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REVIEW

Optimizing CAPD Patient Monitoring Through Automated Vs Rule-Based Artificial Intelligence: A Systematic Comparative Review

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Abstract: Continuous Ambulatory Peritoneal Dialysis (CAPD) is a flexible renal replacement therapy that is widely used in developing and middle-income countries. Despite being beneficial, CAPD remains vulnerable to complications, such as peritonitis and fluid overload. In this systematic review, two prevailing artificial intelligence (AI) paradigms—rule-based systems and automatic machine learning approaches— were compared to enhance CAPD monitoring and decision-making. Literature published between January 1, 2020, to May 20, 2025, was assessed for clinical effectiveness, patient adherence, operational efficiency, cost, and usability. Automated AI systems for dialysate image classification have also been examined. Our findings suggest that automated AI systems provide greater precision and earlier detection, whereas rule-based models offer practical advantages in a low-resource structured environment such as Indonesia's healthcare system. These findings validate the value of integrating both paradigms, and propose a hybrid integration model to achieve the highest clinical accuracy, cost-effectiveness, and accessibility for CAPD monitoring. A total of 156 articles were identified, including 42 from PubMed, 37 from Scopus, 58 from Google Scholar, and 19 from IEE Xplore. Following screening and eligibility assessment, 24 studies were included for full synthesis. Of these, 12 investigated automated AI systems including machine learning based dialysate image classification and predictive modeling while 3 evaluated rule-based systems using predefined clinical logic. Overall 14 studies were identified as eligible studies that assessed the implementation of AI systems for the monitoring and management of CAPD. The proposed hybrid implementation model combines the strengths of both paradigms, tailored to national clinical guidelines and insurance schemes.
Keywords: CAPD, artificial intelligence, rule-based, automated, predictive monitoring

Introduction

Patients end-stage renal disease (ESRD) can benefit greatly from continuous ambulatory peritoneal dialysis (CAPD), particularly in areas where in-center hemodialysis is difficult to access.[1] CAPD is patient-centered, with the potential to provide flexibility in treatment and quality of life. Its success depends heavily on routine monitoring and patient compliance, both of which are prone to inconsistency and neglect, in the absence of systematic support mechanisms. Globally, the prevalence of ESRD is increasing, with more than 3 million patients requiring dialysis, according to WHO estimates in 2023.[1,2] In Indonesia, the rate of dialysis incidence is increasing annually, and CAPD is also promoted as a home therapy by the Ministry of Health.[2] CAPD plays a critical role in this landscape owing to its feasibility for home-based care, reduced infrastructure needs, and alignment with patient-centered care models. In Indonesia, the prevalence of end-stage renal disease (ESRD) in adults is 0.18%, equivalent to over 600,000 individuals, and more than 134,000 patients have been reported to undergo hemodialysis in 2024 alone.[3] The leading to the development of hypertension and diabetes mellitus, highlighting the urgent need for scalable and efficient renal care solutions.[1,2]

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Artificial Intelligence (AI) has shown growing promise in enhancing early detection and real-time monitoring across various chronic care domains, including renal replacement therapies.[4] It has increasingly permeated healthcare as a tool for predictive diagnostics, automated monitoring, and decision support. Two principal approaches utilizing artificial intelligence have been identified in continuous ambulatory peritoneal dialysis (CAPD): (1) rule-based systems, which operate according to established protocols and predetermined alert thresholds; and (2) automated systems, which employ machine learning or deep learning techniques to adaptively forecast risks and outcomes by analyzing ongoing data inputs. These innovations have the capacity to reduce complications and enhance individualized patient management. However, the success of CAPD depends on the timely and accurate detection of clinical complications, an area where artificial intelligence (AI) is increasingly required to overcome the limitations of conventional methods.[4,5]

Several systematic reviews have explored AI and remote monitoring in peritoneal dialysis. Ali et al (ASAIO J. 2023) conducted a meta-analysis of remote monitoring in automated peritoneal dialysis (APD) and found that it improved patient outcomes. However, to date, no review has provided a direct comparison of automated and rule-based AI models specifically in CAPD. This systematic comparative review was therefore undertaken to address this gap by evaluating both approaches in parallel and by proposing a hybrid model aimed at optimizing CAPD monitoring within low- and middle-income healthcare systems.[4,5]

Despite their theoretical advantages, practical adoption of AI in CAPD monitoring remains inconsistent. Barriers include data availability, infrastructure limitations, user training, and system costs.[3,5] Moreover, comparative implementation studies between rule-based and automated AI models are sparse, particularly in low-to-middle-income settings. This review aims to critically analyze existing implementations, their effectiveness, and their contextual suitability in healthcare environments with varying resource levels.[3]

This systematic comparative review addresses these gaps by analyzing studies published between 2020 and 2025 that have applied either rule-based or automated AI models in CAPD monitoring. Emphasis is placed on clinical accuracy, patient engagement, cost-effectiveness, and alignment with the national clinical standards and insurance strategies in Indonesia. Ultimately, this review proposes a hybrid implementation framework optimized for both high- and low-resource environments, with the overarching goal of optimizing CAPD patient monitoring through data-driven, context-sensitive AI solutions.

Materials and Methods

This systematic review was conducted according to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses guidelines (2020), focusing on studies related to AI applications in CAPD. Literature searches were performed using from January 1, 2020, to May 20, 2025, PubMed, Scopus, IEEE Xplore, and Google Scholar using combinations of search keywords such as "CAPD artificial intelligence", "automated monitoring in Peritoneal Dialysis (PD)", and "rule-based decision support CAPD". A total of 156 articles were identified, 42 from PubMed, 37 from Scopus, 58 from Google Scholar (58), and 19 from IEEE Xplore (19).

Inclusion Criteria

This review applied the PRISMA 2020 framework and used the following inclusion criteria:

Studies focused on CAPD patient monitoring using artificial intelligence technologies. Interventions must involve either rule-based systems (predefined rules/logic) or automated learning systems (eg, machine learning and deep learning). Studies must report at least one outcome relevant to clinical effectiveness, patient adherence, usability, cost-efficiency, or operational performance. Only peer-reviewed, full-text articles published in English between 2020 and 2025 were included. Studies conducted in both high-income and low-to-middle-income settings were considered. The eligible study types included observational studies, clinical trials, comparative evaluations, and implementation reviews.

Exclusion Criteria

To ensure relevance and quality, the following exclusion criteria were applied: The studies did not focus on CAPD or included only general PD without clear CAPD-specific insights. Articles that addressed only hemodialysis or kidney transplantation without any CAPD component. AI applications are not related to clinical monitoring such as those used

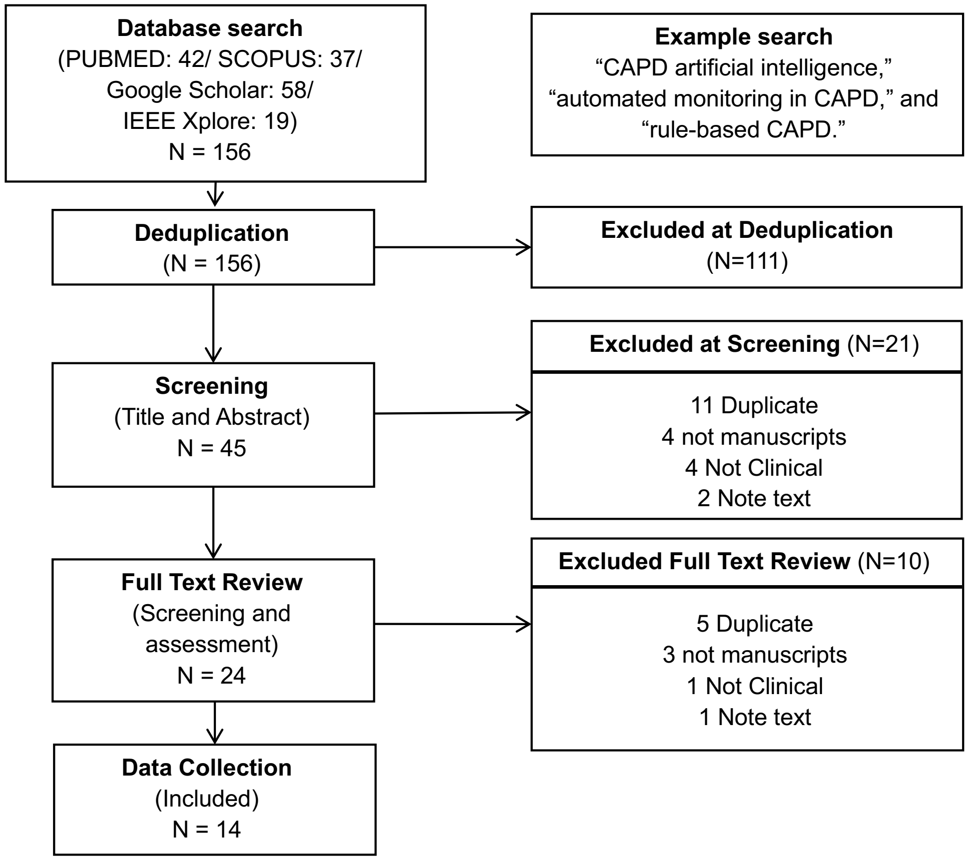

Figure 1 PRISMA flowchart for including articles in our study.
Notes: PRISMA figure adapted from Liberati A, Altman D, Tetzlaff J, et al. The PRISMA statement for reporting systematic reviews and meta-analyses of studies that evaluate health care interventions: explanation and elaboration. *J Clin Epidemio.* 2009;62(10):e1-34. Creative Commons.[6]

for administrative support, hospital logistics, or inventory management. Non-peer-reviewed documents, such as preprints, conference abstracts, letters to the editor, and expert opinion. Articles published in languages other than English. Studies lacking specific outcomes aligned with review objectives such as effectiveness, efficiency, and adherence.

Data Extraction & Comparison Criteria

Automated models that use dialysate image classification have been reviewed as a subset of automated AI systems. These models evaluate their ability to detect abnormalities in the appearance of effluents, such as turbidity or discoloration of the infrastructure. Notably, discoloration of the infrastructure may indicate deviation in treatment.

Data from qualified studies were extracted and compared using standardized performance metrics, implementation feasibility, and clinical utility. The main evaluation areas were as follows.

Clinical accuracy, including sensitivity, specificity, and AUC-ROC, Operational efficiency, such as alert latency, time savings, and automation level, Implementation costs and required technological infrastructure, Patient adherence and responsiveness to behavioral changes, Time-to-alert refers to the latency between abnormal input and alert generation. Usability of the system for both healthcare providers and patients. Compliance with data privacy and security regulations. Sustainability and scalability in various clinical environments were evaluated. Studies were further examined for relevance in low- to middle-income countries with a particular focus on Indonesia's national insurance system and healthcare infrastructure. A flowchart of the study is presented in Figure 1.

Table 1 Summary of CAPD Vs PD in Inclusion Criteria

Criteria Aspect	CAPD-Specific Studies	General PD Studies
Number of Studies	6	8
AI Implementation Style	Often mobile, manual-data focused	Often hospital, machine-based
Indonesian Relevance	Very High (matches national push)	Varies (APD less applicable)

Results

Clarifying CAPD Vs PD in Inclusion Criteria

Britto et al, (2019) have demonstrated that AI-assisted Continuous Ambulatory Peritoneal Dialysis (CAPD) systems can predict creatinine target ranges with >95% accuracy, reduce recurrence rates, support fluid status assessments, and ensure safe utilization. This data was supported by Yang et al (2024), Navastara et al, (2023), Smart PD system et al, (2025), Ratnadeep Biswas et al, (2025), in their study, which highlight the accuracy of AI-based automated system. CAPD and Peritoneal Dialysis (PD) remain critical therapeutic modalities for patients with End-Stage Kidney Disease (ESKD).[7–11]

A recent meta-analysis by Hatem Ali et al (2023), which evaluated remote monitoring in automated peritoneal dialysis (APD), further supports the growing role of digital and telemonitoring tools in peritoneal dialysis. Our review extends this evidence by specifically examining CAPD-focused solutions and comparing both AI-based and rule-based approaches within this modality.[12]

This means that, although CAPD remains one of the areas of focus, a number of studies have grouped modalities under the general heading of PD. Caution must be exercised in the direct application of the PD findings to CAPD regimens. CAPD is more commonly used than ambulatory peritoneal dialysis (APD) in Indonesia, but both are under-utilized when compared to hemodialysis.[13] The key characteristics of the included studies are summarized in Table 1. CAPD are generally considered to be more cost-effective due to the absence of expensive cycler equipment and lower operational costs.[3,13] Maintaining residual renal function and increasing overall toxin clearance.[14,15] This can lead to improved biochemical outcomes, symptoms, and physical health. However, some patients may experience reduced satisfaction owing to lifestyle constraints.[16] Modality selection should be personalized based on patient preferences, clinical suitability, and lifestyle considerations.[14,17]

Key Messages – Suitability for Indonesia's Health System

Suitability was assessed based on alignment with Indonesia's infrastructure and insurance system, including Universal Health Coverage, National Clinical Practice Guidelines for CAPD, and telemedicine readiness) as described in Table 2. Overall, 12 of the 14 studies were rated as highly or moderately suitable for implementation in Indonesia, particularly when incorporated into the national health insurance system and remote patient-monitoring strategies. In response, we have conducted a formal assessment of the methodological quality and risk of bias using the Newcastle–Ottawa Scale (NOS) adapted for cohort studies, as summarized in Table 3. Based on total scores, the majority of studies were rated as having low risk of bias, with only a few categorized as moderate or high risk.[18] Table 4 provides a summary of the compatibility levels of the studies on Indonesia's health systems.

Discussion

Each model provides distinct benefits. The Indonesian image-based model is cost-effective and well aligns with the Universal Health Coverage system. The integration of AI systems must consider regional limitations, technological readiness, and clinical workflows.[19] The studies included in this review varied considerably in their design, reporting of outcomes, and validation methods. Such heterogeneity makes direct comparison challenging and emphasizes the importance of adopting more consistent methodologies and clearer reporting standards in the future of AI-based nephrology research. In addition, our findings complement those of Ali H. et al (ASAIO J. 2023), which showed that remote monitoring in automated peritoneal dialysis (APD) reduced hospitalization and technique failure. While their

Table 2 AI Rule Base and Automated Studies Involved in CAPD, PD

NO	Study Source	AI Method	CAPD/PD Focus	Automated vs Rule-Based	Outcome	Effectiveness	Accuracy	Strengths	Weaknesses	Suitability for Indonesia
1	Brito et al (2019)[8]	Data Mining Classificati on	CAPD Creatinine Pattern	Automated	95% Accuracy on Creatinine Class	Very High (creatinine classification)	Accuracy 95%	Simple deployment with structured data, High model precision, user- friendly platform	Limited to structured blood test data, Needs clinical correlation	Highly suitable (simple data needs), High (can be adapted in CDSS tools)
2	Burlacu et al (2020)[19]	Review (Mixed: Fuzzy Logic, ML, Rule-Based)	General AI in Dialysis and Transplant (incl. PD)	Automated	Identified AI applications in PD (peritonitis, CV risk, adequacy)	Summarized performance of 8 PD studies	Variable (based on included studies)	Comprehensive, cross	Not CAPD-specific, variable quality	Moderate (guideline formation, tech planning)
3	Noh et al (2020)[20]	Deep Neural Networks, Survival Decision Trees	Mortality prediction in PD	Automated	5-year mortality risk and decision tree modeling	Deep Learning AUC=0.841	AUC: 0.804–0.841 C-index = 0.769	Nationwide cohort, validated models	Needs further clinical validation	Moderate (complex but scalable)
4	Bai & Tang (2022)[5]	XGBoost, CatBoost, SVM	PD overall (peritonitis prediction)	Automated	Prediction of complications, gh potential in clinical data modeling	Effective for stable monitoring	XGBoost: 88%, CatBoost: AUC 0.80	Flexible models, good prediction	Requires large data, validation	Moderate to Low - infra dependent
5	Navastara et al (2023)[9]	Deep Learning (ResNet50)	CAPD (dialysate image classification)	Automated	>85% Accuracy in Image Analysis	Effective with mobile integration	Accuracy = 95%	Good for visual screening, mobile integration, High model precision, user-friendly platform	Requires annotated image datasets	High - mobile friendly and adaptable
6	Nakamoto et al (2023)[21]	Rule-Based Telemedicine	APD - Remote Monitoring	Rule-Based	Improved Remote Monitoring	Effective for stable monitoring	No specific metrics reported	Integrates well with telehealth, stable rules	Limited adaptivity, rule rigidity, Manual entry, not adaptive	Moderate - good for hospitals

(*Continued*)

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Table 2 (Continued).

NO	Study Source	AI Method	CAPD/PD Focus	Automated vs Rule-Based	Outcome	Effectiveness	Accuracy	Strengths	Weaknesses	Suitability for Indonesia
7	Huang et al (2023)[22]	Multiple ML techniques	Predicting diabetic	Automated	Predictive diagnostics for	AUROC >0.85 fo	AUROC: 0.746–0.942	Covers multiple complications,	General diabetes context, not CAPD-	Low (not CAPD specific)
8	Lin et al (2023)[23]	AI Chatbot with prediction games	CAPD education and infection prevention	Rule-Based + Inter	Improved patient self-care skills and infection awareness	90.8% patient satisfaction with educational tools	N/A (behavioral impact measured)	Behavioral training and risk awareness via gamification	Short-term study, needs clinical outcomes	High (education-focused, accessible tech)
9	Ratnadeep Biswas (2024)[11]	Predictive analytics, RPM with AI-based platforms (Sharesour ce)	CAPD	Automated	Improved adherence, reduced hospitalization, enhanced patient survival	High (lower mortality and peritonitis incidence)	Not quantitative y stated but supports precision, RPM gains	Comprehensive AI integration, real-time RPM, personalization	Access inequality, data security, training needs	High - aligns with Indonesia's national goals for RPM and cost-efficiency in CAPD
10	Yang et al (2024)[7]	CatBoost (ML), SHAP analysis	PD Prognosis Prediction	Automated	High-risk patient prediction	High (prognosis stratification)	AUC 0.80, Accuracy 78%	Adaptive, scalable, high predictive power	Needs large training data and computational power	Moderately suitable (needs infra), High (can integrate into national EHR)
11	Fukushima et al (2025)[24]	Text Mining on Case Reports from PubMed	PD Trend & Topic Extraction	Automated (Text)	Emergent trend extraction in PD care	Identified key topics (eg, EPS, peritonitis)	N/A (Textual mining only)	Broad surveillance on literature trends	Cannot be used for real-time patient decision-making	Moderate (inform policy and training)
12	SmartPD System (2025)[10]	Deep Learning (Turbidity Classificati on, Infusion Monitoring)	CAPD Home Monitoring	Automated	Real-time turbidity detection, infusion volume control, heating	Accurate DL based fluid assessment, safety automation	Precision > 95%, AUC > 0.95	Mobile-capable, cloud platform, real- time monitoring	Infrastructure-dependent, IoT cost	High (if integrated with Indonesia's national health insurance system or telemedicine services)

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13	Monaghan et al (2025)[25]	Machine Learning (SHAP,	Predictors of home dialysis (HHD/PD)	Automated	Improved prediction of home modality	Predicted >60% improvement in home dialysis	AUROC: 0.79 (PD prediction)	Large dataset (198,000 +), real- world utility	Not focused exclusively on CAPD	Moderate to High (if national registry adopted)
14	de Fijter et al (2025)[26]	eHealth App with alert system	CAPD patient monitoring via smartphone	Rule-Based (Alerts	Reduction in hospitalizations, improved patient safety	62% reduction in admissions, 90% fewer hospitalization days	N/A (real-world effectiveness S not predictive score)	Patient-driven care, scalable solution	Limited by voluntary use, observational study	High (mobile-based, value based care)

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Table 3 14 Studies Were Rated Highly or Moderately Suitable, and Risk of Bias Assessment with the Newcastle–Ottawa Scale Indicated That Most Carried Low Risk. A Hybrid Tiered Model That Combines Both Automated and Rule-Based Approaches Appears Most Practical to Strengthen CAPD Care in Low- and Middle-Income Countries[18]

Study/Source	Selection (Max 4)	Comparability (Max 2)	Outcome (Max 3)	Total Score (Max 9)	Risk of Bias
Britto et al (2019)[8]	3	1	2	6	MODERATE
Burlacu et al (2020)[19]	3	2	1	6	MODERATE
Noh et al (2020)[20]	1	1	3	5	MODERATE
Bai & Tang (2022)[5]	3	1	2	6	MODERATE
Lin et al (2022)[23]	3	2	2	7	LOW
Huang et al (2023)[22]	1	0	2	3	HIGH
Navastara et al (2023)[9]	2	1	2	5	MODERATE
Nakamoto et al (2023)[21]	1	0	1	2	HIGH
Yang et al (2024)[7]	3	2	2	7	LOW
Ratnadeep Biswas (2024)[11]	3	1	3	7	LOW
Fukushima et al (2025)[24]	2	0	1	3	HIGH
Monaghan et al (2025)[25]	3	1	3	7	LOW
de Fijter et al (2025)[26]	4	1	3	8	LOW
SmartPD System (2025)[10]	4	1	3	8	LOW

Table 4 AI Rule Base and Automated Studies Involved in CAPD, PD for Indonesia Health System[2,5,7–11,20–27]

Suitability Category	Number of Studies	Sample Descriptions
High	5	"Mobile-friendly", "Accessible tech", "Value-based care"
Moderate to High	2	"If integrated with health insurance registry or national standards"
Moderate	5	"Policy-informing", "Guideline planning", "Scalable"
Moderate to Low	1	"Infrastructure-dependent"
Low	1	"Not CAPD-specific"

focus was on APD, our review extends the evidence to CAPD and provides a direct comparison between automated and rule-based AI models, underscoring the added value of a hybrid approach for wider clinical application. Future work should include longer-term studies of hybrid AI models and consider how these tools can be implemented in low- and middle-income countries in alignment with national health insurance and universal health coverage policies.[28]

Based on all 14 studies included in this review, we proposed several insights regarding automated vs rule-based artificial intelligent, as follows;

Introduction AI Improve Healthcare Delivery to CAPD or PD

AI has transformed data collection in PD or CAPD by introducing tools that automate and enhance the process.[10,19] AI power platforms can gather and analyze large volumes of data from patients, reduce the risk of human error, and enable more sophisticated data processing.[29] These platforms utilize algorithms to detect patterns in the data that may indicate potential complications, allowing for early intervention. The integration of AI in healthcare is not just about enhancing diagnostics, but also about improving patient outcomes through early interventions.[11]

Automated AI System

Artificial intelligence (AI) technologies, including machine learning, deep learning, and decision support systems, were utilized in 11 studies. AI power analytic employs algorithms to detect patterns and predict future outcomes, enabling early identification of diseases and potential complications.[11] Automated models have become predominant, particularly in areas such as turbidity classification, predictive diagnostics, and risk stratification.[30]

There are several key messages regarding Automated AI systems, including prevention of early detection and intervention; AI models can analyze data from electronic health records, wearable sensors, dialysate logs, and genetics, to provide personalized healthcare solutions as in the study conducted by Ratnadeep Biswas et al, (2025), Monaghan et al, (2025), Smart PD system et al, (2025).[11,24,25] The risk profiles for unsatisfactory clinical outcomes in the CAPD and PD sessions were determined as reported in the study by Yang et al (2024), Burlaccu et al (2020), Huang et al (2023), Smart PD system et al, (2025), Not et al (2020).[7,11,19,22] Early detection enables timely correction of risk factors, thereby supporting high-quality dialysis sessions and favorable outcomes. The algorithm demonstrated excellent discrimination, with an AUROC greater than 0.85 for several complications. AI can help personalize treatment plans for individual patients and improve their adherence and overall quality of life (QoL).[8,9,19,22]

This systematic review revealed that automated artificial intelligence (AI) systems in continuous ambulatory peritoneal dialysis (CAPD) and peritoneal dialysis (PD) employ diverse machine learning methods ranging from classical classifiers (eg, logistic regression and random forests) as in the study conducted by Yang et al (2024) to deep learning architectures (eg, convolutional neural networks (CNNs) and artificial neural networks (ANNs)) to facilitate early risk prediction and complication monitoring as in the study conducted by Navastara et al (2023). They process structured clinical data (eg, labs, vitals, patient demographics), unstructured data (eg, symptom logs and adherence patterns), and image-based inputs (eg, photos of dialysate effluent) to generate real-time diagnostic alerts or risk stratification scores.[7,9]

The first pathway was image-based classification (eg, CNNs), exemplified by the study of Navastara et al (2023), where AI was applied to dialysate effluent images to detect turbidity and flag potential peritonitis in home-based CAPD systems.[9] The second pathway was predictive risk modeling (eg, XGBoost, CatBoost, ANN), demonstrated in the works of Bai and Tang (2022), Monaghan et al (2025), Yang et al (2024), and Huang et al (2023), which estimated patient-specific risks such as mortality, ultrafiltration failure, and complications in comorbid populations (eg, diabetic PD patients), typically trained on registry or longitudinal EHR data.[5,7,22,25] The third pathway was remote monitoring and behavioral analytics (eg, RPM-integrated ML), described by Burlacu et al (2020) and Ratnadeep Biswas et al (2024), in which AI embedded in cloud platforms (such as Sharesource) processed dialysis logs and wearable sensor data to detect anomalies in adherence, fluid shifts, and early signs of systemic distress. These approaches provide substantial diagnostic support by enabling early detection, personalized alerts, and preventive interventions.[11,19] Compared with traditional rule-based systems, as reported by Lin et al (2022), Nakamoto et al (2023), and De Fijter et al (2023), these models adapt to real-world variations, learn from historical trends, and reduce manual workload. Nonetheless, their accuracy and clinical utility remain dependent on data quality, local infrastructure, and integration into clinical workflows.[21,23,26]

Rule-Based System

A rule-based system (RBS) is an expert framework that uses predefined "if–then" logic to support clinical decision making. In contrast to machine learning models, which adapt through training on large datasets, RBS depends on fixed clinical rules typically formulated with input from nephrology experts. This concept has been investigated by Lin et al (2022), Nakamoto et al (2023), and De Fijter et al (2023).[21,23,26] Lin et al found in a retrospective internal validation cohort that fixed algorithms did not consistently predict creatinine targets or lower recurrence rates.[23] Nakamoto et al reported that fluid status assessment and safe application were restricted by rigid thresholds, which limited clinical usefulness.[21] De Fijter et al, in a prospective external cohort, confirmed these limitations and emphasized that although RBS enables structured monitoring and generates alerts, it lacks the adaptability needed in complex and evolving clinical contexts.[26] Collectively, these findings indicate that RBS remains relevant for structured monitoring in resource-limited settings, but its predictive power and flexibility are inferior to automated AI systems.

Several important messages arise from these studies by Lin et al (2022), Nakamoto et al (2023), and De Fijter et al (2023). First, rule-based models cannot match the capacity of AI-based platforms for early detection and proactive intervention. AI systems are designed to perform continuous learning, support adherence, and strengthen e-Health applications, particularly in Continuous Ambulatory Peritoneal Dialysis (CAPD). These applications enhance monitoring, help prevent complications such as infection, and reduce hospital visits by enabling practical home-based follow-up.[26] Second, rule-based platforms retain diagnostic utility within defined workflows. Data input may be entered manually by patients, collected through biometric sensors, or retrieved from peritoneal dialysis devices.[21] The system then evaluates the data against predefined clinical rules to recognize potentially serious conditions. For instance, when a patient records abdominal pain and the dialysate fluid appears cloudy, the algorithm can trigger an alert to nursing staff for possible peritonitis.[26,31] Finally, with embedded medical rules, these platforms can activate visual or audio alarms on mobile applications or dashboards, deliver notifications to caregivers or nephrologists, and recommend specific interventions such as scheduling a clinical consultation.[23,26]

Conclusion

This review examined 14 studies on the use of artificial intelligence in CAPD monitoring. Automated systems showed strong potential for early detection of complications, while rule-based approaches provided simple, affordable solutions that fit well in resource-limited settings. Taken together, the evidence suggests that a hybrid model combining both approaches may offer the best balance between accuracy and accessibility. Still, most studies were limited by small samples, varied methods, and short follow-up. Future work should include longer-term studies of hybrid AI models and consider how these tools can be implemented in low- and middle-income countries in alignment with national health insurance and universal health coverage policies.

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Author Contributions

Satriyo Dwi Suryantoro, Chastine Fatichah, Dini Adni Navastara, have contributed to conceptualization and supervision of the manuscript. Fiqey Indriati Eka Sari, Muchamad Maroqi Abdul Jalil, have contributed to the literature search, screening, and review. Metalia Puspitasari, Imam Manggalya Adhikara, and Dwita Dyah Adyarini, contributed to data analysis. Ajeng Ayu Erawati and Bagus Aulia Mahdi contributed to the writing, revision, and editing of the manuscript.

All authors made a significant contribution to the work reported; took part in drafting, revising, or critically reviewing the article; gave final approval of the version to be published; agreed on the journal to which the article has been submitted; and agree to be accountable for all aspects of the work.

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Disclosure

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