Clinica Chimica Acta 586 (2026) 120908

Contents lists available at ScienceDirect

Clinica Chimica Acta

journal homepage: www.elsevier.com/locate/cca

Artificial intelligence and machine learning applications in dialysis: Current applications, challenges, and future directions

Aanuoluwapo Clement David-Olawade [a], Muyiwa Ademola Ogunbona [b], Olabanke Florence Olawuyi [c], Babajide David Makanjuola [d], John Oluwatosin Alabi [e], David B. Olawade [f,g,h,*]

[a] Endoscopy Unit, Glenfield Hospital, University Hospitals of Leicester, NHS Trust, Leicester, United Kingdom
[b] Cell Biology and Genetics Unit, Department of Zoology, University of Ibadan, Ibadan, Nigeria.
[c] Department of Biomedical Sciences, College of Medical Sciences, University of Calabar, Calabar, Cross River State, Nigeria
[d] Sheffield Business School, Department of Accounting, Banking and Finance, Sheffield Hallam University, Howard St, Sheffield City Centre, Sheffield S1 1WB, United Kingdom
[e] Department of Business and Management, University of Sussex Business School, University of Sussex, Falmer, Brighton BN1 9RH, United Kingdom
[f] Department of Allied and Public Health, School of Health, Sport and Bioscience, University of East London, London, United Kingdom
[g] Department of Research and Innovation, Medway NHS Foundation Trust, Gillingham ME7 5NY, United Kingdom
[h] Department of Public Health, York St John University, London E14 2BA, United Kingdom

ARTICLE INFO

Keywords:
Artificial intelligence
Machine learning
dialysis
Intradialytic hypotension
Clinical decision support

ABSTRACT

Artificial intelligence (AI) and machine learning (ML) applications have emerged as transformative technologies in nephrology, particularly in dialysis care. The availability of multimodal datasets including electronic health records, hemodialysis machine data, laboratory values, and imaging has enabled the development of sophisticated prognostic, diagnostic, and treatment support tools. This comprehensive review narratively examines current AI/ML applications in dialysis, evaluates their clinical performance, and identifies future research directions. We conducted a comprehensive literature search of PubMed, Web of Science, and other major databases from 2020 to 2025, focusing on peer-reviewed studies that employed AI/ML techniques in dialysis care. Studies were categorised by application domain and analysed for methodology, performance metrics, and clinical implications. Our analysis identified five major application domains: (1) prediction and prognosis, including intradialytic hypotension (IDH) prediction with AUROC values ranging 0.89–0.95, mortality prediction achieving C-indices up to 0.83, and hospitalisation risk assessment; (2) early detection of chronic kidney disease (CKD) progression and dialysis risk; (3) clinical decision support for anaemia management and treatment optimisation; (4) vascular access monitoring with AI-driven image analysis achieving AUROC ≈ 0.96; and (5) natural language processing (NLP) applications for symptom detection. Federated learning (FL) approaches are emerging to enable multi-centre collaboration while preserving data privacy. AI/ML technologies demonstrate significant promise in enhancing dialysis care through improved prediction accuracy, personalised treatment approaches, and clinical decision support. However, widespread clinical adoption remains limited due to challenges including data privacy concerns, model interpretability issues, regulatory complexity, and the need for diverse, representative datasets.

1. Introduction

End-stage kidney disease (ESKD) affects millions of individuals globally, with dialysis serving as a life-sustaining treatment for patients awaiting transplantation or unsuitable for transplant procedures [1]. Despite significant advances in dialysis technology and clinical protocols, patient outcomes on maintenance dialysis remain suboptimal than for the general population. Contemporary epidemiological data indicate an annual mortality rate of 10–20% and a 5-year survival rate of approximately 40–50%. These figures translate into a mortality risk around 10–20 times higher than that of age matched individuals without end stage kidney disease, driven largely by cardiovascular causes.

* Corresponding author at: Department of Allied and Public Health, School of Health, Sport and Bioscience, University of East London, London, United Kingdom.
E-mail addresses: aanuclement23@gmail.com (A. Clement David-Olawade), d.olawade@uel.ac.uk (D.B. Olawade).

https://doi.org/10.1016/j.cca.2026.120908
Received 15 January 2026; Received in revised form 11 February 2026; Accepted 12 February 2026
Available online 15 February 2026

Patients on chronic dialysis also experience frequent complications, including intradialytic hypotension, cardiovascular events, and hospitalisation, all of which are strongly associated with adverse long-term outcomes [2–5]. The complexity of dialysis care, involving multiple physiological parameters, treatment variables, and patient-specific factors, presents an ideal scenario for artificial intelligence (AI) and machine learning (ML) applications.

The nephrology field has traditionally lagged behind other medical specialties in adopting AI/ML technologies, despite the abundance of structured clinical data and the mathematical nature of kidney care that makes it particularly suitable for computational approaches. Recent years have witnessed rapid growth in AI and machine learning research within nephrology, with bibliometric studies demonstrating a marked increase in annual publications on AI applications to kidney disease and kidney transplantation from the mid-2010s to the early 2020s [6,7]. This growth reflects the recognition that AI/ML can address unmet clinical needs in areas such as early detection of acute kidney injury (AKI), drug dosing optimisation, dialysis adequacy assessment, and prognostic modelling.

Modern dialysis generates vast amounts of multimodal data, including real-time machine telemetry recorded every few seconds, vital signs monitored every few minutes, laboratory trends spanning days to weeks, and comprehensive electronic health records (EHRs) containing demographic, clinical, and treatment information [8]. This data richness, combined with advances in computational power and algorithm sophistication, has enabled the development of predictive models that can identify patterns invisible to traditional statistical approaches. Deep learning architectures, particularly recurrent neural networks (RNNs) and attention-based models, have shown particular promise in handling the temporal nature of dialysis data [9].

The clinical applications of AI/ML in dialysis span multiple domains, from real-time monitoring and complication prediction to long-term outcome prognostication and treatment personalisation. In hemodialysis (HD) populations, advanced intradialytic hypotension prediction models have reported AUROC values of approximately 0.94, while machine learning–based mortality models have achieved discrimination metrics around 0.83; taken together, these performance metrics characteristics indicate sufficient predictive accuracy to support a transition from reactive to proactively guided dialysis care [10–12]. Additionally, AI-powered clinical decision support systems are showing promise in optimising anaemia management, predicting hospitalisation risk, and supporting vascular access surveillance. As illustrated in Fig. 1, AI tools can be embedded across multiple stages of the dialysis care pathway, from data acquisition to decision support and outcome-driven model

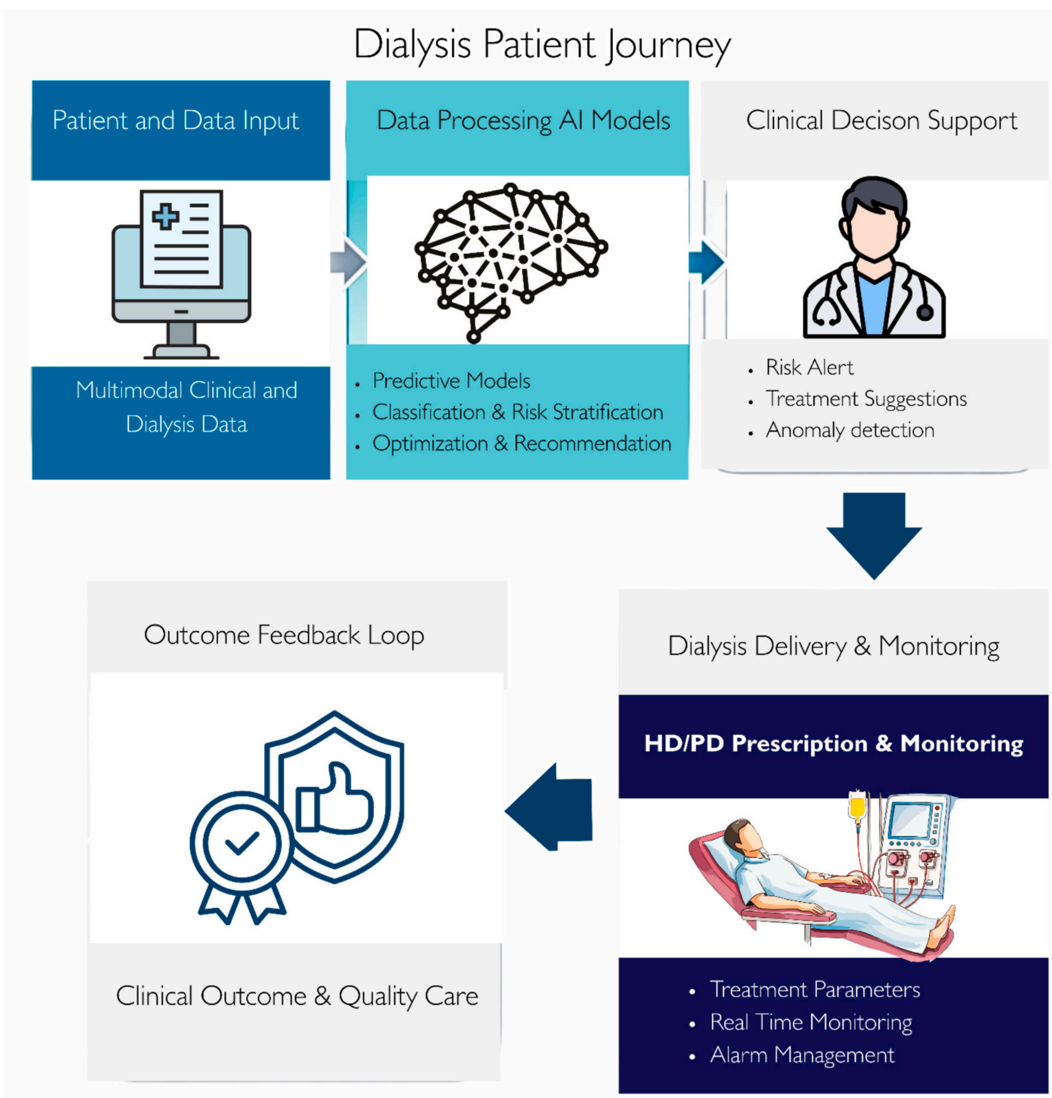

Fig. 1. Conceptual overview of how artificial intelligence can be integrated along the dialysis care pathway, from multimodal data collection and model development to clinical decision support, dialysis delivery, and outcome feedback that enables continuous learning and model refinement.

refinement.

However, several significant challenges impede the widespread clinical implementation of AI/ML in dialysis care. These include data privacy and security concerns, particularly in federated learning scenarios; model interpretability and the "black box" problem that limits clinician trust and adoption; regulatory compliance with emerging AI governance frameworks; bias and fairness issues related to underrepresented populations in training datasets; and the complexity of integrating AI tools into existing clinical workflows. The purpose of this comprehensive narrative review is to examine the current landscape of AI/ML applications in dialysis, evaluate their clinical performance and implementation challenges, assess the quality and limitations of existing evidence, and identify priority areas for future research and development. Our objectives include: (1) cataloguing and categorising current AI/ML applications across different aspects of dialysis care; (2) evaluating the predictive performance and clinical utility of existing models; (3) identifying key barriers to clinical implementation and regulatory approval; (4) assessing the methodological quality and potential biases in current research; and (5) proposing future directions for AI/ML research in dialysis that could accelerate clinical translation and improve patient outcomes.

2. Methods

2.1. Review design and rationale

This manuscript presents a narrative review of AI/ML applications in dialysis care. We deliberately chose a narrative approach rather than a systematic review for several important reasons. First, the field of AI/ML in dialysis is rapidly evolving and highly heterogeneous, with diverse methodologies, outcome measures, and clinical applications that preclude meaningful quantitative synthesis. Second, our objective was to provide a comprehensive overview of the current landscape, identify emerging trends, and synthesise conceptual frameworks rather than to conduct a meta-analysis of specific interventions or diagnostic tests. Third, the literature includes substantial technical and methodological diversity, ranging from deep learning architectures to traditional machine learning approaches, from real-time prediction to long-term prognostication, and from retrospective validation to prospective clinical implementation, making standardised risk-of-bias assessment and effect size pooling inappropriate. Fourth, we aimed to capture the breadth of innovation across multiple application domains and identify implementation barriers and future directions, which are better served by a narrative synthesis than by the narrow focus required for a systematic review.

Consequently, this review does not follow the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines, as these are specifically designed for systematic reviews and meta-analyses with predefined protocols, standardised risk-of-bias assessments, and quantitative synthesis. We do not provide a PRISMA flow diagram, detailed data extraction tables, or screening statistics across multiple review stages, as these elements are neither applicable nor informative for a narrative review of this scope. Instead, we employed a comprehensive literature search strategy to identify relevant studies and synthesised findings narratively to provide clinicians, researchers, and policymakers with a holistic understanding of the current state of AI/ML in dialysis.

2.2. Literature search strategy

We conducted a comprehensive, but not systematic, literature search of major biomedical databases including PubMed/MEDLINE, Web of Science Core Collection, Scopus, and IEEE Xplore from January 2020 to December 2025. The search strategy employed both controlled vocabulary terms and free-text keywords related to artificial intelligence, machine learning, dialysis, and nephrology. Specific search terms included: ("artificial intelligence" OR "machine learning" OR "deep learning" OR "neural network" OR "predictive modelling") AND ("dialysis" OR "hemodialysis" OR "peritoneal dialysis" OR "renal replacement therapy") AND ("prediction" OR "prognosis" OR "clinical decision support").

Inclusion criteria encompassed peer-reviewed original research articles published in English that employed AI/ML techniques for any aspect of dialysis care, including but not limited to: prediction and prognosis models, clinical decision support systems, diagnostic applications, treatment optimisation, and monitoring technologies. We included studies involving adult patients (≥18 years) receiving any form of dialysis therapy, with clearly defined AI/ML methodologies and performance metrics.

Exclusion criteria included: conference abstracts and non-peer-reviewed publications, studies focusing solely on chronic kidney disease without dialysis components, purely technical AI/ML papers without clinical application, systematic reviews and meta-analyses (though these were reviewed for additional references), and studies with insufficient methodological detail or missing performance data.

Data extraction was performed by two independent reviewers using a standardised data extraction form capturing: study characteristics (design, setting, population), AI/ML methodology (algorithm type, features, training approach), clinical application domain, performance metrics (AUROC, sensitivity, specificity, C-index), validation methodology, and implementation considerations. Disagreements were resolved through consensus discussion between the two reviewers, with a third reviewer consulted as a tie-breaker when necessary.

Quality assessment employed adapted criteria from TRIPOD (Transparent Reporting of a multivariable prediction model for Individual Prognosis or Diagnosis) and TRIPOD-AI guidelines and CONSORT-AI extensions where applicable. We acknowledge that these are reporting guidelines rather than validated quality assessment tools; however, they provided a useful framework for evaluating methodological rigour, appropriate validation strategies, risk of bias, and clinical applicability in the absence of a standardised risk-of-bias tool specifically designed for AI/ML prognostic studies in narrative reviews.

Data synthesis followed a narrative approach due to heterogeneity in study populations, AI/ML methods, and outcome measures. Studies were grouped by clinical application domain, with performance metrics summarised descriptively and trends identified across different algorithmic approaches and clinical settings.

3. Main application domains

Table 1 demonstrates the impressive technical achievements across clinical domains, with intradialytic hypotension prediction models achieving AUROCs exceeding 0.95 and mortality prediction systems reaching C-indices above 0.83, though most validation remains retrospective. Due to the narrative nature of this review and the substantial heterogeneity across studies in terms of outcome definitions, prediction horizons, validation strategies, and data sources, we present a summary table of key studies rather than a comprehensive systematic data extraction table. Table 1 provides representative examples of high-performing models across major application domains to illustrate the state of the field.

3.1. Prediction and prognosis

Intradialytic hypotension (IDH) is widely recognised as one of the most frequent and clinically significant complications of maintenance hemodialysis, with prevalence estimates ranging from approximately 8% to 40% of dialysis sessions across studies, and is associated with increased morbidity, higher cardiovascular and all-cause mortality, and impaired health related quality of life [20,21]. Recent advances in AI/ML have demonstrated remarkable success in predicting IDH episodes with clinically actionable accuracy. A machine learning model using real

Table 1
Performance Metrics of AI/ML Applications in Dialysis by Clinical Domain.

Application Domain	Reference	Algorithm Type	Dataset Size	Performance Metric	Clinical Validation
Intradialytic Hypotension [12]		Recurrent Neural Network	261,647 sessions	AUROC: 0.94	Retrospective
Intradialytic Hypotension [11,13]		Machine Learning Ensemble	42,656 sessions	AUROC: 0.89	Real-time validation
Intradialytic Hypotension [11,14]		Temporal Fusion Transformer	302,774 sessions	AUROC: 0.953	Retrospective internal validation
Mortality Prediction (HD) [10,15]		Random Forest + RNN	3284 patients	AUC: 0.84	Prospective or inception cohort
Mortality Prediction (PD) [16]		Survival Tree	1730 patients	C-index: 0.769	Retrospective
CRRT Survival [17]		Gradient Boosting and related Ensemble Models	Multi-centre	AUROC: 0.84–0.86	External validation
Vascular Access [18]		Computer Vision	Variable	AUROC: 0.96	Limited validation
Anaemia Management [19]		Artificial Neural Network	Variable	Clinical improvement	Clinical deployment

time electronic health record and intradialytic monitor data from 693 in centre hemodialysis patients (42,656 sessions) achieved an AUROC of 0.89 for predicting intradialytic hypotension 15–75 min in advance. In a separate cohort, a deep learning recurrent neural network trained on 261,647 hemodialysis sessions with 1,600,531 independent timestamps attained an AUROC of 0.94 (95% CI 0.94–0.94) for predicting intradialytic hypotension within 1-h, outperforming comparator machine learning models [12,13].

The most sophisticated approaches employ deep learning architectures specifically designed for temporal sequence modelling. A study developed a temporal fusion transformer (TFT)-based model that achieved AUROCs of 0.953, 0.892, and 0.889 for predicting different definitions of IDH and intradialytic hypertension respectively [22]. These models leverage multimodal features including demographic data, treatment parameters, vital signs, and historical patterns, with the most recent intradialytic systolic blood pressure and IDH rate being identified as top predictors.

Prognostic modelling represents another major application domain, with AI/ML approaches demonstrating superior performance compared to traditional statistical methods. A study analysed 3284 hemodialysis patients from a nationwide prospective cohort, finding that random forest models achieved an AUC of 0.8321 for first-year mortality prediction, which was further improved by recurrent neural networks with autoencoders (AUC 0.8357) [23]. Importantly, the survival analysis revealed that comorbidities, particularly the modified Charlson Comorbidity Index, were more influential than age in predicting early

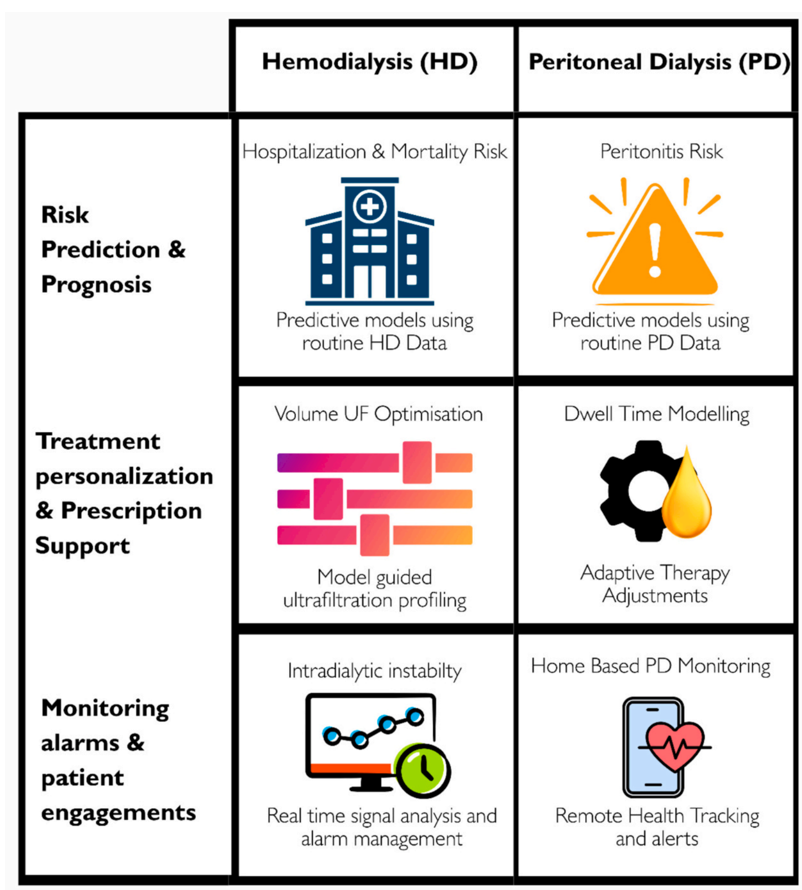

Fig. 2. Main application domains of artificial intelligence in hemodialysis and peritoneal dialysis, including risk prediction and prognosis, treatment personalization and prescription support, and monitoring, alarm handling, and patient engagement.

mortality.

In peritoneal dialysis (PD), Noh et al. showed that a survival-tree algorithm outperformed conventional Cox regression for predicting 5-year mortality, with a concordance index of 0.769 versus 0.745 in a cohort of 1730 PD patients [24]. In the critical care setting, Zamanzadeh and colleagues developed a machine-learning model to predict short term survival among patients initiated on continuous renal replacement therapy (CRRT), achieving an AUROC of 0.848 (95% CI 0.822–0.870) on a held out test set using routinely collected EHR variables [25].

AI/ML models have shown promise in predicting hospitalisation events, enabling proactive interventions and care coordination. These models typically incorporate laboratory trends, vital sign patterns, treatment adherence metrics, and historical utilisation data to identify patients at elevated risk of adverse events requiring hospital admission. Fig. 2 provides a structured overview of major AI application domains in hemodialysis and peritoneal dialysis, illustrating how current and emerging tools cluster around prediction, personalisation, and monitoring.

3.2. Early detection and risk stratification

AI and machine learning are increasingly being used to predict progression to kidney failure and dialysis among patients with pre-dialysis chronic kidney disease. These models typically integrate longitudinal electronic health record data, laboratory trends, comorbidities, and medication histories to estimate individualised risk over horizons ranging from months to several years [26,27]. Novel data augmentation methods, including Binary Gaussian Copula Synthesis, have been developed to address severe class imbalance in progression prediction datasets. These approaches have demonstrated improvements in detecting future dialysis risk by approximately 72% over standard statistical methods [28].

While not specific to dialysis populations, acute kidney injury (AKI) prediction models have significant implications for preventing dialysis requirement. DeepMind's algorithm achieved approximately 90% accuracy in predicting AKI up to 48 h in advance using data from over 700,000 veterans, though generalisation to diverse populations, particularly women, remains a challenge [29,30].

3.3. Clinical decision support and treatment optimisation

AI-powered anaemia control models, such as the Anaemia Control Model (ACM), rank among the most mature and clinically deployed AI applications in dialysis, with prospective implementations showing reduced haemoglobin variability and erythropoiesis-stimulating agent (ESA) costs compared to traditional management [31]. These systems employ artificial neural networks, including gated recurrent units with attention (e.g., GAM) and other recurrent architectures, to predict future haemoglobin levels and recommend ESA and iron dosing adjustments [32]. The models integrate patient-specific data, such as baseline haemoglobin, prior ESA/iron dosing history, iron studies (e.g., ferritin, transferrin saturation), and inflammatory markers alongside dialysis parameters, to generate personalised anaemia protocols [32,33].

ML algorithms are being developed to optimise dialysis prescription parameters, including session duration, blood flow rates, and dialysate composition. These models consider patient-specific factors such as body composition, residual kidney function, and treatment tolerance to maximise solute clearance while minimising complications [34,35]. NLP techniques applied to electronic health record notes have demonstrated superior sensitivity in detecting symptom burden in dialysis patients compared to diagnostic code-based methods [36]. These approaches can identify patient-reported symptoms, quality of life issues, and treatment-related side effects that may not be captured through traditional structured data collection.

3.4. Vascular access monitoring and intervention

AI-driven image analysis applications demonstrate high accuracy in vascular access surveillance, with convolutional neural networks (CNNs) achieving over 90% classification accuracy for arteriovenous fistula aneurysms in validation sets [37]. Computer vision models classifying arteriovenous fistula aneurysm severity exhibit strong performance; related deep learning models for vascular access quality classification reach 92% accuracy post-feature selection [37,38]. These systems analyse ultrasound or photoplethysmography images to identify structural abnormalities like stenosis, enabling timely nephrology or surgical referral to prevent access failure [38,39].

3.5. Remote monitoring and home Dialysis applications

The expansion of home-based dialysis modalities, accelerated by the COVID-19 pandemic, has created new opportunities for AI-enhanced remote patient monitoring. Predictive models are being developed to detect complications in peritoneal dialysis patients, monitor adherence to treatment protocols, and identify early signs of technique failure or infection [40].

4. Technical architecture and implementation considerations

4.1. Data integration and multimodal approaches

Modern AI/ML applications in dialysis leverage multimodal data integration, combining real-time machine telemetry (recorded every few seconds), physiological monitoring (every few minutes), laboratory trends (daily to weekly), and longitudinal clinical records (spanning months to years). This temporal heterogeneity requires sophisticated feature engineering and sequence modelling approaches to capture both short-term fluctuations and long-term trends [41,42].

4.2. Model architecture and performance

The choice of AI/ML architecture influences model performance and clinical utility in dialysis applications, with architecture-specific optimisations needed for tasks like mortality or haemoglobin forecasting [43,44]. Deep learning approaches, particularly recurrent neural networks and transformer architectures, have consistently outperformed traditional machine learning methods for temporal prediction tasks in dialysis [45]. However, simpler models may offer advantages in terms of interpretability and implementation complexity.

4.3. Cloud computing and real-time processing

The implementation of cloud-based infrastructure enables real-time processing of dialysis machine data and electronic health records, supporting the development of predictive models that can provide actionable insights during ongoing treatment sessions [46]. This approach allows for scalable deployment across multiple dialysis centres while maintaining data security and privacy.

4.4. Federated learning and multi-Centre collaboration

Federated learning (FL) represents an emerging paradigm that addresses data privacy concerns while enabling collaborative model development across multiple institutions. FL approaches allow healthcare organisations to train shared AI models without transferring raw patient data, instead sharing only model parameters and updates [47,48]. This approach is particularly relevant in dialysis care, where patient data is often distributed across different providers and regulatory jurisdictions. Recent work has proposed federated learning models for predicting survival in hemodialysis patients across centres in different countries, enabling shared learning while maintaining data sovereignty. These approaches require careful consideration of data harmonisation, model aggregation strategies, and communication protocols to ensure model performance and fairness across diverse patient populations [48,49].

4.5. Model interpretability and clinical integration

The “black box” nature of many AI/ML models presents a significant barrier to clinical adoption. Advanced interpretability techniques, including attention mechanisms and SHAP (SHapley Additive exPlanations) values, are being employed to provide clinicians with insights into model decision-making processes. These approaches can identify the most influential features for individual predictions and provide confidence intervals for model outputs [50,51]. Successful integration of AI/ML models into clinical workflows requires careful consideration of user interface design, alert fatigue prevention, and workflow optimisation. Clinical decision support systems embedding AI/ML models should provide actionable recommendations alongside comprehensive patient data without disrupting routine clinical practices [34,41].

4.6. Regulatory framework and compliance

The regulatory landscape for AI/ML applications in healthcare is rapidly evolving, with implications for dialysis-specific applications. Recent frameworks including TRIPOD-AI, CONSORT-AI, and the EU AI Act affect medical devices and clinical decision support systems, particularly since 2024–2025. While TRIPOD-AI and CONSORT-AI are primarily reporting guidelines for authors submitting to journals, they reflect broader regulatory expectations for transparency, validation, and bias assessment in AI/ML systems deployed in clinical practice. Recent analyses of the Food and Drug Administration's (FDA's) public list indicate that approximately 900–1000 AI enabled medical devices have received authorisation, with the large majority concentrated in radiology applications. For dialysis specific AI/ML tools regulated as software as a medical device, the authorisation pathway generally requires robust evidence of analytical and, where appropriate, clinical performance, demonstration of clinical utility, and assurance of safety across diverse patient populations [52–55].

5. Implementation barriers and challenges

Table 2 systematically categorises the substantial implementation barriers spanning technical infrastructure challenges, clinical workflow integration difficulties, and regulatory compliance complexities that continue to impede widespread adoption despite promising performance metrics.

Table 2
Challenges and Barriers to AI/ML Implementation in Dialysis Care.

Challenge Category	Specific Barriers	Impact Level	Mitigation Strategies
Technical [41,56]	Data heterogeneity, missing values, computational requirements	High	Data standardisation, cloud infrastructure, preprocessing pipelines
Clinical [31,41]	Clinician acceptance, workflow integration, alert fatigue	High	Education programs, user-centred design, validation studies
Regulatory [50]	Privacy compliance, bias assessment, transparency requirements	Medium-High	Privacy-preserving techniques, diverse datasets, explainable AI
Organisational [34]	Resource constraints, technical expertise, change management	Medium	Strategic planning, partnerships, phased implementation
Ethical [51]	Fairness, consent, data governance	Medium	Ethical frameworks, diverse representation, governance policies

5.1. Technical and infrastructure challenges

The heterogeneity of electronic health record systems, dialysis machine platforms, and local data collection protocols across providers poses major obstacles to developing and deploying generalisable AI/ML models in nephrology and dialysis care. Substantial preprocessing is typically required, including data harmonisation to common schemas, handling of missing values, and feature standardisation, before models can be reliably trained and validated across sites [56]. Real-time prediction models, particularly those employing deep learning architectures, require significant computational resources and low-latency processing capabilities. The implementation of cloud-based solutions must balance performance requirements with data privacy and security considerations [41,46]. The integration of AI/ML models into existing clinical information systems and dialysis machine interfaces requires extensive software development, testing, and validation. Interoperability standards and Application Programming Interface (API) development are essential for seamless integration.

5.2. Clinical and organisational barriers

Adoption of AI/ML tools in clinical practice is consistently described as depending on clinician understanding of model assumptions, limitations, and appropriate use, as well as sufficient trust in the predictions to incorporate them into day-to-day decision making. Educational initiatives, and structured change management programmes are therefore regarded as essential components of successful implementation strategies for AI enabled decision support [50,57]. AI/ML tools must be designed to enhance rather than disrupt existing clinical workflows. Alert fatigue, false positive rates, and the cognitive burden of interpreting AI recommendations are significant concerns that must be addressed through careful user interface design and validation studies. The implementation and maintenance of AI/ML systems require significant financial investment, technical expertise, and ongoing support. Healthcare organisations must balance the costs of implementation with potential benefits in terms of improved outcomes and efficiency [56,58].

5.3. Regulatory and ethical considerations

The use of patient data for AI/ML model development and deployment raises substantial privacy and confidentiality concerns, which are amplified in multi-institutional and federated learning settings where data remain distributed across sites. Compliance with regulations such as the Health Insurance Portability and Accountability Act (HIPAA), the General Data Protection Regulation (GDPR), and emerging AI-specific frameworks is essential [47,48]. Many early AI/ML datasets in healthcare exhibit inadequate representation of diverse patient populations, with some studies reporting female representation as low as 25–43% in medical imaging datasets used for training. This underrepresentation raises concerns about model bias and reduced performance in minority groups, underscoring the need for demographic transparency and balanced cohorts in nephrology AI research [59]. The requirement for explainable AI in healthcare applications necessitates the development of interpretable models and decision support tools that can provide clinicians with insights into model reasoning and confidence levels.

6. Future directions and emerging technologies

Table 3 outlines the research priorities and development timeline from near-term goals focused on improving interpretability and bias mitigation to long-term visions of autonomous dialysis management and artificial kidney control, illustrating both the transformative potential and the substantial work required to achieve meaningful clinical translation of these technologies.

Table 3
Future Research Priorities and Development Areas.

Research Area	Short-term Goals (1–3 years)	Medium-term Goals (3–5 years)	Long-term Vision (5+ years)
Algorithm Development [50,51]	Improved interpretability, bias mitigation, federated learning	Foundation models, causal inference, real-time Optimisation	Artificial general intelligence applications
Clinical Applications [41,43]	IDH prevention, mortality prediction, treatment personalisation	Integrated care platforms, precision medicine, outcomes prediction	Autonomous dialysis management, predictive health
Technology Integration [46]	Cloud deployment, EHR integration, mobile applications	IoT integration, wearable monitoring, digital therapeutics	Artificial kidney control, bio-hybrid devices
Implementation Science [54]	Clinical validation, workflow integration, user acceptance	Health economics, value demonstration, regulatory approval	Global deployment, health equity, population health
Regulatory Framework [51]	Privacy compliance, bias assessment, safety validation	International harmonisation, adaptive regulation, quality assurance	Ethical AI governance, autonomous system oversight

6.1. *Advanced AI architectures*

The development of large-scale foundation models trained on diverse healthcare data could enable more generalisable and robust AI applications in dialysis care. These models could leverage text, images, time-series data, and clinical notes to provide comprehensive clinical insights [60]. Future AI/ML applications will likely incorporate causal inference methodologies to better understand treatment effects and provide more interpretable predictions. This could enable the development of personalised treatment recommendations based on predicted counterfactual outcomes [44]. Emerging federated learning techniques, including federated transfer learning and privacy-preserving aggregation methods, could enable more sophisticated multi-centre collaborations while maintaining data privacy and security [61].

6.2. *Integration with emerging technologies*

The integration of continuous monitoring devices, wearable sensors, and home-based diagnostic tools could provide AI/ML models with richer, more frequent data streams for improved prediction accuracy and patient monitoring [62]. AI-powered digital therapeutics could provide personalised interventions, educational content, and behavioural support tailored to individual patient needs and preferences [62]. As artificial kidney technologies advance, AI/ML could play a crucial role in automated control, personalisation, and early failure detection in bio-artificial and wearable dialysis devices.

6.3. *Clinical translation and implementation*

Future research priorities include the development of robust real-world evidence frameworks for evaluating AI/ML model performance in diverse clinical settings and patient populations. The demonstration of economic value and improved outcomes associated with AI/ML implementation will be crucial for healthcare system adoption and reimbursement considerations [63]. AI/ML technologies could address healthcare disparities and resource limitations in low- and middle-income countries by enabling more efficient utilisation of scarce nephrology expertise and dialysis resources [64].

7. Limitations of the review

7.1. *Methodological limitations*

This narrative review does not follow the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines, as PRISMA is specifically designed for systematic reviews and meta-analyses with predefined protocols, standardised risk-of-bias assessments, and quantitative synthesis. Consequently, we do not provide a PRISMA flow diagram showing the number of records identified, screened, assessed for eligibility, and included at each stage of the review process. We also do not present a comprehensive data extraction table with standardised fields across all included studies, as such detailed tabulation is a hallmark of systematic reviews but not necessary for narrative syntheses. Similarly, we do not report screening statistics (e.g., number of articles screened by two independent reviewers at title/abstract and full-text levels, inter-rater agreement metrics) as these are elements of systematic review methodology designed to ensure reproducibility and minimise selection bias in quantitative evidence synthesis.

The decision to conduct a narrative rather than a systematic review was deliberate and justified by several factors. First, the AI/ML literature in dialysis is characterised by extreme methodological heterogeneity, diverse algorithms (from logistic regression to deep neural networks), varied outcome definitions (multiple IDH thresholds, different mortality timeframes), inconsistent validation strategies (internal vs. external, retrospective vs. prospective), and disparate clinical settings (single-centre vs. multi-centre, academic vs. community), making standardised data extraction, risk-of-bias assessment, and quantitative pooling inappropriate. Second, the field is rapidly evolving, with new architectures (e.g., transformers, federated learning) and applications emerging continuously, favouring a broader conceptual synthesis over a narrowly focused systematic question. Third, our objectives were to map the landscape of AI/ML applications across multiple domains, identify implementation barriers, and propose future directions, goals better suited to narrative synthesis than to the hypothesis-testing and effect-size estimation central to systematic reviews.

We acknowledge that the absence of PRISMA-compliant reporting limits the reproducibility and transparency of our literature search and selection process. Readers cannot independently verify our search strategy, assess the comprehensiveness of our literature identification, or evaluate potential selection bias in study inclusion. Furthermore, without standardised risk-of-bias assessment using validated tools (e.g., PROBAST for prediction models, QUADAS-2 for diagnostic accuracy studies), our quality appraisal relies on adapted TRIPOD and CONSORT-AI criteria, which are reporting checklists rather than formal bias assessment instruments. This approach provides a general sense of methodological rigour but does not offer the systematic, domain-specific bias evaluation that tools like PROBAST would provide.

The rapidly evolving AI/ML field creates challenges for any review due to publication lag and exponential growth in literature. Our English-language restriction and focus on biomedical databases may have missed relevant studies from non-English publications and computer science venues. Subjective judgments about “dialysis applications” scope may have excluded relevant methodological innovations from broader nephrology research.

7.2. *Publication and selection Bias*

Publication bias favours positive results and high-performing models, while negative findings and implementation failures are underreported. Industry-sponsored research may introduce commercial bias. Many studies report optimistic development-phase results without rigorous external validation, potentially overestimating AI/ML effectiveness.

7.3. Data quality and reporting issues

Reporting quality varies significantly across studies, with insufficient methodological detail about data preprocessing, validation procedures, and model development. Dataset characteristics and patient demographics are often poorly described. Performance metrics and outcome definitions lack standardisation, making comparisons difficult. Table 1 in this review provides representative examples of key studies but does not include the comprehensive standardisation (e.g., detailed sample sizes, precise outcome definitions, prediction horizons, confidence intervals for all metrics, data source specifications) that would be expected in a systematic review's data extraction table. This limitation reflects the narrative nature of our synthesis and the heterogeneity of the underlying literature. True external validation across different healthcare systems is uncommon.

7.4. Clinical translation gaps

Most studies report retrospective analyses without real-world prospective validation. Our review highlights strong predictive performance metrics (e.g., AUROCs >0.90 for IDH prediction), but we acknowledge the critical distinction between predictive discrimination and demonstrated clinical benefit. High AUROC values indicate that models can distinguish between patients who will and will not experience an outcome, but they do not prove that acting on these predictions improves patient outcomes, reduces complications, or enhances quality of life. Few studies in the dialysis AI/ML literature include prospective validation with clinician-in-the-loop decision-making, randomised controlled trials comparing AI-guided care to standard care, health economic evaluations demonstrating cost-effectiveness, or patient-centred outcome assessments capturing quality of life, treatment satisfaction, or shared decision-making. This gap between algorithmic performance and clinical impact evidence limits our ability to confidently recommend widespread implementation. Implementation challenges, workflow integration, and long-term sustainability are inadequately addressed. Economic evaluation and patient perspectives are substantially underrepresented, limiting understanding of cost-effectiveness and patient-centred outcomes.

7.5. Temporal and geographic limitations

Rapid technological advancement during our five-year review period makes earlier studies appear outdated. Research concentration in high-resource academic medical centres limits **generalisability** to community hospitals and resource-constrained settings. The short half-life of AI/ML methodological relevance creates uncertainty about recommendation durability.

8. Conclusion

This comprehensive narrative review demonstrates that artificial intelligence and machine learning applications in dialysis care have achieved remarkable technical sophistication and clinical promise over the past five years. The evidence clearly shows that AI/ML approaches consistently and substantially outperform traditional statistical methods across multiple critical clinical domains, with performance metrics suggesting genuine potential for transformative clinical impact. Intradialytic hypotension prediction models have achieved AUROC values exceeding 0.95, mortality prediction systems have demonstrated concordance indices above 0.83, and clinical decision support tools have shown measurable improvements in patient outcomes.

The breadth of AI/ML applications is impressive, spanning real-time complication prediction, long-term prognostic modelling, personalised treatment optimisation, and sophisticated decision support systems. The evolution from simple regression models to advanced deep learning architectures including transformer models demonstrates the rapid field maturation. Cloud computing integration has enabled real-time processing at scale, while federated learning approaches offer solutions to data privacy and multi-centre collaboration challenges.

However, significant barriers continue to impede widespread clinical translation. Data privacy concerns, regulatory compliance requirements, model interpretability limitations, and workflow integration challenges represent substantial hurdles requiring systematic attention. The underrepresentation of diverse patient populations in training datasets raises important questions about algorithmic fairness and generalisability. Economic considerations, including substantial upfront investment requirements and uncertain financial returns, complicate implementation decisions for healthcare organisations.

The regulatory landscape continues evolving rapidly, with frameworks such as the EU AI Act and FDA guidance creating both opportunities and challenges for clinical deployment. These developments provide clearer approval pathways but also increase complexity and compliance costs for AI/ML development and deployment.

Looking forward, the field appears well-positioned for continued growth and innovation. Emerging technologies including large language models, multimodal foundation models, and advanced federated learning techniques offer exciting possibilities for more sophisticated applications. The integration of Internet of Things (IoT) devices, wearable sensors, and digital therapeutics could provide richer data streams and more comprehensive patient monitoring capabilities.

The development of causal inference methodologies and reinforcement learning approaches promises to advance applications beyond prediction toward active treatment optimisation and personalised intervention strategies. These could enable adaptive treatment protocols that continuously learn from patient responses, potentially discovering novel therapeutic approaches exceeding current best practices.

However, realising this transformative potential requires sustained collaboration between technologists, clinicians, regulators, and patients to ensure these tools are developed and deployed safely, fairly, and effectively. Educational initiatives must prepare healthcare providers to work effectively with AI/ML technologies while maintaining clinical reasoning capabilities. Quality assurance frameworks must ensure ongoing monitoring of system performance, safety, and equity across diverse populations.

The ethical implications of widespread AI/ML adoption require proactive management to ensure these technologies reduce rather than amplify existing healthcare disparities. Patient engagement processes must evolve to incorporate AI/ML while preserving autonomy and informed consent principles.

The evidence strongly suggests that AI/ML technologies can fundamentally transform dialysis care from reactive, standardised approaches toward predictive, personalised precision medicine. The technical capabilities demonstrated provide compelling proof-of-concept evidence that these technologies can meaningfully improve patient outcomes, reduce complications, and enhance quality of life for individuals with kidney disease.

The successful realisation of this potential depends critically on continued commitment to rigorous validation, ethical development practices, stakeholder engagement, and implementation science principles. The challenges identified are substantial but not insurmountable, and the potential benefits justify continued investment toward overcoming these barriers.

The ultimate measure of success will be meaningful improvements in patient outcomes, quality of life, healthcare equity, and system sustainability rather than technical performance metrics. The foundation for such impact has been established through the research documented in this review, but translating this into widespread clinical benefit requires sustained collaboration across the healthcare ecosystem.

As we advance toward AI-enhanced dialysis care, maintaining focus on patient-centred outcomes, health equity, and improving quality of life for individuals with kidney disease remains crucial. The technical achievements provide compelling evidence of possibilities when advanced computational methods are thoughtfully applied to clinical challenges. The future appears bright with potential for predictive, personalised approaches that could transform outcomes for millions of patients worldwide.

The journey toward widespread implementation will present additional challenges and opportunities difficult to anticipate. However, the strong foundation of technical capability, clinical evidence, and growing stakeholder engagement provides optimism that these technologies can meaningfully improve lives while advancing healthcare equity, quality, and sustainability goals.

CRediT authorship contribution statement

Aanuoluwapo Clement David-Olawade: Writing – review & editing, Writing – original draft, Validation, Methodology, Investigation, Formal analysis, Conceptualization. **Muyiwa Ademola Ogunbona:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis. **Olabanke Florence Olawuyi:** Writing – review & editing, Writing – original draft, Methodology, Investigation. **Babajide David Makanjuola:** Writing – review & editing, Writing – original draft, Methodology, Investigation. **John Oluwatosin Alabi:** Writing – review & editing, Writing – original draft, Methodology, Investigation. **David B. Olawade:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Methodology, Investigation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

References

[1] J.S. Thurlow, M. Joshi, G. Yan, K.C. Norris, L.Y. Agodoa, C.M. Yuan, et al., Global epidemiology of end-stage kidney disease and disparities in kidney replacement therapy, Am. J. Nephrol. 52 (2) (2021) 98–107.

[2] NIDDK, Kidney disease statistics for the United States [internet], National Institute of Diabetes and Digestive and Kidney Diseases. (2023). Available from: https://www.niddk.nih.gov/health-information/health-statistics/kidney-disease.

[3] A.K. Bello, I.G. Okpechi, M.A. Osman, Y. Cho, H. Htay, V. Jha, et al., Epidemiology of haemodialysis outcomes, Nat. Rev. Nephrol. 18 (18) (2022). Available from: https://pubmed.ncbi.nlm.nih.gov/35194215/.

[4] P. Jayaraman, L. Chan, Differences in Dialysis, Survival Kidney360 [Internet] 6 (7) (2025) 1060–1062. Available from: https://pmc.ncbi.nlm.nih.gov/articles/PMC12338342/.

[5] M. Zhi, Y. Zeng, C. Chen, S. Deng, Y. Liu, Y. Huang, et al., The relationship between intradialytic hypotension and health-related quality of life in patients undergoing hemodialysis: a cross-sectional study, Sci. Rep. 15 (1) (2025) 11532. Available from: https://www.nature.com/articles/s41598-025-96286-y.

[6] Y.J. He, P.L. Liu, T. Wei, T. Liu, Y.F. Li, J. Yang, et al., Artificial intelligence in kidney transplantation: a 30-year bibliometric analysis of research trends, innovations, and future directions, Ren. Fail. 47 (1) (2025) 2458754. Available from: https://pubmed.ncbi.nlm.nih.gov/39910843/.

[7] Y.S. Ho, T. Fülöp, P. Krisanapan, K.M. Soliman, W. Cheungpasitporn, Artificial intelligence and machine learning trends in kidney care, Am. J. Med. Sci. 367 (5) (2024) 281–295.

[8] N. Laurier, J. Robert, A. Tom, J. McKinnon, N. Filteau, L. Horowitz, et al., Optimizing use of an electronic medical record system for quality improvement initiatives in hemodialysis: review of a single center experience, Hemodial, Int 29 (1) (2024) 74–82.

[9] Z. Chen, M. Chen, X. Sun, X. Guo, Q. Li, Y. Huang, et al., Analysis of the impact of medical features and risk prediction of acute kidney injury for critical patients using temporal electronic health record data with attention-based neural network, Front. Med. 4 (2021) 8.

[10] K. Sheng, P. Zhang, X. Yao, J. Li, Y. He, J. Chen, Prognostic machine learning models for first-year mortality in incident Hemodialysis patients: development and validation study, JMIR Med. Inform. 8 (10) (2020) e20578.

[11] J. Dong, K. Wang, J. He, Q. Guo, H. Min, D. Tang, et al., Machine learning-based intradialytic hypotension prediction of patients undergoing hemodialysis: a multicenter retrospective study, Comput. Methods Programs Biomed. 25 (240) (2023) 107698.

[12] H. Lee, D. Yun, J. Yoo, K. Yoo, Y.C. Kim, D.K. Kim, et al., Deep learning model for real-time prediction of intradialytic hypotension, Clin. J. Am. Soc. Nephrol. 16 (3) (2021) 396–406.

[13] H. Zhang, L.C. Wang, S. Chaudhuri, A. Pickering, L. Usvyat, J. Larkin, et al., Real-time prediction of intradialytic hypotension using machine learning and cloud computing infrastructure, Nephrology Dialysis Transplantation. 38 (7) (2023) 1761–1769.

[14] S. Masum, A. Hopgood, N. Sangala, R. Lewis, POS-640 Machine Learning For Intradialytic Hypotension Prediction In Haemodialysis Patients, Kidney International Reports. 7 (2) (2022) S274.

[15] V. García-Montemayor, A. Martín-Malo, C. Barbieri, F. Bellocchio, Soriano de SPR, et al., Predicting mortality in hemodialysis patients using machine learning analysis, NDT Plus 14 (5) (2020) 1388–95. Available from https://academic.oup.com/ckj/article/14/5/1388/5891276.

[16] C. Díez-Sanmartín, A.S. Cabezuelo, A.A. Belmonte, A new approach to predicting mortality in dialysis patients using sociodemographic features based on artificial intelligence, Artif. Intell. Med. 136 (2023) 102478.

[17] E.A. Betiru, E. Mamo, D.J. Boneya, A. Adem, D. Abebaw, Survival analysis and its predictors among Hemodialysis patients at Saint Paul hospital millennium medical college and Myungsung Christian medical Center in Addis Ababa, Ethiopia, 2021, Int. J. Nephrol. Renov. Dis. 16 (2023) 59–71.

[18] M. Hanna, L. Pantanowitz, B. Jackson, O. Palmer, S. Visweswaran, J. Pantanowitz, et al., Ethical and Bias considerations in artificial intelligence/machine learning, Mod. Pathol. 38 (3) (2024) 1–13. Available from: https://www.sciencedirect.com/science/article/pii/S0893395224002667.

[19] W. Van Biesen, J.B. Ponikvar, M. Fontana, P. Heering, M.S. Sever, S. Sawhney, et al., Ethical considerations on the use of big data and artificial intelligence in kidney research from the ERA ethics committee, Nephrology Dialysis Transplantation. 40 (3) (2024) 455-64 Available from: https://academic.oup.com/ndt/advance-article/doi/10.1093/ndt/gfae267/7906607.

[20] M. Kanbay, L.A. Ertuglu, B. Afsar, E. Ozdogan, D. Siriopol, A. Covic, et al., An update review of intradialytic hypotension: concept, risk factors, clinical implications and management, Clin. Kidney J. 13 (6) (2020) 981–993. Available from: https://academic.oup.com/ckj/article/13/6/981/5868598.

[21] A. Davenport, Why is Intradialytic Hypotension the Commonest Complication of Outpatient Dialysis Treatments? Kidney International Reports. 8 (3) (2022).

[22] D. Yun, H.L. Yang, S.G. Kim, K. Kim, D.K. Kim, K.H. Oh, et al., Real-time dual prediction of intradialytic hypotension and hypertension using an explainable deep learning model, Sci. Rep. 13 (1) (2023).

[23] J. Noh, S.Y. Park, W. Bae, K. Kim, J.H. Cho, J.S. Lee, et al., Predicting early mortality in hemodialysis patients: a deep learning approach using a nationwide prospective cohort in South Korea, Sci. Rep. 14 (1) (2024). Available from: https://www.nature.com/articles/s41598-024-80900-6.

[24] J. Noh, K.D. Yoo, W. Bae, J.S. Lee, K. Kim, J.H. Cho, et al., Prediction of the mortality risk in peritoneal Dialysis patients using machine learning models: a nation-wide prospective cohort in Korea, Sci. Rep. 10 (1) (2020).

[25] D. Zamanzadeh, J. Feng, P. Petousis, A. Vepa, M. Sarrafzadeh, S.A. Karumanchi, et al., Data-driven prediction of continuous renal replacement therapy survival. Nature, Communications 15 (1) (2024) 5440. Available from: https://www.nature.com/articles/s41467-024-49763-3.

[26] M.A. Isaza-Ruget, N. Yomayusa, C.A. González, C. Alvarado, H. Fabio, A. Cely, et al., Predicting chronic kidney disease progression with artificial intelligence, BMC Nephrol. 25 (1) (2024).

[27] A.T. Hoang, P.A. Nguyen, T.P. Phan, G.T. Do, H.D. Nguyen, Chiu I-Jen, et al., Personalised prediction of maintenance dialysis initiation in patients with chronic kidney disease stages 3–5: a multicentre study using the machine learning approach, BMJ Health & Care Informatics. 31 (1) (2024) e100893. Available from: https://informatics.bmj.com/content/31/1/e100893.

[28] H. Khosravi, S. Das, A. Al-Mamun, I. Ahmed, Binary Gaussian Copula Synthesis: A Novel Data Augmentation Technique to Advance ML-based Clinical Decision Support Systems for Early Prediction of Dialysis Among CKD Patients. arXiv.org, Available from: https://arxiv.org/abs/2403.00965, 2024.

[29] N. Tomašev, X. Glorot, J.W. Rae, M. Zielinski, H. Askham, A. Saraiva, et al., A clinically applicable approach to continuous prediction of future acute kidney injury, Nature 572 (7767) (2019) 116–119.

[30] I. Vagliano, N.C. Chesnaye, J.H. Leopold, K.J. Jager, A. Abu-Hanna, M.C. Schut, Machine learning models for predicting acute kidney injury: a systematic review and critical appraisal, Clin. Kidney J. 15 (12) (2022) 2266–2280.

[31] A. Burlacu, A. Iftene, D. Jugrin, I.V. Popa, P.M. Lupu, C. Vlad, et al., Using artificial intelligence resources in Dialysis and kidney transplant patients: a literature review, Biomed. Res. Int. (2020) (2020) 1–14.

[32] C. Kang, J. Han, S. Son, S. Lee, H. Baek, D.D.J. Hwang, et al., Optimizing anemia management using artificial intelligence for patients undergoing hemodialysis, Sci. Rep. 14 (1) (2024).

[33] T. Ohara, H. Ikeda, Y. Sugitani, H. Suito, V.Q.H. Huynh, M. Kinomura, et al., Artificial intelligence supported anemia control system (AISACS) to prevent anemia in maintenance hemodialysis patients, Int. J. Med. Sci. 18 (8) (2021) 1831–1839.

[34] E. Nobakht, W. Raru, S. Dadgar, O. El Shamy, Precision Dialysis: leveraging big data and artificial intelligence, Kidney Medicine. 6 (9) (2024) 100868. Available from: https://www.sciencedirect.com/science/article/pii/S2590059524000797.

[35] H.W. Kim, S.J. Heo, J.Y. Kim, A. Kim, C.M. Nam, B.S. Kim, Dialysis adequacy predictions using a machine learning method, Sci. Rep. 11 (1) (2021).

[36] L. Chan, K. Beers, A.A. Yau, K. Chauhan, Á. Duffy, K. Chaudhary, et al., Natural language processing of electronic health records is superior to billing codes to identify symptom burden in hemodialysis patients, Kidney Int. 97 (2) (2020) 383–392.
[37] W. Krackov, M. Sor, R. Razdan, H. Zheng, P. Kotanko, Artificial intelligence methods for rapid vascular access aneurysm classification in remote or in-person settings, Blood Purif. 50 (4–5) (2021) 636–641.
[38] S. Julkaew, T. Wongsirichot, K. Damkliang, P. Sangthawan, Improving accuracy of vascular access quality classification in hemodialysis patients using deep learning with K highest score feature selection, J. Int. Med. Res. 52 (4) (2024).
[39] J. Carroll, E. Colley, M. Cartmill, S.D. Thomas, Robotic tomographic ultrasound and artificial intelligence for management of haemodialysis arteriovenous fistulae, J. Vasc. Access 26 (1) (2023) 242–250.
[40] R. Scarpioni, A. Manini, P. Chiappini, Remote patient monitoring in peritoneal dialysis helps reduce risk of hospitalization during Covid-19 pandemic, J. Nephrol. 33 (6) (2020) 1123–1124.
[41] P. Kotanko, H. Zhang, Y. Wang, Artificial Intelligence and machine learning in dialysis, Clin. J. Am. Soc. Nephrol. 18 (6) (2023) 803–805.
[42] S. Chaudhuri, A. Long, H. Zhang, C. Monaghan, J.W. Larkin, P. Kotanko, et al., Artificial intelligence enabled applications in kidney disease, Semin. Dial. 34 (1) (2020) 5–16.
[43] J. Huang, L. Chen, H. Luo, K. Chen, T. Wang, B. Peng, et al., Use of machine learning models to predict mortality in dialysis patients, Front. Public Health 13 (2025).
[44] Y. Lu, C. Chen, J. Qiu, Q. Ji, L. Zhou, H. Xiong, et al., Systematic review and comparison of machine learning and conventional statistical models for predicting cardiovascular events in dialysis patients, Ren. Fail. 47 (1) (2025). Available from, https://pmc.ncbi.nlm.nih.gov/articles/PMC12632218/.
[45] E. Adiyeke, Y. Ren, M.M. Ruppert, B. Shickel, S.L. Kane-Gill, Raghavan Murugan, et al., A deep learning–based dynamic model for predicting acute kidney injury risk severity in postoperative patients, Surgery 174 (3) (2023) 709–714. Available from, https://www.sciencedirect.com/science/article/abs/pii/S0039606023002726?via%3Dihub.
[46] A. Ehteshami, M. Esmailzadeh, A. Rezaei, A scoping review of cloud computing solutions in enhanced Dialysis information exchange, Evidence Based Health Policy Management and Economics 8 (2) (2024) 149–159.
[47] T.J. Loftus, M.M. Ruppert, B. Shickel, Tezcan Ozrazgat-Baslanti, J. Balch, P. A. Efron, et al., Federated learning for preserving data privacy in collaborative healthcare research, Digital Health. 8 (2022), 205520762211344–205520762211344.
[48] H. Zhao, D. Sui, Y. Wang, L. Ma, L. Wang, Privacy-preserving federated learning framework for multi-source electronic health records prognosis prediction, Sensors 25 (8) (2025) 2374. Available from: https://www.mdpi.com/1424-8220/25/8/2374.
[49] N. Tahir, C.R. Jung, S.D. Lee, Nur Azizah, W.C. Ho, T.C. Li, Federated learning-based model for predicting mortality: systematic review and meta-analysis, J. Med. Internet Res. 27 (2025) e65708.
[50] M. Ennab, H. Mcheick, Enhancing interpretability and accuracy of AI models in healthcare: a comprehensive review on challenges and future directions, Front. Robot. AI 11 (2024).
[51] Y. Ning, M. Liu, N. Liu, advancing ethical AI in healthcare through interpretability, Patterns 6 (6) (2025) 101290.
[52] G.S. Collins, K.G.M. Moons, P. Dhiman, R.D. Riley, A.L. Beam, Ben Van Calster, et al., TRIPOD+AI statement: updated guidance for reporting clinical prediction models that use regression or machine learning methods, BMJ 385 (2024) e078378-8.
[53] E.P. Vardas, M. Marketou, P.E. Vardas, Medicine, healthcare and the AI act: gaps, challenges and future implications, Eur. heart j. - Digit. health. 6 (4) (2025) 833–839.
[54] D. Windecker, G. Baj, I. Shiri, P.M. Kazaj, J. Kaesmacher, C. Gräni, et al., Generalizability of FDA-approved AI-enabled medical devices for clinical use, JAMA Netw. Open 30;8(4) (2025) e258052. Available from, https://jamanetwork.com/journals/jamanetworkopen/fullarticle/2833324?resultClick=1.
[55] Singh R, Bapna M, Diab AR, Ruiz ES, Lotter W. How AI is used in FDA-authorized medical devices: a taxonomy across 1,016 authorizations. NPJ Digit. Med. 2025;8 (1). Available from: https://www.nature.com/articles/s41746-025-01800-1#citeas.
[56] M. Hueso, L. de Haro, J. Calabia, R. Dal-Ré, C. Tebé, K. Gibert, et al., Leveraging data science for a personalized haemodialysis, Kidney Dis. 6 (6) (2020) 385–394. Available from, https://www.karger.com/Article/FullText/507291.
[57] D. van de Sande, E.F.F. Chung, J. Oosterhoff, J. van Bommel, Diederik Gommers, Michel, To warrant clinical adoption AI models require a multi-faceted implementation evaluation, NPJ Digit. Med. 7 (1) (2024).
[58] Y. Liu, C. Liu, J. Zheng, C. Xu, D. Wang, Improving explainability and integrability of medical artificial intelligence to promote healthcare professional acceptance and usage: a mixed systematic review, J. Med. Internet Res. 27 (2025) e73374.
[59] A.U. Otokiti, H. Shih, K.S. Williams, Gender and racial bias unveiled: clinical artificial intelligence (AI) and machine learning (ML) algorithms are fanning the flames of inequity, Oxf. Open Digit. Health 3 (2025) oqaf027.
[60] Y. Qiao, H. Zhou, Y. Liu, R. Chen, X. Zhang, S. Nie, et al., A multi-modal fusion model with enhanced feature representation for chronic kidney disease progression prediction, Brief. Bioinform. 26 (1) (2024) bbaf003.
[61] A. Akhmetov, Z. Latif, B. Tyler, A. Yazici, Enhancing healthcare data privacy and interoperability with federated learning, PeerJ Computer Science. 8 (11) (2025) e2870.
[62] Z. Zhang, X.T. Liang, X.W. He, X. Zhang, R. Tang, R.D. Fang, et al., Enhancing treatment adherence in dialysis patients through digital health interventions: a systematic review and meta-analysis of randomized controlled trials, Ren. Fail. 47 (1) (2025).
[63] A. Shiwlani, S. Kumar, S. Kumar, S. Hasan, M. Hifazat, A. Shah, Pakistan journal of life and social sciences transforming healthcare economics: machine learning impact on cost effectiveness and value-based care, Pak j life soc Sci. 22 (2024) (2): 20367–82. Available from, https://www.pjlss.edu.pk/pdf_files/2024_2/20367-20382.pdf.
[64] C.C. Wu, Mdmohaimenul Islam, Tahmina Nasrin Poly, Y.C. Weng, Artificial intelligence in kidney disease: a comprehensive study and directions for future research, Diagnostics 14 (4) (2024) 397. Available from: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC10887584/.