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Advances in AI-based combination therapies versus standard treatments for heart failure in patients with advanced kidney injury

Avanços em terapias combinadas baseadas em IA versus tratamentos padrão para insuficiência cardíaca em pacientes com lesão renal avançada

Avances en las terapias combinadas basadas en IA frente a los tratamientos estándar para la insuficiencia cardiaca en pacientes con lesión renal avanzada

Stefannie Michelle Rea Chela
https://orcid.org/0009-0001-4765-6168
Ministerio de Salud, Ecuador
stefanniemichellereachela@gmail.com (correspondence)

Segundo Fernando Morales Quilligana
https://orcid.org/0009-0006-5944-2067
Universidad Técnica de Ambato, Ecuador

Jeison Andres Morales Olivera
https://orcid.org/0000-0002-4076-9127
Keralty Clinical Center Ibague, Colombia

Renato Castaño Alarcón
https://orcid.org/0000-0003-1107-2766
Hospital Universitario Hernando Moncaleano Perdomo, Colombia

Víctor Daniel Cruz Celi
https://orcid.org/0009-0004-9039-5532
Universidad de Guayaquil, Ecuador

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AI-based therapies
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The study highlights the practical application of AI in enhancing HF management and AKI detection through innovations like unsupervised machine learning, predictive modeling, and AI-enhanced remote monitoring. These advancements enable clinicians to deliver more precise, individualized care, potentially leading to better outcomes in complex renal and cardiac conditions.
Originality/value:
The originality of the article lies in its wide-ranging analysis of cutting-edge AI and ML technologies in the context of HF and AKI management. This allows for discussion on how these advancements are transforming patient care by offering tailored, adaptive treatment strategies that meet the specific needs of each patient, which represents a significant shift from standard treatment approaches.

ABSTRACT

Background: Recent advancements in AI and Machine Learning (ML) can help manage kidney disease and heart failure by providing predictive analytics and personalized treatment plans, improving diagnostic accuracy, and assisting clinicians in controlling chronic disease symptoms like acute kidney injury (AKI) and Managing Heart Failure (HF). We evaluated AI and ML role in predicting AKI and managing HF patients and it involved analyzing various predictive models and technologies to improve early detection provide personalized treatment, and enhance overall patient outcomes in complex renal and cardiac conditions. **Methodology**: We conducted our search on databases Scopus, PubMed, and Web of Science. Empirical evidence and state of the art of cutting-edge literature and real-time field research was analyzed. **Results**: AI advancements in HF management for advanced kidney disease AKI include unsupervised machine learning for risk stratification, reinforcement learning for predictive modeling and dynamic management, and LLMs and chatbots for diagnostic support and patient education. New developments in AI and medical technology are predictive analytics for AKI, automated ultrasound interpretation, AI-enhanced dialysis monitoring, HF risk prediction, remote monitoring, and telehealth integration, and making personal treatment strategies according to patient needs. Innovations like wearable dialysis devices, bioengineered kidney tissues, ECMO, LVADs, TAVR, SGLT2 inhibitors, CRT, and nephroprotective drugs have also improved patient outcomes as these have enabled personalized care and early intervention strategies. **Conclusion**: It is possible to conclude that AI has revolutionized AKI and HF management. Novel technologies offer precise and adaptive care that strictly addresses individual patient needs.

Keywords: AI-based therapies, machine learning, predictive analytics, acute kidney injury, heart failure management, advanced kidney disease.

RESUMO

Contexto: Os avanços recentes em IA e aprendizado de máquina (ML) podem ajudar a gerenciar doenças renais e insuficiência cardíaca ao fornecer análises preditivas e planos de tratamento personalizados, melhorando a precisão diagnóstica e auxiliando os clínicos no controle dos sintomas de doenças crônicas como a lesão renal aguda (AKI) e o manejo da insuficiência cardíaca (IC). Avaliamos o papel da IA e do ML na predição de AKI e no manejo de pacientes com IC, envolvendo a análise de vários modelos preditivos e tecnologias para melhorar a detecção precoce, fornecer tratamentos personalizados e melhorar os desfechos gerais dos pacientes com condições renais e cardíacas complexas. **Metodologia:** Realizamos nossa pesquisa nas bases de dados Scopus, PubMed e Web of Science. Evidências empíricas e o estado da arte da literatura de ponta e pesquisas de campo em tempo real foram analisadas. **Resultados:** Os avanços em IA para o manejo de IC e AKI incluem aprendizado de máquina não supervisionado para estratificação de risco, aprendizado por reforço para modelagem preditiva e gestão dinâmica, além de LLMs e chatbots para suporte diagnóstico e educação do paciente. Novos desenvolvimentos em IA e tecnologia médica incluem análises preditivas para AKI, interpretação automatizada de ultrassons, monitoramento de diálise aprimorado por IA, predição de risco de IC, monitoramento remoto e integração de telessaúde, criando estratégias de tratamento personalizadas de acordo com as necessidades do paciente. Inovações como dispositivos portáteis de diálise, tecidos renais bioengenheirados, ECMO, LVADs, TAVR, inibidores de SGLT2, CRT e medicamentos nefroprotetores também melhoraram os desfechos dos pacientes, permitindo cuidados personalizados e estratégias de intervenção precoce. **Conclusão:** É possível concluir que a IA revolucionou o manejo de AKI e IC. As novas tecnologias oferecem cuidados precisos e adaptativos que aderem estritamente às necessidades individuais dos pacientes.

Palavras-chave: Terapias baseadas em IA, aprendizado de máquina, análise preditiva, lesão renal aguda, gerenciamento de insuficiência cardíaca, doença renal avançada.

RESUMEN

Antecedentes: Los avances recientes en IA y aprendizaje automático (ML) pueden ayudar a gestionar la enfermedad renal y la insuficiencia cardíaca al proporcionar análisis predictivos y planes de tratamiento personalizados, mejorando la precisión diagnóstica y asistiendo a los clínicos en el control de síntomas de enfermedades crónicas como la lesión renal aguda (AKI) y la gestión de la insuficiencia cardíaca (IC). Evaluamos el papel de la IA y el ML en la predicción de AKI y la gestión de pacientes con IC, lo que implicó el análisis de varios modelos predictivos y tecnologías para mejorar la detección temprana, proporcionar tratamientos personalizados y mejorar los resultados generales de los pacientes con afecciones renales y cardíacas complejas. **Metodología:** Realizamos nuestra búsqueda en las bases de datos Scopus, PubMed y Web of Science. Se analizaron evidencias empíricas y el estado del arte de la literatura más avanzada y la investigación en tiempo real en el campo. **Resultados:** Los avances en IA para la gestión de la IC y la AKI incluyen el aprendizaje automático no supervisado para la estratificación de riesgos, el aprendizaje por refuerzo para la modelización predictiva y la gestión dinámica, y los LLMs y chatbots para el apoyo diagnóstico y la educación del paciente. Los nuevos desarrollos en IA y tecnología médica incluyen análisis predictivos para AKI, interpretación automatizada de ultrasonidos, monitoreo de diálisis mejorado con IA, predicción de riesgos de IC, monitoreo remoto e integración de la telemedicina, creando estrategias de tratamiento personalizadas según las necesidades del paciente. Innovaciones como dispositivos portátiles de diálisis, tejidos renales bioingenierizados, ECMO, LVADs, TAVR, inhibidores de SGLT2, CRT y fármacos nefroprotectores también han mejorado los resultados de los pacientes al permitir una atención personalizada y estrategias de intervención temprana. **Conclusión:** Es posible concluir que la IA ha revolucionado la gestión de la AKI y la IC. Las tecnologías novedosas ofrecen un cuidado preciso y adaptativo que se adhiere estrictamente a las necesidades individuales de los paciente.

Palabras clave: Terapias basadas en IA, aprendizaje automático, análisis predictivo, lesión renal aguda, tratamiento de la insuficiencia cardiaca, enfermedad renal avanzada.

INTRODUCTION

Heart failure (HF) and acute kidney injury (AKI) are prevalent comorbidities and are posing profound stress on overall global health as their coexistence is intricate and is impacting mortality, morbidity, and healthcare expenditures significantly. Epidemiological data reveal that AKI commonly coexists with HF is occurring among 13% of these patients as stated by Holgado., 2020 research. New-onset AKI incidence among hospitalized HF patients is about 20% (Doshi., 2020). Wang et al. (2021) have suggested that AKI is an independent predictor of mortality both during hospitalization and within the first year post-discharge for HF patients.

Research also indicates that AKI is associated with an increased risk of cardiovascular events most commonly it leads to recurrent HF after hospital discharge, so this association is further linked to a higher likelihood of developing chronic kidney disease (CKD). It is an accelerated progression to end-stage renal disease and reduced health-related quality of life, as noted by Cheungpasitporn et al. (2024) evidence.

Placing the study within a broad context highlights its significance in advancing medical treatment for patients suffering from both heart failure (HF) and advanced kidney disease (CKD). Heart failure is a condition where the heart cannot pump sufficient blood to meet the body’s needs, is exacerbated in patients with CKD, leading to a complex interplay of cardiovascular and renal dysfunctions. (Holgado, et al 2020) chronic kidney disease (CKD) among heart failure patients presents significant challenges and most common issue is late diagnosis as CKD remains asymptomatic in its early stages which is leading to detection when substantial renal function is already lost and so it is further complicating treatment and worsening patient outcomes. (Zahir et al., 2024) Monitoring CKD progression is difficult because traditional markers like creatinine which is serum and estimated glomerular filtration rate (eGFR) lack sensitivity to early changes. CKD often coexists with other chronic conditions such as diabetes and hypertension, increasing the risk of polypharmacy and adverse drug interactions (Stehle., 2024). Socioeconomic factors further exacerbate access to quality care, with marginalized populations facing higher disease progression and lower kidney transplantation rates.

Heart failure also presents complex challenges, including a broad spectrum of pathophysiological mechanisms that necessitate personalized treatment approaches. Ensuring patient adherence to complex medication regimens, involving drugs like diuretics, ACE inhibitors, and beta-blockers, is a significant hurdle, as is reducing high hospital readmission rates due to fluid overload and medication non-compliance. Empowering patients through effective education programs for self-management is essential yet difficult. Recent advancements offer hope: in CKD, biomarker research and genetic studies promise earlier and more accurate detection, while telemedicine enhances access to care. For heart failure, innovations in implantable devices and the use of biomarkers improve diagnosis and management, and novel pharmacotherapies like SGLT2 inhibitors and ARNIs significantly enhance therapeutic outcomes by reducing hospitalization and mortality rates.

Technological constraints, such as inadequate sensitivity of biomarkers and insufficient real-time monitoring, hinder precise management. (Lidgard., 2024) Consequently, there is a pressing need for AI-based combination therapies that leverage machine learning to predict disease trajectories, optimize drug regimens, and personalize interventions. These advanced approaches can integrate multifaceted data, offering a nuanced understanding of patient-specific dynamics and potentially improving outcomes where standard treatments fall short. (Li et al., 2024).

Our idea of this paper is exploring AI-based combination therapies compared to standard treatments for heart failure and what advancements are now been made. Epistemological significance lies in integrating advanced AI methodologies to tailor and potentially revolutionize therapeutic approaches.

METHODS

The research methodology involves searching across several key databases, including Scopus, PubMed, and Web of Science. The primary keywords used in the search include *"Artificial Intelligence," "Machine Learning," "Acute Kidney Injury," "chronic kidney disease," "Heart Failure," "Predictive Analytics," "Personalized Treatment," "Ultrasound Interpretation," "Dialysis Monitoring," "Risk Prediction," "Telehealth," "Drug Development," "Chatbots," and "Clinical Decision Support Systems."* These terms encompass the core concepts related to advancements in AI and machine learning in the context of kidney and heart diseases.

We also decided to select some secondary keywords and so we can complement these primary terms. So, our secondary keywords were: *"AI," "ML," "AKI," "CKD," "HF," "EHR," "Wearable Devices," "Convolutional Neural Networks," "Deep Learning," "Natural Language Processing," "SGLT2 Inhibitors," "Bioengineered Kidney Tissues," "CRRT," "ECMO," "LVADs," "TAVR," "HDF," and "PD."* These additional terms help to capture more specific aspects and technologies associated with the primary topics. To further refine research and bring most convenient methodology to get targeted papers of databases we selected Mesh terms used to refine the search including "*Artificial Intelligence/therapeutic use,*" "*Machine Learning/methods,*" "*Acute Kidney Injury/diagnosis,*" "*Chronic Kidney Disease/therapy,*" *and* "*Heart Failure/complications.*" We combined all primary and secondary terms with Boolean operators such as AND, OR, and NOT to create needed mesh strings that encompass both primary and secondary key terms.

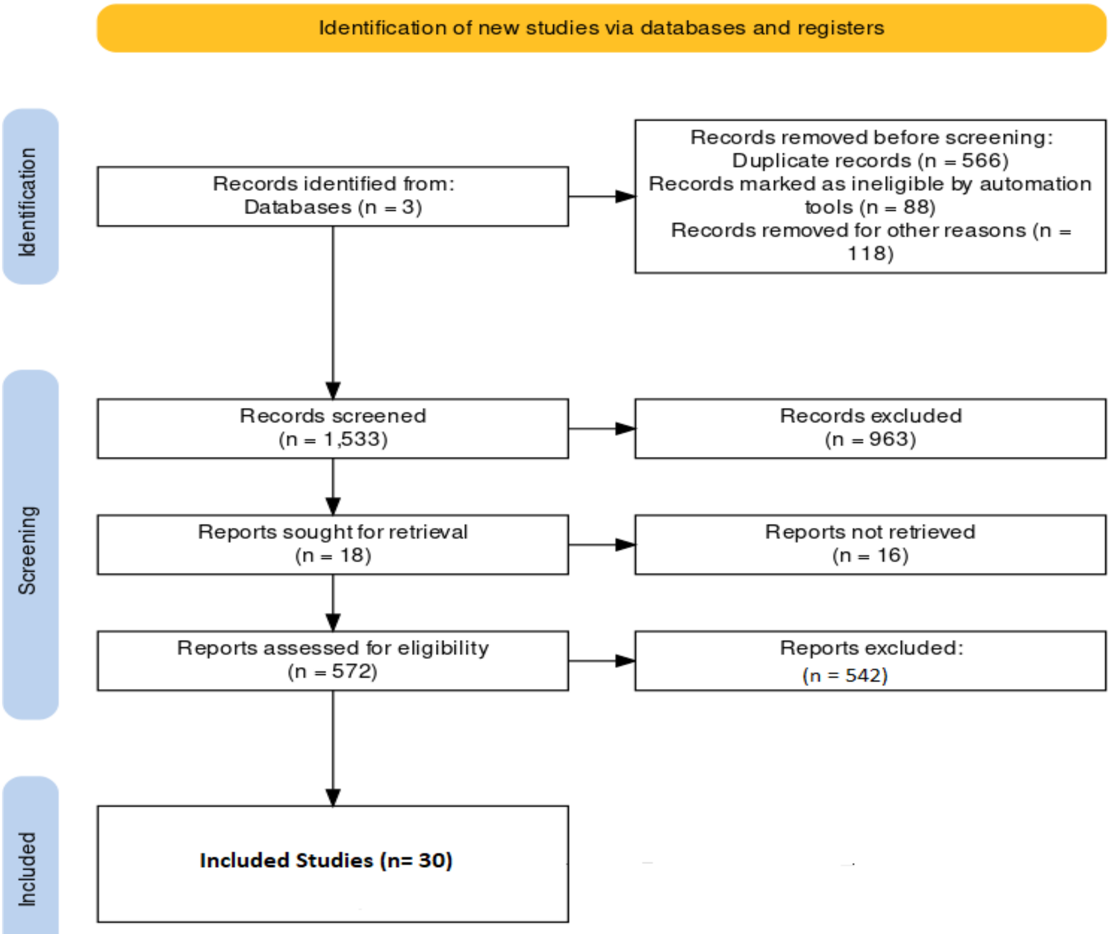
Inclusion criteria

We included studies and advancements focusing applications and novel innovations of artificial intelligence (AI) and machine learning (ML) in managing acute and advanced kidney diseases and heart failure. Our key criteria of inclusion discuss predictive analytics, personalized treatment plans, automated diagnostic tools, and AI-enhanced monitoring systems. This paper contains studies published in reputable databases such as Scopus, PubMed, and Web of Science. Most of the data is driven from studies that are published in 2024 to keep our research current and up-to-date.

Exclusion Criteria

We excluded those studies that do not address the use of AI or ML in acute or advanced kidney disease and heart failure management. We do not try to cover non-technical advancements, general treatments without an AI component in this review, or those that do not involve AI-based prediction, monitoring, or decision support systems. Also excluded are studies not published in the selected databases or those papers that were about traditional statistical methods or medicines which were not integrating AI or ML.

Figure 1. PRISMA flow chart



Source: Author's preparation

RESULTS

Table 1 presents the literature advancements that demonstrate the potential of AI to transform the management and treatment of acute and advanced kidney disease and heart failure, leading to improved patient outcomes and more efficient healthcare delivery (Bajaj & Koyner, 2022; Fragasso et al., 2023; Gameiro et al., 2020).

Table 1. Novel advancements of AI in acute and advanced kidney disease and heart failure

Patients	Advancement	Description	Functioning of Tools
Predictive Analytics for Acute Kidney Injury (AKI)	AI algorithms predict AKI by analyzing patient data, including vital signs, lab results, and medical history.	Machine learning models, such as deep learning and decision trees, process large datasets to identify early signs and risk factors of AKI, enabling timely intervention.	Early prediction allows for preventive measures, such as adjusting medications, optimizing fluid management, and monitoring renal function more closely.
Personalized Treatment Plans for Chronic Kidney Disease (CKD)	AI develops personalized treatment plans by analyzing genetic, lifestyle, and clinical data.	AI platforms like IBM Watson use natural language processing (NLP) to extract relevant information from patient records and suggest tailored treatments.	Personalized plans can include specific dietary recommendations, medication adjustments, and lifestyle modifications to slow disease progression and improve quality of life.
Automated Ultrasound Interpretation	AI algorithms interpret renal ultrasound images to detect abnormalities and monitor kidney function.	Convolutional neural networks (CNNs) analyze ultrasound images to identify structural changes, cysts, and signs of inflammation with high accuracy.	Improved diagnostic accuracy aids in early detection and monitoring of kidney diseases, allowing for timely interventions and adjustments in treatment plans.
AI-Enhanced Dialysis Monitoring	AI monitors dialysis sessions, optimizing fluid removal and treatment duration based on patient-specific data.	AI systems integrate data from dialysis machines and patient records, using predictive models to adjust treatment parameters in real-time.	Optimized dialysis sessions reduce complications such as hypotension and improve overall treatment efficiency, leading to better patient outcomes and quality of life.
Heart Failure Risk Prediction	AI predicts the risk of heart failure in kidney disease patients by analyzing comorbidities and historical data.	Predictive models analyze electronic health records (EHRs), lab results, and imaging data to identify patients at high risk for developing heart failure.	Early identification of at-risk patients allows for proactive management strategies, such as lifestyle modifications, medication adjustments, and closer monitoring.
Remote Monitoring and Telehealth Integration	AI integrates with wearable devices and telehealth platforms to monitor kidney and heart function remotely.	Wearable sensors collect continuous data on vital signs, which AI algorithms analyze to detect early signs of deterioration and alert healthcare providers.	Remote monitoring enables timely interventions, reducing hospital admissions and allowing for better management of chronic conditions from the comfort of the patient's home.
AI-Assisted Drug Development	AI accelerates drug discovery for kidney and heart diseases by predicting molecular interactions and drug efficacy.	Machine learning models analyze vast datasets of chemical compounds, genetic information, and clinical trial data to identify promising drug candidates.	Faster identification of effective treatments can lead to the development of new medications that specifically target the underlying mechanisms of kidney and heart diseases.
Chatbots for Patient Education and Support	AI-powered chatbots provide education, medication reminders, and emotional support to kidney and heart failure patients.	Natural language processing (NLP) enables chatbots to understand patient queries and provide accurate information, while machine learning enhances interaction over time.	Improved patient engagement and adherence to treatment plans, leading to better disease management and outcomes, while reducing the burden on healthcare providers.
Clinical Decision Support Systems (CDSS)	AI-based CDSS assist clinicians in diagnosing and managing kidney and heart diseases by providing evidence-based recommendations.	CDSS integrate patient data with clinical guidelines, using machine learning to offer recommendations on diagnostics, treatment options, and patient management.	Enhanced decision-making leads to more accurate diagnoses, optimized treatment plans, and improved patient outcomes, especially in complex cases of kidney and heart diseases.

Source: Author's preparation with the retrieved literature

Table 2 advancements highlight a range of innovative treatments and technologies that are transforming the management of acute and advanced kidney disease and heart failure, improving patient outcomes and quality of life. (Saunders et al., 2024; Selewski & Wille, 2021; Narayana Health, 2024; Samoni et al., 2021).

Table 2: *Novel advancements in treatments for acute and advanced kidney disease and heart failure patients*

Advancement	Description	Functioning of Tools	Treatment Specifications
CRRT (Continuous Renal Replacement Therapy)	A blood purification therapy for severe acute kidney injury (AKI).	Utilizes specialized dialysis machines to continuously filter blood, removing waste products and excess fluid, closely mimicking natural kidney function.	Used in intensive care units (ICUs) for patients with severe AKI, providing gentle and continuous treatment that can be better tolerated by unstable patients.
Hemodiafiltration (HDF)	An advanced dialysis technique combining hemodialysis and hemofiltration for chronic kidney disease (CKD) patients.	Uses both diffusion and convection to remove waste products and excess fluid, improving the clearance of middle and large molecules from the blood.	HDF has shown to improve patient outcomes, including better removal of toxins, reduced inflammation, and improved cardiovascular health compared to traditional hemodialysis.
Peritoneal Dialysis (PD)	A home-based dialysis treatment option for CKD patients.	Involves the infusion of a dialysis solution into the peritoneal cavity, where waste products and excess fluids are removed through the peritoneal membrane.	Allows for greater flexibility and independence for patients, with the possibility of continuous ambulatory peritoneal dialysis (CAPD) or automated peritoneal dialysis (APD).
Wearable Dialysis Devices	Portable dialysis devices designed for continuous renal replacement therapy (CRRT) and long-term use.	Compact devices that allow for continuous blood filtration and waste removal, enabling patients to maintain mobility and quality of life.	Provide an alternative to traditional in-center dialysis, reducing the burden of treatment and improving patient autonomy and lifestyle.
Renal Denervation Therapy	A minimally invasive procedure to treat resistant hypertension in CKD patients.	Uses catheter-based radiofrequency ablation to disrupt renal nerves, reducing sympathetic nervous system activity and lowering blood pressure.	Can significantly lower blood pressure in patients with resistant hypertension, potentially improving kidney function and reducing cardiovascular risk.
Bioengineered Kidney Tissues	Research into growing functional kidney tissues from stem cells or other sources.	Utilizes tissue engineering techniques to create kidney tissues that can potentially replace damaged areas or support kidney function.	Still in experimental stages, bioengineered kidney tissues hold promise for regenerative treatments, reducing the need for dialysis or transplantation in the future.
Extracorporeal Membrane Oxygenation (ECMO)	A life-support technique used in severe cases of heart failure or lung failure.	Involves circulating blood through an artificial lung (membrane oxygenator) that removes carbon dioxide and adds oxygen, allowing the heart and lungs to rest.	Used in critical care settings for patients with severe heart failure or respiratory failure, providing temporary support until recovery or decision for further treatment.
Left Ventricular Assist Devices (LVADs)	Mechanical pumps that support heart function and blood flow in patients with severe heart failure.	LVADs are implanted in the chest and help the left ventricle pump blood to the rest of the body used as a bridge to heart transplant or as long-term therapy.	Improve survival rates and quality of life for patients with advanced heart failure, reducing symptoms and hospitalizations while awaiting heart transplant or as destination therapy.
Transcatheter Aortic Valve Replacement (TAVR)	Minimally invasive approach that replaces narrowed aortic valve in heart failure patients.	Involves threading a catheter through a blood vessel to the heart and implanting a new valve within the diseased aortic valve, improving blood flow and reducing symptoms.	An alternative to open-heart surgery for patients with severe aortic stenosis, offering reduced recovery times, lower risk of complications, and improved survival rates.
SGLT2 Inhibitors	A class of medications that lower blood sugar and protect kidney function in diabetes and CKD patients.	Inhibit the sodium-glucose co-transporter-2 (SGLT2) in the kidneys, reducing glucose reabsorption, lowering blood sugar, and providing protective effects on the kidneys and heart.	SGLT2 inhibitors like empagliflozin and dapagliflozin have reduced the progression of CKD and lower cardiovascular risk.
Cardiac Resynchronization Therapy (CRT)	A treatment for heart failure that improves the heart's rhythm and efficiency.	Involves implanting a device that sends electrical impulses to both ventricles, synchronizing their contractions and improving the heart's pumping ability.	Can significantly improve symptoms, exercise capacity, and survival rates in patients with heart failure and ventricular dyssynchrony, reducing hospitalizations and mortality.
Nephroprotective Drugs	Includes drugs such as ACE inhibitors, ARBs, and new agents like finerenone, which reduce proteinuria, control blood pressure, and protect against fibrosis and inflammation.	Nephroprotective drugs specifically designed to protect kidney function and slow disease progression in CKD patients.	Help to slow the progression of CKD, reduce complications, and improve overall kidney function, delaying the need for dialysis or transplantation.

Source: Author's preparation with the retrieved literature

Standard treatment is recommended for heart failure in patients with advanced kidney disease face significant challenges due to the intricate interplay between the two conditions. Renal impairment often limits the use of conventional heart failure medications, such as ACE inhibitors and diuretics, due to their potential nephrotoxicity and altered pharmacokinetics. Furthermore, fluid management becomes particularly complex, requiring a delicate balance to avoid exacerbating either condition. AI-based combination therapies emerge as a promising solution, leveraging machine learning to optimize individualized treatment plans by analyzing vast datasets, predicting outcomes, and adjusting therapies in real time. This innovative approach holds the potential to improve patient outcomes by providing more precise, adaptive care tailored to the unique needs of each patient (World Health Organization: WHO, 2021; Xanthopoulos et al., 2023).

Congestion is a prevalent issue in decompensated heart failure (HF) and is a known contributor of AKI (AKI) so congestion severity and persistence are closely tied to poorer outcomes making effective decongestive measures critical, particularly through timely and suitable diuretic therapies. Hemodynamic factors such as lower cardiac output and ongoing congestion along with the renal effects of medications like angiotensin-converting enzyme (ACE) inhibitors and diuretics exacerbate acute kidney injury (AKI) (Chahal et al., 2020).

In acute decompensated heart failure (ADHF), chronic kidney disease (CKD) raises chances of acute kidney injury (AKI) by impairing the kidneys' ability to manage fluid and electrolyte imbalances. Older age exacerbates it as human ultimately decrease renal function and resilience due to weakness. Diabetes mellitus contributes through diabetic nephropathy which further compromises renal function. Another factor is liver disease which may further complicates fluid management and stresses the kidneys. Right ventricular failure increases fluid congestion and pressure on the kidneys while a low baseline left ventricular ejection fraction indicates poor cardiac output while reducing renal perfusion. If in case, diastolic function becomes impaired it will be causing elevated pressures in the pulmonary circulation, adding to renal stress.

To improve the understanding of data issues related to the prognosis of acute kidney injury (AKI) in heart failure (HF) patients, there are multiple statistical models have been employed (Chahal et al., 2020). Multivariable logistic regression and Cox proportional hazard analysis are most commonly used methods. Researchers isolate individual risk factors and assess their impacts on patient outcomes but certain challenges persist in these predictions like reliance on historical data or potential for confounding variables and necessity to validate findings across diverse patient populations. Selection of predictors and potential incorporation of new biomarkers or clinical variables will influence the accuracy and applicability of these models (Chahal et al., 2020).

Bacci et al., (2023) reviewed ML algorithms for AKI prediction; found deep learning and logistic regression effective, but noted limitations in data diversity and model transparency. Rewa et al., (2023) examined CKRT in critically ill AKI patients; found variability in practice, with 41.1% survival to discharge and sepsis as a major AKI cause. Hong et al. (2022) predicting Aki in hf patients using traditional statistical approaches among those with acute kidney injury (AKI) in heart failure (HF) through traditional statistical methods has yielded a variety of insights across different studies.

Forman et al. explored a cohort of 1,004 individuals with acute decompensated heart failure (ADHF), characterizing acute kidney injury (AKI) by a rise in serum creatinine exceeding 0.3 mg/dL. The study evaluated parameters including a history of prior heart failure, diabetes, systolic blood pressure, and admission serum creatinine. C-statistic or area under the curve (AUC) for this model was not reported and no validation group this paper includes. Verdiani et al. (2010) researched 394 ADHF patients, using the same AKI definition. Their model considered age, serum creatinine levels, heart rate, and the use of calcium channel blockers and digoxin. Like Forman's study, this research did not provide a reported C-statistic or AUC and lacked a validation cohort. Breidthardt et al. (2011) developed Basel risk score with 657 ADHF patients defining AKI similarly and the key parameters included chronic kidney disease (CKD) serum bicarbonate levels and outpatient diuretic use. Basel risk score achieved an AUC of 0.71 but did not include a validation group. Wang et al. (2021) study included 1,709 ADHF patients and defined AKI using the AKIN criteria and the study model integrated age, heart failure functional class, admission frequency for ADHF, systolic blood pressure, serum creatinine, sodium levels, proteinuria, and intravenous furosemide use. The model achieved a development AUC of 0.76 with the same score in validation across different patient subsets. Zhou et al. (2016) analyzed 507 ADHF patients, with a development cohort of 321. They used the KDIGO criteria for AKI and considered sex, age, CKD, NT-proBNP, serum albumin, urine angiotensinogen (uAGT), and urine neutrophil gelatinase-associated lipocalin (uNGAL) as key parameters and their model demonstrated a development AUC of 0.859 and a validation AUC of 0.847.

Wang et al. (2021) also studied 675 ADHF patients, employing KDIGO criteria and focusing on age, diabetes, previous renal dysfunction, serum creatinine, BNP, and serum albumin and model provided a development AUC of 0.766 with a bootstrap validation AUC of 0.763. Lassus et al. (2007) in a prospective multicentre study by involving 480 patients with acute heart failure (AHF), cystatin C levels were measured to assess their prognostic value. The study found that the 12-month all-cause mortality rate was 25.4%, with cystatin C, creatinine, age, gender, and systolic blood pressure identified as independent risk factors. Patients with cystatin C levels above the median (1.30 mg/L) had the highest adjusted hazard ratio of 3.2 (95% CI

2.0–5.3, P < 0.0001), and mortality increased significantly across tertiles of cystatin C. Notably, elevated cystatin C in patients with normal plasma creatinine was linked to a mortality rate of 40.4% compared to 12.6% for those with both markers normal (P < 0.0001). The findings suggest that cystatin C is a strong independent predictor of 12-month outcomes in AHF and could enhance risk stratification, particularly in patients with normal creatinine levels. On the other hand, Lee et al. (2020) conducted a validation study encompassing 10,364 ADHF hospitalizations. They compared various prediction models and reported AUCs for the Wang model (0.73), Forman model (0.70), Basel risk score (0.60), Verdiani model (0.59), and Zhou model (0.54). All these papers analysis shows range of predictive capabilities and methodologies applied in assessing AKI risk in HF patients and variation in AUCs reflects differences in model performance and the lack of validation in some studies are stressing out need for further refinement and external validation. Advancements in digital tools and novel biomarkers or application of artificial intelligence (AI) and machine learning hold promise for enhancing the accuracy and clinical utility of these traditional statistical models as all these kinds of technological innovations could provide real-time risk assessments while improve HF and AKI symptoms. (Cheungpasitporn et al., 2024).

In this context, Cheungpasitporn et al. (2024) rapid proliferation of electronic health records has opened new frontiers in medical analysis for understanding complex conditions such as heart failure (HF) and acute kidney injury (AKI)., Both ML and AI are emerging as transformative forces in these landscapes and both are reshaping our approach to these interlinked conditions. AI represents a broad paradigm wherein machines are engineered to perform tasks that mimic human intelligence as it encompasses a range of technologies designed to exhibit behaviors we would deem "smart" or "intelligent". While machine learning is the specialized subset of AI which is deigned to focus on enabling machines to learn more from provided information and make decisions depending on patterns and inference rather than explicit programming thus it makes a distinction that is indeed crucial for ML capabilities in the medical field (Elahi et al., 2023).

Machine learning itself is a diverse field and is categorized into several methodologies each with its unique approach to learning and prediction. Supervised learning is one of the primary branche which involves training algorithms on datasets where outcomes are pre-labeled. This makes model learn from known input-output pairs and apply this knowledge to new and unseen data Unsupervised learning. On the other hand, it operates without labeled outcomes focusing instead on uncovering the underlying structure of the data. This approach is discovering patterns that are not immediately apparent. Reinforcement learning is another advanced form which teaches algorithms to make decisions through interactions with an environment which is rapidly optimizing strategies to maximize cumulative rewards based on trial and error (Hong et al., 2020). In recent developments, Abedi et al. (2023) stated sophisticated ML techniques like large language models (LLMs) and chatbots have made significant strides. LLMs are more trained on vast amounts of text data and this makes them capable of understanding and generating human like text enhancing the interpretative power of data. Chatbots are also simulating human conversation either through voice or text and now are providing a more interactive interface for managing and interpreting health data. AI and ML techniques integration into the study of HF and AKI is not merely academic but it has led to tangible advancements and now these technologies are beginning to deliver promising results in predicting patient outcomes and providing more personalizing therapy strategies which is improving health ultimately, suggested by Bajaj and Koyner (2022).

AKI in heart failure (HF) patients demands nephrologists and cardiologists' collaborations where chatbots and large language models (LLMs) can be used for advanced diagnostic support by analyzing extensive data to provide precise suggestions. These tools are known to enhance patient education by delivering condition-specific insights on renal and cardiac health fostering patient betterment as these also have a great influence on mental health and can make patient to stick to a healthy lifestyle. Chatbots assist with integrated treatment plans based on up-to-date research and they provide comprehensive care for both heart and kidney health. Real-time monitoring features make patients alert and connect with healthcare professionals to alarming patterns from daily input metrics. In telemedicine these chatbots optimize clinician time by collecting initial data and addressing minor issues while escalating serious concerns on the other hand. A study by Skalidis et al (2023) found ChatGPT's performance on the European Exam in Core Cardiology (EECC) comparable to traditional materials, and results were positive with 58.8% accuracy rate and a passing score of around 60% though it struggled with image-based questions. Tran et al. (2019) explore AI potentials along with ML to enhance acute kidney injury (AKI) prediction among critically burned patients. Traditional biomarkers like urine output and creatinine may be inadequate for early AKI detection sometimes and now, it is time to use k-nearest neighbor (k-NN) algorithm model which has shown significant promise which are in ML. By analyzing data from 50 burn patients, the researchers have demonstrated ML models incorporating neutrophil gelatinase-associated lipocalin (NGAL) and other indicators achieved up to 100% accuracy in detecting AKI so now, this approach markedly improved early recognition compared to conventional methods, research by Tran et al. (2019) stated

Recent advancements in supervised machine learning (ML) shows potential in predicting AKI among patients with heart failure HF. In a comprehensive study led by Liu and colleagues, data from 2,678 individuals having HF were scrutinized and out of which 919 developed AKI. The analysis incorporated 39 variables spanning demographic details and clinical data, and treatment information. The researchers employed five distinct ML algorithms: random forest, decision tree, K-nearest neighbor, support vector machine, and logistic regression. Among these, the random forest algorithm emerged as the most effective, achieving an AUROC of 0.96, an accuracy rate of 88.36%, a sensitivity of 96.04%, and a specificity of 73.91%. Logistic regression also showed robust performance, with an AUROC of 0.92, an accuracy of 86.42%, a sensitivity of 91.42%, and a specificity of 77.02%. Cheungpasitporn et al. (2024).

Key predictors identified included the SOFA score, partial pressure of oxygen, eGFR, serum bicarbonate, hemoglobin, platelet count, blood lactic acid, serum creatinine, serum magnesium, and blood glucose. A simplified model using these ten variables proved highly effective. AKI was defined as an increase in serum creatinine of ≥0.3 mg/dL within 48 hours of ICU admission. The AKI group had lower baseline eGFR and higher rates of comorbidities such as diabetes, coronary heart disease, hypertension, and atrial fibrillation, along with lower use of RAAS inhibitors and digoxin. Cheungpasitporn et al. (2024). The study highlighted areas for improvement, such as the need for more details on AKI severity, ejection fraction, CKD status, and novel treatment options for instance SGLT2 inhibitors. It also stressed the necessity for external validation, novel biomarkers, and cost-effectiveness assessments. Compared to another study by Mortazavi et al., which focused on predicting hospital readmissions using similar ML methods, Liu et al.'s research more thoroughly addressed AKI prediction but noted gaps like the omission of detailed kidney function metrics. supervised ML is robust approach for predicting AKI in HF patients as it has potential for clinical integration pending further refinement and validation, Cheungpasitporn et al. (2024) suggested.

Unsupervised machine learning (ML) allows models in identification of patterns within data without predefined labels unlike supervised learning so this clustering approach groups data depending upon similarities which reveal hidden subgroups and patterns. Among Heart failure patients, unsupervised machine learning (ML) may identify patients at increased risk for acute kidney injury (AKI), aiding in personalized care and timely interventions. Hong et al. applied unsupervised ML to 5,075 hospitalizations, identifying high-risk HF patients prone to AKI based on characteristics like age and cardiac function. Urban et al. used k-Medoid clustering to analyze 312 acute decompensated heart failure (ADHF) patients, uncovering three distinct phenotypes with varying incidences of worsening renal function (WRF) and the results from this evidence shows critical unsupervised ML in risk stratification although more research is stressed to predict severe AKI stages among HF patients, as noted by Cheungpasitporn et al. (2024).

FINAL REMARKS

AI and machine learning integration in managing acute and advanced kidney disease and heart failure has shown significant potentials in predictive analytics, personalized treatment plans, and AI-enhanced diagnostic tools that offer early detection and tailored interventions, improving patient outcomes. AI optimize dialysis and predicts heart failure risk and since it is introduced, it has enhanced treatment efficiency in chronic diseases including AKI and HF. Traditional statistical models for predicting AKI in HF patients have provided varying degrees of accuracy but AI advancements promise us greater precision. According to our research findings, we demonstrate AI's capability in timely disease prediction and efficient patient monitoring through chatbots and telehealth. It is important to note that validation and refinement of these technologies are essential. In short, it is concluded that both AI and ML's transformative potential in healthcare could revolutionize patient management and both are offering real-time risk assessments and improved care strategies for complex conditions like kidney disease and heart failure.

Theoretically, integrating AI-based combination therapies with standard treatments for heart failure in patients with advanced kidney disease may overlook the intricate interplay of pathophysiological mechanisms. Methodologically, challenges include data heterogeneity, facing biases in AI algorithms, and the lack of large-scale, multi-center clinical trials validating AI applications. The reliance on recent data may limit the inclusion of longer-term outcomes. Future research should focus on conducting multi-center randomized controlled trials to validate AI-based therapies' efficacy and safety. Emphasizing the development of unbiased algorithms and integrating diverse datasets will enhance generalizability. Additionally, long-term studies exploring patient outcomes and cost-effectiveness are crucial. Research should also investigate ethical considerations and the impact of AI on healthcare delivery models.

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B. data research and statistical analysis:	20%	20%	20%	20%	20%
C. elaboration of figures and tables:	20%	20%	20%	20%	20%
D. drafting, reviewing and writing of the text:	20%	20%	20%	20%	20%
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