REVIEW ARTICLE

The Impact of Artificial Intelligence Technologies on Nutritional Care in Patients With Chronic Kidney Disease: A Systematic Review

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Objectives: Chronic kidney disease is a global health challenge, and effective, individualized nutritional management is crucial for slowing progression and improving quality of life. Artificial intelligence (AI) offers innovative tools to optimize and personalize nutritional care. This review explores AI applications in nutritional management, assessing their impact on clinical outcomes, quality of life, and care efficiency.

Methods: A systematic review was conducted, reported according to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses guidelines. Searches were performed on 5 databases, namely MEDLINE, Embase, Cochrane Library, Cumulative Index to Nursing and Allied Health Literature, and integrated with gray literature sources between September and November 2024. The methodological quality assessment was conducted independently by 2 researchers using the Joanna Briggs Institute methodology.

Results: Of 2,053 initial records, 7 studies met inclusion criteria. AI showed significant potential in personalizing dietary recommendations using machine learning, clinical decision support systems, and generative AI tools. These systems tailored nutritional advice based on patient-specific clinical data, reducing complications such as hyperkalemia and improving adherence. AI also facilitated early risk detection and proactive care by monitoring nutritional parameters and predicting complications. In addition, AI-powered platforms enhanced patient education through culturally relevant, intuitive dietary plans and multilingual materials, increasing engagement. AI also improved health care efficiency by automating tasks and integrating with electronic health records.

Conclusions: AI technologies show promise in enhancing nutritional care for patients with chronic kidney disease. Evidence supports their role in improving care quality and dietary adherence. Further research is needed to validate these technologies in clinical practice and ensure integration into routine care pathways.

Keywords: artificial intelligence; nutrition; chronic kidney disease; dietetic; systematic review

Introduction

CHRONIC KIDNEY DISEASE (CKD) represents one of the major global public health challenges.[1] Artificial intelligence (AI) offers new perspectives for addressing these complex conditions, enabling the early identification of at-risk patients and timely interventions with personalized treatments. AI has shown significant potential in managing metabolism-related diseases, such as diabetes

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and obesity.[2] By analyzing large data sets, AI can personalize care and accelerate research, opening new opportunities for the prevention and treatment of these conditions.[3] These technological advancements provide innovative tools for personalizing and optimizing nutritional management in patients with CKD, a growing global health issue affecting over 10% of the world's population.[4] Nutritional management plays a crucial role in CKD treatment: targeted control of specific nutrients, particularly potassium, phosphorus, and protein intake, can slow disease progression, reduce complications, and significantly enhance patients' quality of life (QoL).[5] However, dietary management for patients with CKD is highly complex and requires a personalized approach. AI is revolutionizing this field by offering innovative solutions for tailored nutrition.[6] Recent studies[7,8] have demonstrated the effectiveness of AI models, including systems based on Web Ontology Language and Semantic Web Rule Language, as well as tools designed to optimize potassium intake, a key factor in preventing cardiovascular complications, simplifying disease management, and improving the QoL for patients with CKD. Similarly, another study[9] used an adaptive neuro-fuzzy inference system to predict renal failure progression in patients with CKD by analyzing a decade of clinical data, such as weight, diastolic blood pressure, and the presence of diabetes, to estimate variations in the glomerular filtration rate. The study demonstrated high prediction accuracy, highlighting how adaptive neuro-fuzzy inference system can serve as an effective tool for managing complex chronic conditions such as CKD. A recent study from 2024[10] further demonstrated how AI can significantly enhance the QoL of peritoneal dialysis patients by optimizing their nutrition, providing a modern, personalized, and cutting-edge approach. Collectively, these findings illustrate how AI is contributing significantly to improving patient outcomes, from preventing complications to personalizing therapies, establishing itself as an indispensable tool for addressing the challenges posed by this complex pathology. In this evolving context, nurses occupy a unique strategic position: they are not only direct users of AI-based technologies but also professional care experts capable of guiding the development and implementation of these tools in nursing care.[11] The active integration of advanced technological tools into health care processes has become a fundamental priority for organizations and professionals in the field. AI emerges as a particularly promising resource, with the potential to enhance nursing care quality, improve patient safety, and increase efficiency, all while maintaining cost-effectiveness.[12] Specifically, the application of AI in nursing care involves the use of dedicated tools, algorithms, and systems that support nurses across a wide range of activities, from clinical responsibilities to administrative functions.[13] This integrated approach allows for the optimization of overall health care quality. However, despite their potential, these technologies present several challenges,[14-17] including the lack of an empathetic component inherent to human interaction, concerns about data privacy, and the complexity of adapting standard protocols to meet the specific needs of individual patients.

This systematic review aims to analyze the impact of AI technologies in nutritional care, focusing on personalized diet recommendations, monitoring nutritional parameters, enhancing patient education, and supporting health care provider efficiency.

Methods

Protocol and Registration

This systematic review was conducted based on a protocol prospectively registered on the Open Science Framework, available at: DOI 10.17605/OSF.IO/RNDVU. The review adheres to the guidelines of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses.[18]

Formulation of Research Question

The research question was developed using the PICO framework,[19] as follows: population (P): patients with CKD; intervention (I): application of AI in managing nutrition; (C): standard nutritional management practices or no AI-based intervention; Outcome (O): impact on clinical outcomes, assistive outcomes, and quality of care in health care settings specializing in CKD management.

Eligibility Criteria

The inclusion criteria were focused on primary studies in English that examined the application of AI-driven tools in nutritional management for patients with CKD. Eligible studies assessed the impact of AI on personalizing dietary interventions, monitoring adherence to dietary plans, or predicting clinical outcomes associated with nutrition. Studies using AI technologies such as machine learning (ML) or neural networks for dietary management were also included. Excluded studies were those that did not involve AI, were not related to nutritional management for CKD, or were not accessible in full text (eg, book chapters or abstracts).

Search Strategy

A systematic literature search was conducted in the PubMed (MEDLINE), Embase, Cochrane Central Register of Controlled Trials, and Cumulative Index to Nursing and Allied Health Literature databases between October and November 2024. Additional sources of gray literature, such as Google Scholar and relevant professional organization Web sites, were also consulted to locate unpublished studies. All references were managed using EndNote 20 (2025 Clarivate). The search process involved 3 key steps to ensure a comprehensive review. Initially, search terms were crafted using keywords tailored to each database, incorporating MeSH terms and Boolean operators to target studies on AI, CKD, and nutritional management. The search was then expanded to other relevant databases using refined search terms to improve both sensitivity and specificity. Finally, a thorough review of the references from the selected studies was conducted to identify additional relevant research (Table S1).

Selection of Evidence Sources

Duplicate records were identified and removed using EndNote 20 (2025 Clarivate) and manual checks. Two researchers independently conducted the screening process, with disagreements resolved by a third researcher.[20] The screening involved an initial review of titles and abstracts, followed by a full-text review based on the predefined inclusion and exclusion criteria. During the final stage, the reference lists of included studies were checked to uncover any further pertinent studies.

Risk of Bias and Methodological Quality Assessment

The risk of bias and methodological quality of the included studies were assessed by 2 independent reviewers, with discrepancies resolved through discussion with a third researcher. To ensure a robust evaluation of study quality, the JBI Critical Appraisal Tools were used.[21] These tools provide a systematic approach for assessing research designs and were used to determine the reliability and relevance of the studies. Based on a previous study,[22] studies scoring over 70% on the JBI scale were classified as high quality, those scoring between 50% and 70% as medium quality, and those scoring below 50% as low quality (Table S2).

Data Extraction and Synthesis

Data extraction included essential study details, such as author, year, country of origin, participant demographics, AI interventions, and outcomes related to CKD and nutritional management. Two researchers independently extracted data, with final consensus achieved through discussion with a third researcher. The extracted data were systematically organized in tables and analyzed according to the review's research objectives. A narrative synthesis was used to summarize the findings, supplemented by tables and figures to enhance clarity. The results were categorized into 4 key themes: AI in personalization of dietary recommendations; AI in monitoring nutritional parameters and predicting complications; AI in enhancing patient education and engagement; AI in supporting health care provider efficiency.

Results

A total of 2053 records were identified through systematic searches across electronic databases: MEDLINE/PubMed (n = 199), Embase (n = 1,782), Cochrane Library (n = 33), CINAHL (n = 20), and gray literature (n = 19). After removing 151 duplicates, 1,902 unique titles were screened. Based on title relevance, 120 articles were selected for further evaluation through abstract review. During this phase, 64 articles were excluded as irrelevant. Subsequently, 56 full-text articles were assessed for eligibility. Of these, 49 studies were excluded for not meeting the selection criteria. After the screening process, a total of 7 studies were included in this systematic review (Fig. 1).

Characteristics of the Studies Included

The studies included[23-29] were conducted in different countries, with many of the analyzed studies originating from India (n = 3; 42.86%),[24,28,29] followed by the USA (n = 1; 14.29%),[26] Iran (n = 1; 14.29%),[23] Thailand (n = 1; 14.29%),[27] and Sri Lanka (n = 1; 14.29%).[24] The articles were published between 2019 and 2024, and all studies were observational. The studies also address 4 main outcomes: AI in personalization of dietary recommendations (n = 5),[23-27] AI in monitoring nutritional parameters and predicting complications (n = 4),[24-26,28] AI in enhancing patient education and engagement (n = 3)[26] and AI in supporting healthcare provider efficiency (n = 4).[23,27,29] The findings exhibit a variety of AI technologies, including ML algorithms (eg, Multiclass Decision Forest, Random Forest, Extreme Gradient Boosting [XGB]), generative AI (eg, ChatGPT, Bard, Copilot), and calculation techniques simulating human reasoning (Fuzzy Inference System). Most studies report high accuracy in predicting CKD-related outcomes with an overall low risk of bias. Quality analysis demonstrated high quality across all included studies, with a mean score of 96.43% (range: 87.5%-100%; Table 1, Table S2).

AI in Personalization of Dietary Recommendations

Personalization of dietary recommendations emerged as a central theme across studies, highlighting the integration of ML and AI tools to customize dietary strategies for patients with CKD. Systems such as the fuzzy logic–based Clinical Decision Support System (CDSS)[23] and ML models[24,25] demonstrated their capability to account for comorbidities, potassium levels, and individual dietary needs, delivering tailored macronutrient and food group recommendations. For instance, Marashi-Hosseini L et al.[23] introduced a CDSS that provided tailored macronutrient and food group recommendations for patients with multiple chronic conditions, achieving a 97% accuracy rate when compared to dietitians' recommendations. This approach allowed dietitians to quickly and precisely customize diets, addressing the complexity of balancing multiple dietary restrictions.

Similarly, ML algorithms, such as the Multiclass Decision Forest (MDF),[24] excelled in classifying potassium zones (SAFE: 3.5-5.0 mEq/L, CAUTION: 5.1-6.0 mEq/L, DANGER: >6.1 mEq/L) and providing personalized dietary adjustments with an accuracy of 99.17%. These algorithms use patient-specific clinical data, such as serum potassium levels and CKD stage, to tailor dietary

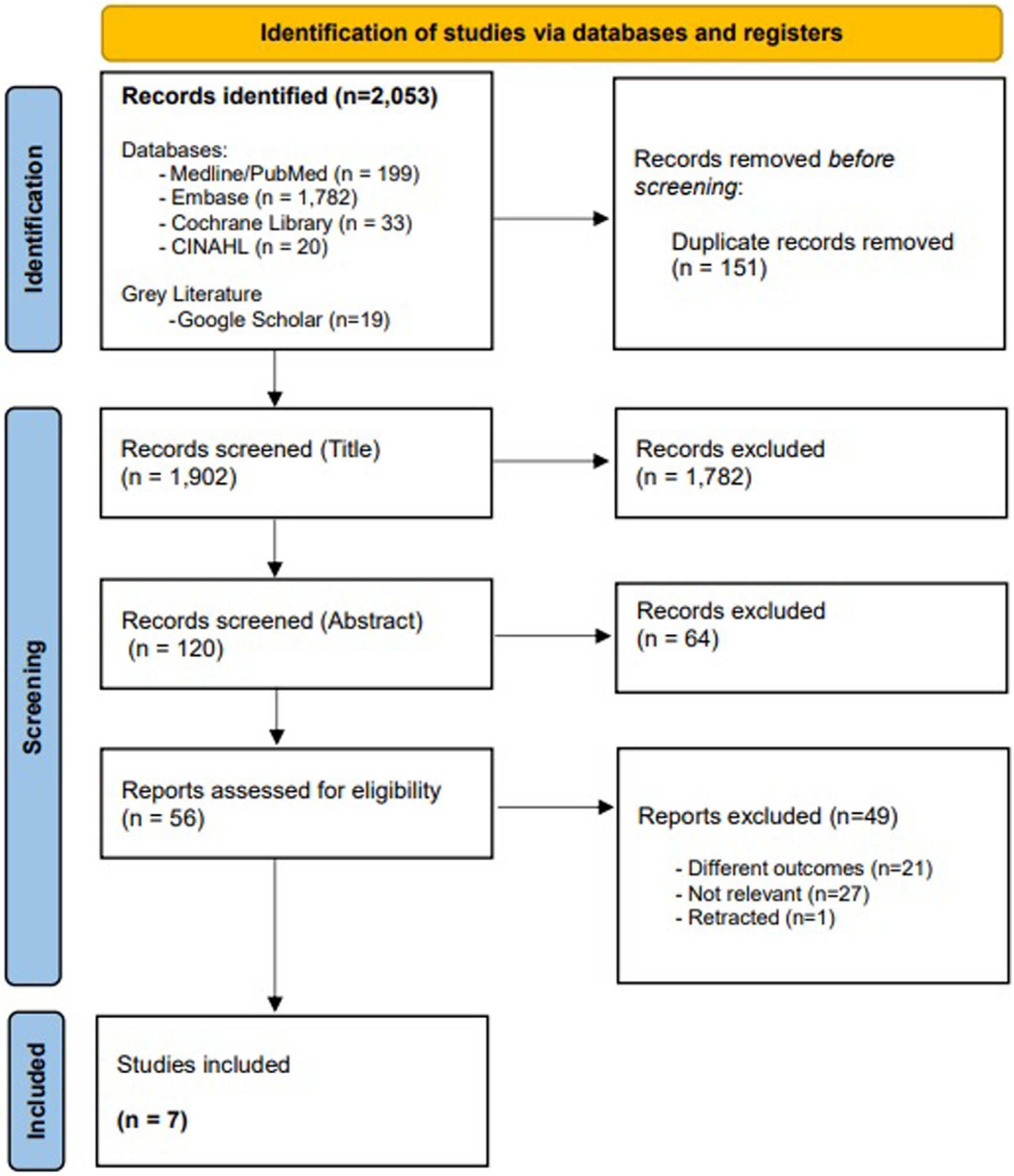

Figure 1. PRISMA flowchart.

recommendations aimed at minimizing complications such as hyperkalemia. In addition, the use of Random Forest models[25] achieved a remarkable 99.75% accuracy in classifying CKD stages and generating food recommendations aligned with potassium levels, further highlighting the potential of AI in managing complex dietary needs. These approaches demonstrate how AI models integrate clinical guidelines with patient-specific data to improve adherence to dietary plans and reduce the burden on healthcare providers.

Generative AI models, such as ChatGPT 4 and Bard AI,[26,27] also contributed significantly to dietary personalization. These tools provided culturally relevant and patient-specific meal plans, aligning closely with individual preferences and nutritional requirements. For instance, Bard AI achieved 100% accuracy in identifying phosphorus content in foods, offering reliable insights for tailoring phosphorus intake. Meanwhile, ChatGPT 4 demonstrated an 81% accuracy rate for potassium classification, supporting the creation of low-potassium meal options critical for CKD management. Beyond nutrient classification, these tools excelled in generating recipes and multilingual meal plans, accommodating diverse patient populations and enhancing accessibility to personalized dietary guidance. Despite these achievements, discrepancies in nutritional analysis, such as the underestimation of protein and potassium levels by up to 54%,[26] highlight the importance of integrating AI tools with validated nutritional databases to

Table 1. Characteristics of the Studies Included

Author, Year	Study Type	Country	Population	AI Technology	Objective	Results	Quality/ Bias
Wang et al., 2024[26]	Observational	USA	20 virtual dialysis patients (Monte Carlo simulation)	ChatGPT	Evaluate ChatGPT for personalized nutritional recommendations	Daily menus with recipes; multilingual translation	+++/low
Marashi-Hosseini et al., 2023[23]	Observational	Iran	100 nutrition records of MCC	Fuzzy inference system	Assist dietitians in creating personalized diets	High accuracy in macronutrient estimation and restriction balance	+++/low
Wickramasinghe et al., 2023[24]	Observational	Sri Lanka	UCI data repository (400 instances and 25 attributes)	Multiclass decision forest	Identify optimal CKD dietary plan	99.17% accuracy in potassium classification (safe, caution, danger)	+++/low
Qarajeh et al., 2023[27]	Observational	Thailand	240 food items (Mayo Clinic Renal Diet Handbook)	GPT-4, Bard, Copilot	Evaluate AI for critical nutrient analysis in CKD	GPT-4: 81% potassium accuracy, Bard: 100% phosphorus, Copilot: 89% phosphorus	+++/low
Kanda et al., 2022[28]	Observational	Japan	24,949 patients with CKD (stage $\geq$3a, hyperkalemia)	XGB, Logistic Regression	Predict hyperkalemia-related adverse events	XGB: AUROC $>$0.8 in predicting mortality and cardiovascular events	+++/low
Maurya et al., 2019[29]	Observational	India	Real-time data (1,000 instances and 25 attributes)	Multiclass decision forest	Develop personalized CKD diet system	99.17% accuracy in potassium classification, targeted dietary recommendations	+++/low
Banerjee et al., 2019[6]	Observational	India	400 patients (61 food items)	Random forest, SVM, naïve Bayes	Generate food recommendations based on CKD stages	Random Forest: 99.75% accuracy in CKD classification	+++/low

AI, artificial intelligence; AUROC, area under receiver operating characteristic curve; CDSS, clinical decision support system; CKD, chronic kidney disease; eGFR, estimated glomerular filtration rate; MCCP, multiple chronic conditions patients; ML, machine learning; SVM, support vector machine; UCI, UCI Machine Learning Repository; XGB, extreme gradient boosting.

Chronic_Kidney_Disease Dataset, Archive.ics.uci.edu.

Critical appraisal score according to JBI Critical Appraisal Tools.

enhance reliability. In fact, the large language models analyzed in these studies are inherently unable to reliably leverage external data sources in a reliable and consistent way. Therefore, their estimations are based on the sparse information provided during the training phase and not on validated datasets, leading to inconsistent results and hallucinations. This issue might be mitigated by the use of advanced prompting strategies (i.e., chain of thoughts), retrieval augmented generation, or the so-called "thinking models" (eg, OpenAI o1, DeepSeek R1).

Moreover, AI tools also facilitate the management of complex dietary challenges posed by comorbid conditions, such as diabetes and hypertension. By accounting for overlapping dietary restrictions, these systems ensure that patients receive comprehensive and holistic dietary care. For example, in a study,[23] CDSS not only considered CKD-related needs but also adjusted dietary plans for other chronic conditions, enabling dietitians to provide integrated care with improved confidence and precision. The process of AI-based dietary personalization is summarized in Figure 2.

AI in Monitoring Nutritional Parameters and Predicting Complications

The integration of AI and ML technologies has significantly advanced the monitoring of nutritional parameters and the prediction of complications in CKD and hyperkalemia patients. These tools leverage patient-specific clinical data to enable early risk detection, optimize dietary interventions, and improve overall disease management. For instance, ML models, such as MDF and XGB, have demonstrated high accuracy in classifying potassium zones and CKD stages, facilitating tailored dietary adjustments to manage electrolyte imbalances and slow disease progression.[24,25] AI systems have identified key clinical predictors of adverse outcomes, such as serum albumin, potassium, and creatinine levels, which have proven critical for optimizing therapeutic strategies. Correlation analysis, as described by Gupta et al.,[28] revealed additional variables, including blood sugar and creatinine levels, as significant contributors to CKD risk and dietary recommendations. By integrating these insights, AI tools have enhanced the precision of dietary planning, supporting more effective and personalized care.

Several studies have emphasized the practical applications of AI in nutritional monitoring. Wang et al.[26] explored the use of ChatGPT to generate culturally appropriate and user-friendly meal plans for dialysis patients. While the system excelled in tailoring menus, it displayed significant discrepancies in nutritional analysis, underestimating key nutrients, such as protein and potassium by up to 54%. This underscores the need to integrate AI tools with validated nutritional databases to enhance their reliability and accuracy in clinical practice, as discussed earlier.

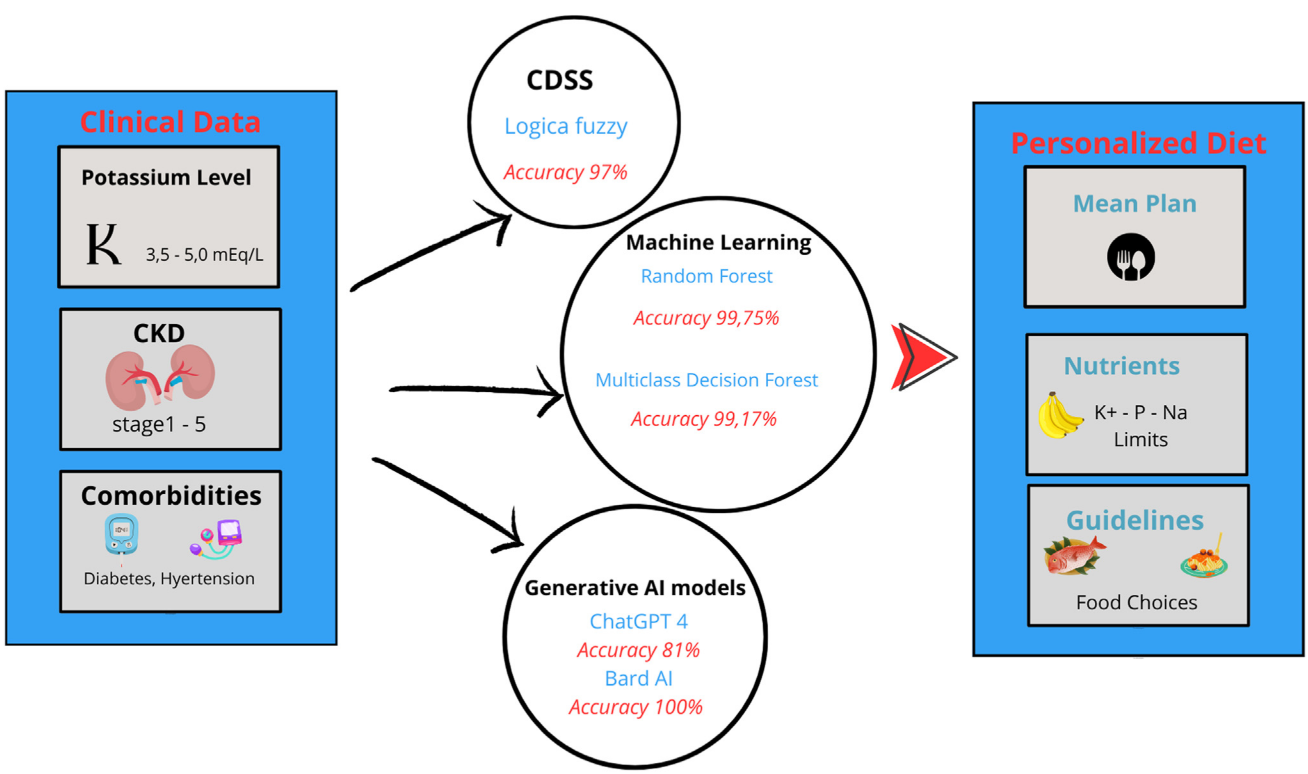

Figure 2. AI in personalization of dietary recommendations. CDSS, clinical decision support system; CKD, chronic kidney disease; ML, machine learning; K+, potassium; P, phosphorus; Na: sodium; AI, artificial intelligence.

Real-time monitoring capabilities further underscore the transformative role of AI in nutritional care. AI-driven systems have been shown to flag deviations in critical biomarkers, such as serum potassium, phosphorus, and creatinine, enabling timely interventions to prevent complications.[29] Furthermore, the integration of these systems with electronic health records allows for dynamic updates to patient profiles, ensuring accurate monitoring and continuity of care.[28] By automating data collection and analysis, these tools reduce the cognitive load on health care providers while enhancing the precision of medical and dietary interventions.

AI in Enhancing Patient Education and Engagement

AI tools have demonstrated significant potential in enhancing patient education and engagement, particularly in the management of CKD. These technologies, powered by AI, offer innovative solutions that improve communication between health care providers and patients, making complex medical information more accessible and understandable. Research has shown that AI-driven platforms, such as ChatGPT, are capable of generating meal plans and recipes that are not only clear and easy to follow but also culturally relevant and tailored to meet the specific dietary restrictions required for patients with CKD. This personalization is crucial, as it ensures that the dietary recommendations align with both medical needs and cultural preferences, leading to improved patient comprehension and adherence to dietary guidelines.[26]

In addition to their personalized recommendations, AI tools such as these offer multilingual capabilities, which significantly enhance their reach and effectiveness. By providing recommendations in various languages, these platforms can serve a diverse range of populations, ensuring that individuals from different linguistic and cultural backgrounds can access the necessary information. Furthermore, these AI systems can adapt their suggestions based on cultural contexts, making it easier for patients to incorporate dietary changes into their everyday lives. This ability to cater to different cultures and languages broadens the accessibility of nutritional management tools for patients with CKD and fosters better engagement, ultimately contributing to improved health outcomes and patient satisfaction.[27]

AI in Supporting Health Care Provider Efficiency

AI and ML tools are revolutionizing health care by streamlining processes and reducing the workload of health care providers. These technologies excel in automating labor-intensive tasks, such as dietary planning and nutrient analysis, which enables dietitians and clinicians to focus more on direct patient care. CDSS, like the fuzzy logic–based tool described by Marashi-Hosseini et al.,[23] demonstrated their ability to significantly improve the efficiency of dietitians. By rapidly generating accurate, personalized dietary recommendations for patients with multiple chronic conditions, these systems minimized time spent on manual calculations while maintaining high precision. The intuitive design of the CDSS facilitated seamless management of complex cases involving overlapping dietary restrictions, enhancing workflow and confidence among dietitians while remaining transparent and auditable.

Ml-powered dietary management software has further supported health care providers by automating the classification of CKD stages and tailoring dietary recommendations to specific biomarkers, such as potassium levels.[29] This automation not only accelerates early detection and intervention for patients with CKD but also reduces the cognitive and administrative burden on health care professionals.

Generative AI models such as ChatGPT and Bard AI have also shown promise in categorizing nutrient levels and developing meal plans, achieving high accuracy rates (e.g., 81% in identifying high-potassium foods).[27] These tools streamline menu creation and reduce variability in dietary recommendations, enabling renal dietitians to provide consistent, evidence-based advice more efficiently.

Integration with real-time clinical data has further enhanced the relevance and timeliness of dietary recommendations. For instance, Maurya et al.[29] emphasized how synchronization with electronic health records allowed dietary management software to dynamically update patient profiles based on laboratory results, ensuring that interventions remain accurate and up-to-date.

Figure 3 provides an overview of the multifaceted applications of AI in the nutritional management of patients with CKD.

Discussion

This systematic review highlights the transformative role of AI technologies in nutritional care, focusing on personalized dietary recommendations, monitoring nutritional parameters and predicting complications, enhancing patient education, and supporting health care provider efficiency. The findings underscore how AI can revolutionize chronic disease management, including CKD, through advanced technological applications across diverse care settings.[30-32]

AI-based algorithms for personalizing dietary recommendations effectively integrate comorbidities and biochemical markers, such as potassium. These systems offer tailored solutions that align closely with the complex nutritional requirements of patients with CKD. For instance, fuzzy logic–based CDSS can generate precise macronutrient and food group recommendations, achieving an impressive accuracy rate when compared with dietitian-guided plans.[23] Such capabilities not only improve the quality of dietary recommendations but also reduce the cognitive and administrative workload for health care providers.

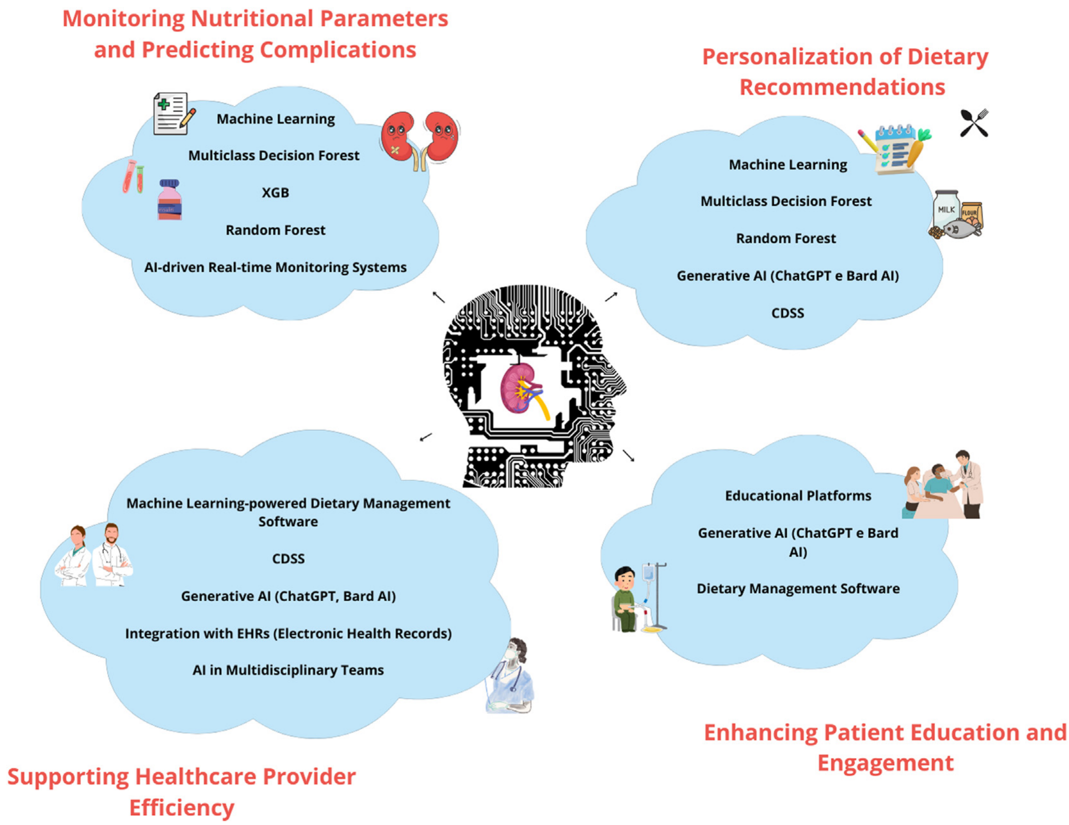

Figure 3. Summary of the role of AI in nutritional management for CKD patients. AI, artificial intelligence; CDSS, clinical decision support system; CKD, chronic kidney disease; EHRs, electronic health records; ML, machine learning; XGB, extreme gradient boosting.

As reported in the literature, managing comorbidities in patients with CKD significantly reduces health care resource utilization and improves patient outcomes.[33] According to Kidney Disease Improving Global Outcomes (KDIGO) guidelines, addressing comorbidities such as diabetes is crucial in CKD management.[34] The UK Prospective Diabetes Study (UKPDS) demonstrated that intensive glucose control in patients with diabetes reduced the risk of death and myocardial infarction, with a particularly notable impact on patients with CKD.[35,36] These findings suggest that AI-based algorithms can serve as reliable tools to deliver personalized diet recommendations safely and effectively, ensuring that care aligns with evidence-based guidelines.[37]

AI's capability to monitor nutritional parameters and predict complications represents a transformative advancement in CKD management. ML models, such as MDF and XGB, have demonstrated exceptional predictive accuracy for critical outcomes such as hyperkalemia and the need for renal replacement therapy, with AUROC values exceeding 0.95 in some studies.[24,28] These tools enable the early identification of at-risk patients, empowering clinicians to implement proactive interventions and mitigate potential complications effectively.

Numerous studies highlight the broader applicability of AI-based algorithms in predicting outcomes across various diseases and complications in diverse care settings.[38,39] For CKD specifically, the ability to forecast complications in nutritional status offers immense clinical value, particularly in the context of ethical considerations related to artificial nutrition.[40] Accurate predictions can help health care providers anticipate nutritional challenges and tailor interventions accordingly, ensuring more precise and patient-centered care. Beyond prediction, AI's integration with telemedicine protocols significantly enhances its utility in monitoring nutritional status. AI-powered devices provide user-friendly interfaces that allow patients to easily track critical parameters, such as hydration levels, which can guide clinicians in prescribing additional fluids.[37] This interactive approach not only simplifies disease management but also fosters patient autonomy by encouraging active participation in their own care. Empowered with real-time insights, patients can make informed decisions about their health, further reinforcing adherence to prescribed dietary and therapeutic regimens.[40,41] Although the included studies provide promising evidence on AI-driven dietary management for patients with CKD, their generalizability is limited by cultural dietary patterns, particularly sodium consumption. Most studies originated in Asian countries (India, Japan, Sri Lanka, Iran, Thailand), where typical diets contain more sodium than Western diets. Crucially, none of these studies reported on patients' sodium intake or compliance with the Kidney Disease Outcomes Quality Initiative recommendation of <2.3 g/day.[42] Given that high sodium intake drives hypertension and accelerates CKD progression, future AI-based nutritional interventions must explicitly integrate sodium targets and adapt to local eating habits to ensure clinical relevance and cross-cultural applicability.

Improving patient education and engagement has emerged as a pivotal outcome of AI applications in nutritional care. AI-driven platforms, such as ChatGPT and Bard AI, provide personalized and culturally relevant educational materials that empower patients to better understand their dietary needs and adhere to nutritional guidelines.[26,27] By tailoring recommendations to individual preferences and cultural contexts, these tools effectively bridge communication gaps, significantly enhancing the overall patient experience.

The effectiveness of AI in CKD nutrition also hinges on the quality of underlying data sets. Accurate, validated food composition and nutrient databases are essential for personalized recommendations. For example, Zheng et al.[43] created a publicly available benchmark data set to test large language models' ability to estimate nutrient content, whereas Lee et al.[44] integrated dietary, lifestyle, and biometric data from wearables to support real-time nutrition guidance. Adopting FAIR (findable, accessible, interoperable, reusable) principles for nutritional databases will further enhance data quality and trustworthiness in AI-driven care.[45]

AI serves as a dynamic resource, offering a more interactive and engaging learning experience for patients.[46] Recent literature underscores the potential of AI to deliver personalized educational materials, facilitate virtual consultations, provide language translation tools, and utilize virtual reality simulations to improve patient understanding and satisfaction.[47] These advancements exemplify how AI can transform the patient-provider relationship, fostering a more collaborative and participatory approach to care.

Notably, AI also plays a crucial role in enhancing the efficiency of health care providers. AI-driven tools have gained recognition for assisting physicians in making informed treatment decisions, particularly by predicting therapy responses and optimizing drug dosages tailored to individual patient needs. These capabilities help minimize risks, predict potential adverse drug events, and ultimately improve patient care outcomes.[48] Furthermore, the integration of AI with telemedicine enables health care providers to manage patients across long distances, ensuring quality care even in geographically remote or underserved regions.[49]

Furthermore, training health care professionals is essential to ensure the effective use of AI tools. Research shows that integrating AI education into medical programs is vital to avoid underuse or misuse,[50] while UK medical students express a strong need for targeted AI education.[51] The involvement of dietitians in developing AI-based tools is also crucial to ensure alignment with clinical needs. AI's role in transforming clinical nutrition, particularly in chronic disease management, is highlighted in studies.[52,53] However, malnutrition and nutrition-related alterations caused by acute and chronic diseases remain major healthcare concerns. In this context, AI applications hold promising potential for the future, although they are still in development and require further research and ethical evaluation.[54-56]

While the integration of AI into modern clinical practice holds transformative potential, it also presents several challenges and limitations. Key concerns include ensuring the safety of AI algorithms, as inaccuracies or errors could result in harm to patients. In addition, adherence to regulatory compliance remains a pressing issue, as AI-based platforms must align with strict standards to safeguard patient privacy and data security.[57] Addressing these challenges is essential to realize the full potential of AI in reshaping health care delivery.

Study Limitations

This study has several limitations that warrant consideration. First, no intervention studies directly compare the effectiveness of various AI algorithms in clinical settings; instead, existing studies evaluate individual algorithms in isolation. Second, the limited number of studies and their restricted geographical origins make it challenging to assess the broader impact of AI applications across different countries and health care systems. Most studies were conducted in Asian countries, where traditional diets tend to have a higher sodium content compared to Western diets. None of the studies explicitly addressed sodium intake or adherence to international guidelines recommending less than 2.3 g of sodium per day for patients with CKD.[42] Greater cultural sensitivity in AI-based dietary interventions, along with additional studies and reviews that incorporate Western dietary habits, is crucial to improve the applicability and effectiveness of AI in CKD patient care. Finally, interpreting the findings requires caution, as variability in interventions among the included studies prevents direct data comparison and limits the generalizability of the results.

Future Directions

Most of the studies included in this review were observational studies, highlighting the need for more rigorous evidence-based research, such as multicenter randomized controlled trials, to evaluate AI's efficacy in nutritional management for patients with CKD. Moreover, the studies predominantly originated from Asia, leaving significant gaps in understanding AI's application in other regions. Cultural and religious differences in dietary habits could significantly influence patient interactions with AI algorithms. For instance, certain foods that are staples in some regions may not be commonly consumed in others cultures. Future research should prioritize exploring these cultural variances and extending investigations to underrepresented regions to ensure AI technologies are globally applicable and culturally sensitive. By addressing these gaps, future studies can enhance the adaptability and inclusivity of AI applications, ultimately advancing nutritional care for patients with CKD worldwide.

Conclusion

This review underscores the transformative potential of AI algorithms in the nutritional management of patients with CKD. By enabling personalized dietary recommendations, monitoring nutritional parameters, predicting complications, enhancing patient education and engagement, and improving health care provider efficiency, AI offers a promising approach to addressing the complex challenges associated with CKD care. While the application of AI-based algorithms for assessing and managing nutritional status in patients with CKD appears to be reliable, certain limitations must be addressed to ensure their optimal integration and effectiveness in clinical practice. Future advancements in AI technology, coupled with rigorous research and careful consideration of cultural and ethical aspects, have the potential to further enhance the quality of care for patients with CKD worldwide.

Author Contributions

S.M.P., S.M., and G.C. contributed to study design. D.G., L.G., and A.P. contributed to data collection. G.F., D.G., L.G., A.P., G.V., E.F., and F.G. contributed to data analysis. S.M.P., G.F., D.G., L.G., A.P., G.V., E.F., and F.G. contributed to article writing. S.M.P., M.S., F.G., A.P., and S.M. contributed to critical revisions for important intellectual content. S.M.P. S.M., and G.G. contributed to study supervision. All authors read and approved the final article. S.M.P., and G.F. provided an equal contribution as first authors in drafting the manuscript; F.G. and S.M. provided equal contribution as last authors in the coordination of the research group.

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Supplementary Data

Supplementary data associated with this article can be found in the online version at https://doi.org/10.1053/j.jrn.2025.06.002.

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