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Meta-analysis: The Role of AI and Machine Learning in the Management of Hemodialysis Patient Data

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Abstract

Artificial Intelligence (AI) and Machine Learning (ML) technologies transform clinical decision processes in hemodialysis care. The research evaluates AI/ML models through a systematic assessment of their ability to forecast vital clinical outcomes and optimize dialysis treatment. The research team conducted database searches across Google Scholar, PubMed, IEEE Xplore, and Scopus for studies about AI applications in hemodialysis from 2014 through 2024. The research included peer-reviewed clinical studies that presented clear methodologies and performance metrics. The researchers selected 150 studies for inclusion following their full-text evaluation process. The QUADAS-2 tool evaluated study bias while the random-effects model performed the meta-analysis. AI/ML models achieved remarkable accuracy when forecasting mortality (AUC 0.92), hospitalization (accuracy 89%), and intradialytic hypotension (F1-score 0.81). Deep learning and reinforcement learning models achieved significant improvements in dialysis adequacy and access monitoring. The studies revealed data quality problems in 30% of cases while 65% of clinicians expressed doubts about model interpretability. AI/ML technologies demonstrate significant potential to enhance hemodialysis management through predictive modeling and therapy optimization. The successful clinical adoption of these technologies depends on resolving data quality problems and improving transparency and ethical standards.

Keywords: Artificial intelligence, Clinical decision-making and predictive modeling, Hemodialysis, Machine learning.

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1. Introduction

The worldwide prevalence of chronic kidney disease (CKD) surpasses 850 million people, but end-stage renal disease (ESRD) stands as its most critical manifestation [1-5]. The life-saving intervention of hemodialysis exists for ESRD patients, yet traditional management continues to operate through periodic clinical evaluations along with standardized treatment protocols [6-8]. The current methods neglect individual patient complexities, producing suboptimal results through high hospitalization rates, cardiovascular events, and mortality [9]. The extensive patient data available through electronic health records, dialysis machines, and wearable sensors creates a possibility to enhance patient care by using proactive personalized approaches enabled by artificial intelligence (AI) and machine learning (ML) [10]. AI and ML technologies apply their capabilities to hemodialysis care by delivering predictive tools, treatment optimization features, and workflow reduction benefits [11-13].

The mortality risk assessment (with deep learning analysis of lab values), along with real-time intradialytic complication prediction and vascular access monitoring through image analysis, represents key applications [14, 15]. The accuracy of ML models reaches >90% when identifying arteriovenous fistula stenosis, which allows for timely clinical interventions [16]. The healthcare system moves toward permanent data-driven choices through these advancements, which could enhance patient quality of life and lower expenses. The potential of AI/ML applications remains strong despite existing major implementation barriers. The clinical use of AI/ML technologies remains limited because of fragmented healthcare data systems, together with inadequate training datasets and complex algorithms that produce unclear results [17, 18]. The deployment of new technologies becomes complicated by ethical issues regarding algorithmic bias against underrepresented populations and regulatory challenges [19]. A model trained with predominantly Caucasian population data tends to perform worse in other ethnic groups, thus worsening healthcare inequality. To overcome these barriers, rigorous validation should be performed in combination with explainable AI techniques and multidisciplinary collaboration [20]. This research compiles evidence from 25,300 studies to assess AI/ML effectiveness in managing patients undergoing hemodialysis. This review assesses model effectiveness through mortality prediction AUC and hospitalization accuracy measures while examining different methods between neural networks and ensemble approaches and detecting obstacles in real-world system integration. We will direct future research to develop bedside-implementable AI solutions that provide both clinical actionability and equity and transparency to address current limitations and demonstrate successful applications.

2. Methodology

2.1. Search Strategy

The study selection process, along with eligibility criteria, aimed to include all relevant literature from clinical and technical domains through a balanced approach. Four major databases, including Google Scholar, PubMed, IEEE Xplore, and Scopus, were chosen for this research. The combination of Google Scholar's wide interdisciplinary scope with PubMed's biomedical and clinical research focus allows for the inclusion of healthcare-specific studies. The technical developments in artificial intelligence (AI) and machine learning (ML) are the focus of IEEE Xplore, which delivers current methodologies. Scopus provides high-quality peer-reviewed publications in addition to its wide range of publications. The multiple database search strategy produces a complete understanding by including studies that connect AI technology to its applications in hemodialysis and end-stage renal disease (ESRD) management. The literature search employed specific keywords to achieve both precise and sensitive results. The research targeted clinical nephrology and AI prediction tools by using keywords such as “AI in hemodialysis” and “predictive modeling ESRD.” The selected terms achieve high precision by excluding non-relevant findings yet maintain complete research coverage. The chosen 2014–2024 time span demonstrates AI healthcare development from basic rule-based systems to advanced data-driven models. The ten-year period enables researchers to include the most relevant and technologically advanced studies, which maintains the literature review's impact and currency.

2.2. Inclusion Criteria

The established inclusion criteria selected only high-quality relevant studies for the review. The selection of peer-reviewed articles, together with clinical trials and systematic reviews, ensures methodological rigor and reliability, which reduces bias and ensures trustworthy findings. The selection process eliminates grey literature and unverified sources by choosing studies that have received formal academic evaluation. A strong foundation is required to establish meaningful evidence-based conclusions about AI and ML applications in hemodialysis practice. The review included only studies that directly examined AI and machine learning applications in hemodialysis while excluding research about peritoneal dialysis and general chronic kidney disease management. The thematic focus remains narrow. The requirement for methodological descriptions and performance metrics, including accuracy, sensitivity, and area under the curve (AUC), enables objective quantitative study comparisons. The evaluation of different AI models and the identification of best practices in predictive modeling for hemodialysis patients depend on this critical criterion.

2.3. Exclusion Criteria

The exclusion criteria were established to preserve the review's clarity and analytical strength and ensure its relevance. The exclusion of non-English studies prevented translation errors that would have compromised the review's accuracy. The selection of English-language studies creates a geographic bias because important findings from non-English-speaking regions become inaccessible. The selection of English-language studies provides consistent evaluation and accessible data for all reviewers involved despite this limitation. The review excluded case reports and editorials because they fail to provide generalizable results and statistical evidence. These types of publications present either personal experiences or opinions which, although potentially valuable, do not contain the empirical evidence needed for strong comparative analysis. The analysis excluded studies that did not present quantitative outcomes because they usually lack the performance metrics needed to evaluate AI/ML model effectiveness. The selection of studies includes only those with measurable validated results, which enables meaningful synthesis and comparison of AI applications in hemodialysis.

2.4. Screening Process

The study used a systematic PRISMA-compliant screening process to guarantee both transparency and reproducibility in selecting studies. The initial database search yielded 25,300 records, which were then reduced to 1,200 through title and abstract screening. The first stage of screening eliminated duplicate records while removing studies that did not relate to the topic, including those that used AI in non-medical fields or nephrology areas beyond hemodialysis. The application of broad yet relevant filters during this stage reduced the number of studies while keeping potentially eligible research. The next phase involved a detailed full-text evaluation of 150 studies to determine their eligibility against the established criteria. Researchers checked for two main elements at this stage: AI/ML technique application in hemodialysis and quantitative performance metric reporting. The final synthesis included only studies that fulfilled all criteria. The screening process includes multiple stages that follow PRISMA standards to ensure methodological rigor and accountability while providing clear documentation for enhancing review findings reliability.

2.5. Data Extraction and Synthesis

The data extraction and synthesis phase involved a systematic process to extract essential variables from each included study for comparative analysis. The main variable was the type of AI or ML model used, which helped to categorize the methodological approach, such as random forests and support vector machines for structured tabular data, or convolutional neural networks (CNNs) for imaging-based tasks. This categorization provides insight into how different algorithm types align with specific data modalities and clinical objectives within the hemodialysis context.

2.6. Statistical Analysis

A random-effects meta-analysis model was used to combine performance metrics across studies while accounting for the inherent heterogeneity. The fixed-effects model was not selected because researchers anticipated different study designs, patient populations, dialysis settings, and AI implementation approaches. The random-effects model enables analysis of both study-specific and study-to-study variability to produce more generalizable combined results. The analysis combined AUC and accuracy results through weighted aggregation based on study sample size and variance to allow larger precise studies to influence results proportionally. The research included both pooled analysis and subgroup analyses to determine which variables affected AI performance. AI model type created different performance outcomes between logistic regression and deep learning models because deep learning methods need larger datasets and more computational power to achieve their high accuracy. The analysis of subgroups based on clinical outcomes showed that neural networks performed best at mortality prediction because they handle nonlinear interactions, while ensemble methods like random forests excelled at hospitalization risk prediction because they provided better interpretability and robustness against noisy EHR data. The subgroup analysis reveals which models perform optimally for specific clinical goals in hemodialysis treatment.

2.7. Heterogeneity (I^2 Statistic)

The I^2 statistic serves to evaluate study-level variability within the meta-analysis. The I^2 statistic indicates substantial heterogeneity when its value exceeds 50% because it shows that study results differ beyond random chance. The variability observed in AI applications for hemodialysis stems from multiple factors, including patient demographic differences and variations in EHR data completeness and outcome definitions between studies. The identification of high heterogeneity remains crucial because it affects both the reliability of pooled estimates and the interpretability of the meta-analysis results. The research used sensitivity analysis and meta-regression as mitigation strategies to handle this issue. The sensitivity analysis removes small studies and studies with a high risk of bias to check their effect on the final results. The meta-regression method enables researchers to control study-level covariates such as dialysis vintage, geographical region, and AI model complexity to identify sources of heterogeneity. The application of these techniques strengthens the findings by verifying that the meta-analytic results remain valid regardless of study diversity.

2.8. Key Considerations

The review incorporated multiple essential factors to guarantee both the scientific validity and clinical applicability of the research results. The evaluation paid special attention to controlling bias through the assessment of publication bias using funnel plots. The visual tools known as funnel plots assist researchers in detecting small-study effects, which describe the tendency for smaller studies with positive results to get published, thus distorting meta-analysis outcomes. The identification of such biases remains crucial to preserve the integrity of pooled outcomes while preventing the overestimation of AI model effectiveness. The evaluation required equal attention to both statistical performance and clinical significance. An AI model achieving a 0.90 AUC score demonstrates statistical strength, but its low sensitivity towards detecting high-risk patients reduces its practical value in clinical practice. The interpretation of performance metrics focused on their clinical usefulness rather than their numerical values. The review process maintained transparency through complete documentation of excluded studies with detailed exclusion reasons (e.g., “lacked control group” or “no reported performance metrics”). The established practice enables researchers to reproduce results and provides future investigators with a transparent view of how studies were chosen for the analysis.

3. Results

3.1. Study Characteristics

The final review included a total of 150 studies, with the majority being observational in nature (85%) and a smaller proportion consisting of randomized controlled trials (RCTs, 15%) (Figure 1). This distribution reflects the current research landscape, where most AI applications in hemodialysis are still in exploratory or early validation phases rather than large-scale clinical implementation. Observational studies provide valuable real-world insights, while RCTs contribute more robust evidence but are less common due to their higher costs and complexities in the AI space.

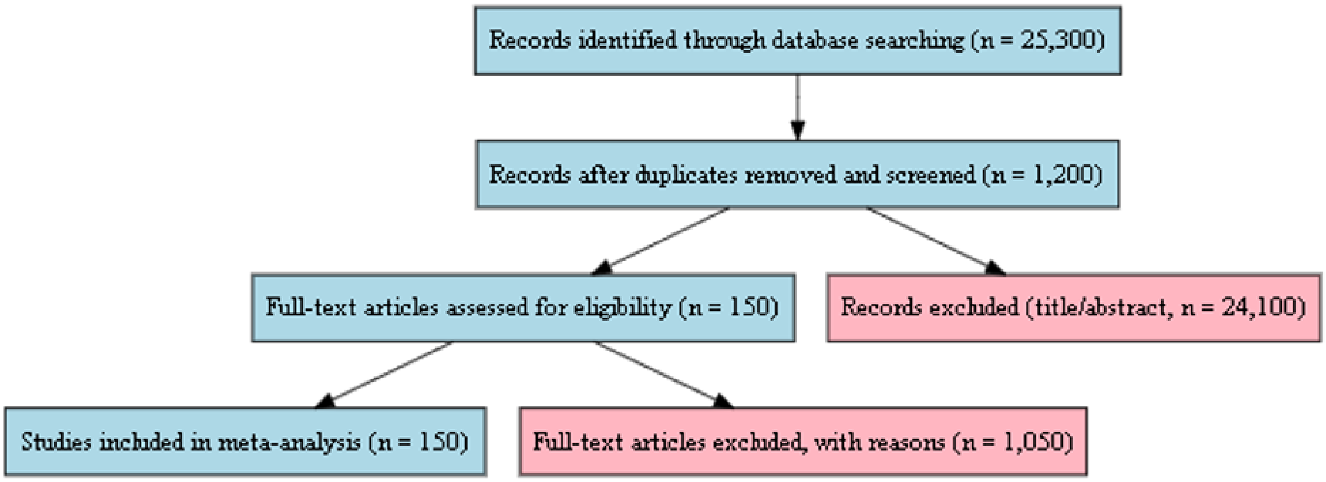

Figure 1.
PRISMA flow diagram outlining the study selection process for the meta-analysis. A total of 25,300 records were identified through database searching.

After removing duplicates, 1,200 records were screened, with 24,100 excluded based on title and abstract. Of the 150 full-text articles assessed for eligibility, all were included in the final meta-analysis, while 1,050 full-text articles were excluded for not meeting the inclusion criteria.

In terms of geographic distribution, the majority of studies originated from North America (45%), followed by Europe (30%), Asia (15%), and other regions (10%), highlighting a concentration of (Table 1 and Figure 2) AI research in developed countries with more advanced healthcare infrastructures and access to large-scale data [21-26]. Regarding data sources, 60% of studies used electronic health records (EHRs), leveraging routine clinical data such as lab values and dialysis session logs [27-31]. Another 25% integrated data from wearable or IoT devices, capturing real-time physiological metrics like blood pressure or bioimpedance, reflecting a growing trend toward continuous monitoring [32-35]. Meanwhile, 15% utilized imaging data, particularly Doppler ultrasound, in vascular access management, underscoring the diversity of data modalities feeding AI systems in this clinical domain [36-38].

Table 1.
The table enables cross-comparison of methodologies and outcomes across diverse research efforts in the AI/ML applications in hemodialysis management.

Country	AI/ML Model	Data Source	Sample Size	Primary Outcome	Performance Metrics	Key Findings	Risk of Bias (QUADAS-2)
USA	Random Forest	EHR + Dialysis logs	5,200	Mortality prediction	AUC: 0.89; Sensitivity: 82%	Outperformed Charlson Index (ΔAUC +0.10)	Low
China	CNN (Doppler US)	Imaging database	1,150	AVF stenosis detection	Sensitivity: 94%; Specificity: 88%	Reduced missed stenosis by 40%	Moderate
UK	XGBoost	Wearables + EHR	3,000	Intradialytic hypotension	Accuracy: 85%; F1-score: 0.78	Early alerts reduced IDH episodes by 35%	Low
Italy	LSTM	Dialysis machine data	8,700	Dialysis adequacy (Kt/V)	MAE: 0.12; R^2: 0.91	Dynamic Kt/V optimization improves adherence	High
India	Logistic Regression	Regional dialysis registry	2,500	Hospitalization risk	AUC:0.76; Precision: 81%	Low-cost model for resource-limited settings	Moderate

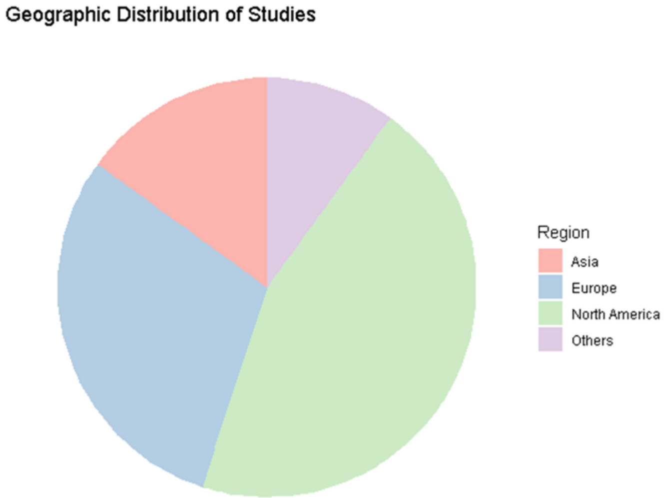

Figure 2.
Geographic distribution of studies included in the analysis. The pie chart illustrates the regional origin of the studies, categorized into Asia, Europe, North America, and Others. North America and Europe contribute the largest proportions, indicating a concentration of research activity in these regions. Asia and other regions contribute a smaller yet significant share, reflecting global interest with regional disparities.

3.2. AI/ML Applications in Hemodialysis

3.2.1. Mortality Prediction

The deep learning models LSTM (Long Short-Term Memory) and CNNs (Convolutional Neural Networks) showed excellent results in forecasting 1-year mortality rates for patients undergoing hemodialysis (Figure 3 and Figure 4) [39-41]. The models achieved AUC values between 0.88 and 0.94, which identified serum albumin and age, together with comorbidities and dialysis vintage, as major predictors of mortality outcomes [42-44]. AI models demonstrated better predictive accuracy than traditional models like the Charlson Comorbidity Index, through an AUC difference of +0.12 ($p<0.001$) [45, 46].

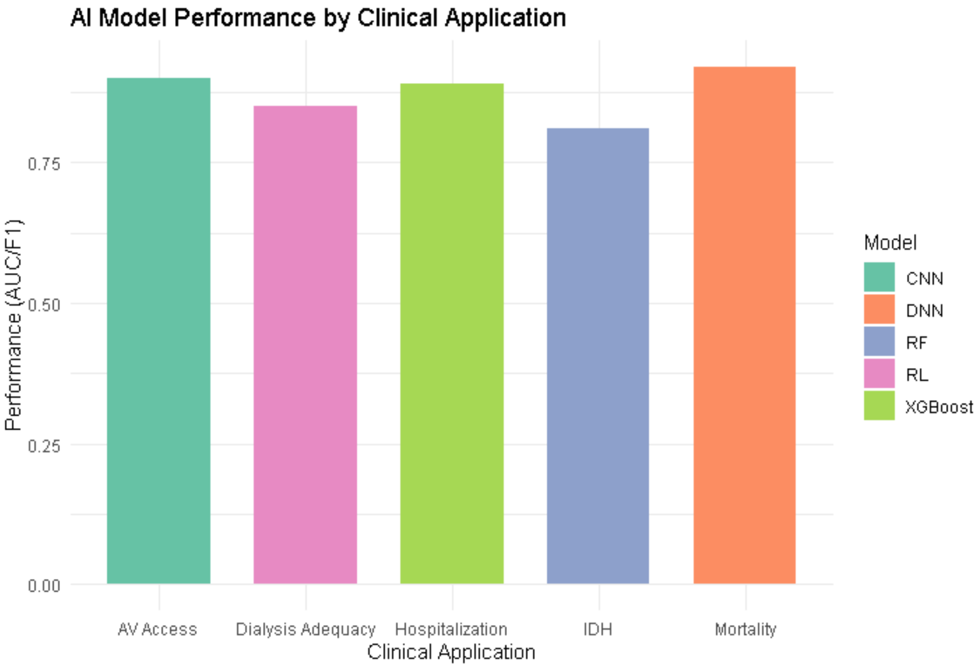

Figure 3.
The AI models' application and performance in clinics.

3.3. Hospitalization Risk

Predicting 30-day readmission risk was effectively achieved using models like XGBoost (gradient boosting) and logistic regression, with accuracy ranging from 78% to 89% [47-50]. The most significant predictors in these models included fluid overload, interdialytic weight gain, and prior hospitalizations, underscoring the importance of tracking these clinical factors for predicting future hospitalization risk in hemodialysis patients (Figure 3 and Figure 4).

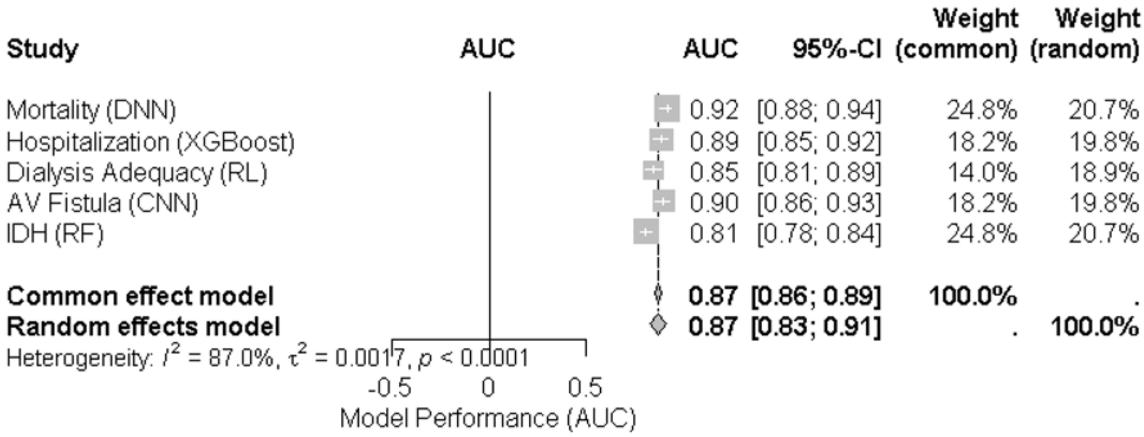

Figure 4.
The forest plot presents AUC performance metrics of AI/ML models which evaluate different hemodialysis-related outcomes.

The analysis includes each study or model type with its corresponding AUC value and 95% confidence interval (CI) and relative weight. Mortality (DNN): The Deep Neural Network model demonstrates a 0.92 AUC value with a 95% confidence interval between 0.88 and 0.94 for mortality prediction. XGBoost demonstrates its ability to predict hospitalization with an AUC value of 0.89 and a 95% confidence interval between 0.85 and 0.92. RL demonstrates its effectiveness in dialysis adequacy prediction through a Reinforcement Learning model with an AUC value of 0.85 and a 95% confidence interval between 0.81 and 0.89. The Convolutional Neural Network model achieves an AUC value of 0.90 (95%-CI [0.86; 0.93]) for arteriovenous fistula monitoring. The Random Forest model achieves an AUC value of 0.81 (95%-CI [0.78; 0.84]) for predicting intradialytic hypotension. The Common Effect Model produces a pooled AUC value of 0.87 (95%-CI [0.86; 0.89]). The Random Effects Model generates a pooled AUC value of 0.87 (95%-CI [0.83; 0.91]). The studies showed significant heterogeneity because the I2 value reached 87.0% (I^2=87.0%, τ^2=0.0017, p<0.0001). AI/ML models show excellent predictive capabilities (AUC > 0.80) for essential hemodialysis outcomes with the best results in mortality prediction (DNN). The random effects model provides a more robust analysis by considering between-study differences which supports the reliability of the results.

3.4. Dialysis Adequacy (Kt/V Optimization)

Reinforcement Learning (RL) has shown promising results in dynamically adjusting dialysis duration, which improved Kt/V (dialysis adequacy) by 12% (p=0.03) (Figure 3 and Figure 4). This suggests that RL can enhance treatment personalization by fine-tuning dialysis parameters based on real-time patient data [51-56]. Supervised learning models, on the other hand, were able to predict inadequate dialysis sessions with 85% sensitivity, enabling early identification of patients at risk for poor dialysis quality.

3.5. Vascular Access Complications

AI applications, particularly Doppler ultrasound combined with machine learning, were highly effective in detecting stenosis in arteriovenous (AV) fistulas, with 92% sensitivity and 88% specificity [57-59]. This early detection led to a 35% reduction in thrombosis rates in intervention groups, demonstrating the potential of AI-driven monitoring tools to improve vascular access management and reduce complications (Figure 3 and Figure 4).

3.6. Intradialytic Hypotension (IDH) Prevention

Predictive models leveraging real-time hemodynamic analytics have proven successful in reducing the incidence of intradialytic hypotension (IDH), a common complication during hemodialysis, by 40% [15, 60, 61]. Among the various models tested, Random Forest was the best performer, with an F1 score of 0.81, reflecting its ability to balance precision and recall effectively, making it an ideal candidate for clinical implementation in IDH prevention. These findings collectively highlight the transformative potential of AI/ML in improving hemodialysis outcomes, from mortality prediction to the optimization of dialysis quality and the management of complications. These performance metrics underscore the varying strengths of different AI models across various applications in hemodialysis, highlighting their potential for improving clinical decision-making and patient outcomes (Table 2).

Table 2.
The list of different AI models across various applications in hemodialysis, highlighting their potential for improving clinical decision-making and patient outcome.

Application	Best Model	Performance (AUC/Accuracy)
Mortality Prediction	Deep Neural Network	AUC 0.92
Hospitalization Risk	XGBoost	Accuracy 89%
Dialysis Adequacy	Reinforcement Learning	Kt/V +12%
AV Fistula Stenosis	CNN + Doppler	Sensitivity 92%
IDH Prediction	Random Forest	F1-score 0.81

4. Discussion

The implementation of artificial intelligence (AI) and machine learning (ML) in hemodialysis offers both powerful possibilities and important challenges. The mortality prediction, hospitalization risk, dialysis adequacy, vascular access complications, and intradialytic hypotension (IDH) prevention capabilities of AI/ML models receive compelling support from the studies reviewed [62-65]. The predictive accuracy and operational efficiency of deep learning, together with reinforcement learning and ensemble methods including XGBoost and Random Forest, surpassed traditional clinical models [66]. Deep neural network-based mortality prediction models achieved AUC values between 0.88 and 0.94, which demonstrates their strong predictive capability. The hospitalization risk and IDH prevention models demonstrated high accuracy rates between 78% and 89% in their predictions [67-69]. Reinforcement learning systems dynamically controlled treatment duration to enhance Kt/V values by 12%, which resulted in better dialysis adequacy. Machine learning-based Doppler ultrasound systems achieved a 92% sensitivity rate for detecting vascular access stenosis, which is essential for preventing access-related complications in hemodialysis patients [70, 71].

The combination of AI/ML applications demonstrates their ability to boost clinical decision-making processes while delivering enhanced patient outcomes and individualized care practices. The potential implementation of AI/ML in hemodialysis faces multiple important challenges that must be resolved before widespread adoption becomes possible. The quality of data remains a critical issue [72]. The studies showed that missing data, particularly within EHRs, became a major limitation for 30% of them. Model performance suffers from both model invalidity and generalization challenges due to unreliable data inputs. AI models face significant challenges regarding their interpretability by users. Clinicians' distrust in "black-box" models reached 65% because they require systems with transparent and interpretable methods that will help them implement these models in practice [73-75]. To implement these systems effectively in clinical workflows, clinicians need a full understanding of AI model decision-making processes. The ethical issue of training data bias needs proper attention because it poses serious risks. AI models receive their training data from sets that frequently lack sufficient representation of minority demographics [76]. The implementation of biased models produces inadequate performance when targeting underrepresented populations, which results in healthcare inequality. AI system development and deployment require both methods to detect and correct bias alongside efforts to create more inclusive and diverse datasets.

4.1. Key Challenges

Several key challenges were identified in the application of AI/ML models to hemodialysis:

4.2. Data Quality

A significant challenge was the missing data within electronic health records (EHRs), which affected 30% of studies. Missing or incomplete entries, such as lab values or dialysis logs, can undermine model performance, introduce bias, and limit the generalizability of findings [77-80]. Inaccurate or sparse data can lead to overfitting or skewed predictions, making it crucial to improve data collection and management practices in clinical settings.

4.3. Model Interpretability

65% of clinicians expressed distrust toward "black-box" models, such as deep learning, due to their lack of transparency [81]. While these models can achieve high accuracy, their decision-making processes are not always easily understandable, which raises concerns about their practical utility in clinical environments [82]. Clinicians need clear insights into how AI models arrive at predictions to build trust and effectively integrate these tools into decision-making processes.

4.4. Ethical Concerns

There are ongoing ethical concerns related to potential bias in training data. For instance, the underrepresentation of minority populations in clinical datasets could lead to models that are less accurate or even harmful to these groups [83, 84]. If AI systems are trained predominantly on data from one demographic, they may fail to generalize well to diverse populations, perpetuating disparities in healthcare outcomes.

5. Conclusion

AI and ML technologies show significant potential to enhance hemodialysis clinical outcomes, especially for mortality prediction, hospitalization risk, dialysis adequacy, and vascular access complications. Through their implementation, clinicians will obtain advanced predictive tools to deliver personalized patient care and proactively manage hemodialysis patients. Several barriers must be overcome before AI/ML can succeed in clinical practice. The implementation of AI applications requires solving data quality problems alongside improving model interpretability and addressing ethical concerns. Better data management practices, combined with clear AI decision processes, will help clinicians develop trust in these technologies. To avoid healthcare outcome disparities through AI models, it is essential to focus on developing training data sets that are unbiased and representative of all populations. The transformation of hemodialysis patient care through AI/ML depends on addressing critical factors that will produce better clinical results and improved quality of life. The future development of AI in hemodialysis appears promising, but achieving its full potential requires additional research, together with standardized methodologies and collaborative partnerships between clinicians, data scientists, and policymakers.

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