GR, Brier ME. Model predictive control of erythropoietin administration in the anemia of ESRD. *American Journal of Kidney Diseases*. 2008;51(1):71–9.
 87. Ohara T, Ikeda H, Sugitani Y, Suito H, Huynh VQH, Kinomura M, et al. Artificial intelligence supported anemia control system (AISACS) to prevent anemia in maintenance hemodialysis patients. *Int J Med Sci*. 2021;18(8):1831–9.
 88. Bucalo ML, Barbieri C, Roca S, Ion Titapiccolo J, Ros Romero MS, Ramos R, et al. The anaemia control model: Does it help nephrologists in therapeutic decision-making in the management of anaemia? *Nefrologia (Engl Ed)*. 2018;38(5):491–502.
 89. Escandell-Montero P, Chermisi M, Martinez-Martinez JM, Gomez-Sanchis J, Barbieri C, Soria-Olivas E, et al. Optimization of anemia treatment in hemodialysis patients via reinforcement learning. *Artificial Intelligence in Medicine*. 2014;62(1):47–60.
 90. Gandjour A, Apel C, Kendzia D, Neri L, Bellocchio F, Usvyat L, et al. Health-economic evaluation of an AI-powered decision support system for anemia management in in-center hemodialysis patients. *BMC Nephrol*. 2025;26(1):496.
 91. Jager KJ, Lindholm B, Goldsmith D, Fliser D, Wiecek A, Suleymanlar G, et al. Cardiovascular and non-cardiovascular mortality in dialysis patients: where is the link? *Kidney Int Suppl (2011)*. 2011;1(1):21–3.
 92. Roberts MA, Polkinghorne KR, McDonald SP, Ierino FL. Secular trends in cardiovascular mortality rates of patients receiving dialysis compared with the general population. *Am J Kidney Dis*. 2011;58(1):64–72.

93. Liu L, Zhang L, Zhang D, Guan T, He T, Liang B, et al. Risk prediction of cardiovascular events in peritoneal dialysis patients. *BMC Nephrol.* 2025;26(1):177.
94. Goldstein BA, Chang TI, Mitani AA, Assimes TL, Winkelmayer WC. Near-term prediction of sudden cardiac death in older hemodialysis patients using electronic health records. *Clinical Journal of The American Society of Nephrology: CJASN.* 2014;9(1):82–91.
95. Mezzatesta S, Torino C, Meo P, Fiumara G, Vilasi A. A machine learning-based approach for predicting the outbreak of cardiovascular diseases in patients on dialysis. *Comput Methods Programs Biomed.* 2019;177:9–15.
96. Kanda E, Epureanu BI, Adachi T, Tsuruta Y, Kikuchi K, Kashiwara N, et al. Application of explainable ensemble artificial intelligence model to categorization of hemodialysis-patient and treatment using nationwide-real-world data in Japan. *PLoS ONE.* 2020;15(5):e0233491.
97. Chen M, Zeng Y, Liu M, Li Z, Wu J, Tian X, et al. Interpretable machine learning models for the prediction of all-cause mortality and time to death in hemodialysis patients. *Therap Apher Dial.* 2025;29(2):220–32.
98. Rankin S, Han L, Scherzer R, Tenney S, Keating M, Genberg K, et al. A Machine Learning Model for Predicting Mortality within 90 Days of Dialysis Initiation. *Kidney360.* 2022;3(9):1556–65.
99. Peng Z, Zhong S, Li X, Yu F, Tang Z, Ma C, et al. An artificial intelligence model to predict mortality among hemodialysis patients: A retrospective validated cohort study. *Sci.* 2025;15(1):27699.
100. Heerspink HJ, Ninomiya T, Zoungas S, de Zeeuw D, Grobbee DE, Jardine MJ, et al. Effect of lowering blood pressure on cardiovascular events and mortality in patients on dialysis: a systematic review and meta-analysis of randomised controlled trials. *Lancet.* 2009;373(9668):1009–15.
101. Wang F, Wang Y, Tian Y, Zhang P, Chen J, Li J. Pattern recognition and prognostic analysis of longitudinal blood pressure records in hemodialysis treatment based on a convolutional neural network. *J Biomed Inform.* 2019;98:103271.
102. Lin Y, Yi C, Cao P, Lin J, Chen W, Mao H, et al. Visit-to-visit blood pressure variability and clinical outcomes in peritoneal dialysis - based on machine learning algorithms. *Hypertens Res.* 2025;48(5):1702–15.
103. Boni TTA, Ayatollahi H, Langarizadeh M. A Clinical Decision Support System for Assessing the Risk of Cardiovascular Diseases in Diabetic Hemodialysis Patients. *Curr Diabetes Rev.* 2020;16(3):262–9.
104. de Gonzalo-Calvo D, Martinez-Camblor P, Bar C, Duarte K, Girerd N, Fellstrom B, et al. Improved cardiovascular risk prediction in patients with end-stage renal disease on hemodialysis using machine learning modeling and circulating microribonucleic acids. *Theranostics.* 2020;10(19):8665–76.
105. Werfel S, Lorenz G, Haller B, Gunthner R, Matschkal J, Braunisch MC, et al. Application of regularized regression to identify novel predictors of mortality in a cohort of hemodialysis patients. *Sci.* 2021;11(1):9287.
106. Noh J, Yoo KD, Bae W, Lee JS, Kim K, Cho JH, et al. Prediction of the Mortality Risk in Peritoneal Dialysis Patients using Machine Learning Models: A Nation-wide Prospective Cohort in Korea. *Sci.* 2020;10(1):7470.
107. Noh J, Park SY, Bae W, Kim K, Cho JH, Lee JS, et al. Predicting early mortality in hemodialysis patients: a deep learning approach using a nationwide prospective cohort in South Korea. *Sci.* 2024;14(1):29658.
108. Zhou Q, You X, Dong H, Lin Z, Shi Y, Su Z, et al. Prediction of premature all-cause mortality in patients receiving peritoneal dialysis using modified artificial neural networks. *Aging (Albany NY).* 2021;13(10):14170–84.
109. Yan Q, Liu G, Wang R, Li D, Chen X, Cong J, et al. Explainable machine learning algorithm to predict cardiovascular event in patients undergoing peritoneal dialysis. *BMC Med Inf Decis Mak.* 2025;25(1):172.
110. Wang Y, Yang L, Li Z, Zhang X, Zhao H, Ji M, et al. Pulse wave-driven machine learning for the non-invasive assessment of coronary artery calcification in patients with end-stage renal disease undergoing hemodialysis. *Biomed.* 2025;24(1):104.
111. Kramann R, Floege J, Ketteler M, Marx N, Brandenburg VM. Medical options to fight mortality in end-stage renal disease: a review of the literature. *Nephrol Dial Transplant.* 2012;27(12):4298–307.