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Artificial Intelligence in Preventive Cardiology: Risk Prediction, Exposomics, and Personalized Interventions

REVIEW

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ABSTRACT

Cardiovascular disease is the leading cause of morbidity and mortality worldwide. Prevention has shifted from a narrow focus on atherosclerosis to the cardiovascular-kidney-metabolic (CKM) framework, which requires integrating data across organ systems, specialties, and care settings. Artificial intelligence (AI) can work with the high-dimensional, weakly structured data this integration produces, and its use in prevention is now endorsed by major cardiovascular societies. This review covers two applications. The first encompasses risk prediction, spanning electrocardiogram-based models that reframe routine tracings as general biomarkers of cardiovascular health, AI-enhanced cardiac imaging that extracts biological signals invisible to standard reads, opportunistic analysis of scans acquired for unrelated indications, and emerging efforts to quantify environmental and neighborhood-level exposomic risk. The second is the management of modifiable risk factors across early CKM stages: lifestyle behavior, obesity phenotyping, hypertension monitoring, dyslipidemia detection, glycemic management, and chronic kidney disease risk stratification. In both domains, retrospective discriminative performance is frequently excellent, while prospective evidence that AI-guided intervention improves patient-relevant outcomes remains limited.

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INTRODUCTION

Cardiovascular disease (CVD) remains the leading cause of morbidity and mortality globally. Over the last decade, preventive cardiology has shifted from targeting isolated risk factors toward a comprehensive, multi-organ paradigm embodied by the cardiovascular-kidney-metabolic (CKM) framework.[1] Managing CKM syndrome requires integrating complex data streams across multiple subspecialties. Artificial intelligence (AI) offers the computational architecture needed to synthesize these longitudinal data streams, promising scalable solutions across the continuum of CKM stages.

In this review, we outline how AI enhances CVD risk prediction across routine clinical and opportunistic imaging modalities, including electrocardiography, dedicated cardiac scans, and standard chest, head, and breast imaging. We then analyze how these computational assets are being deployed directly within the electronic health record (EHR) and consumer space to prevent and manage the various aspects of cardiometabolic disease across the CKM spectrum. In the context of clinical applications, a clear distinction must be made between passive digital health (eg, standard step-tracking wearables, static self-monitoring applications, or scheduled text messaging) and AI-enabled interventions. The latter are defined by algorithms—such as supervised machine learning, deep neural networks, natural language processing, and large language models (LLMs)—that dynamically evaluate and integrate complex inputs, generate predictive outputs, and iteratively adapt to individual clinical trajectories. However, in addressing CKM, active AI interventions were built on top of passive digital health strategies, and both will be briefly reviewed.

AI applications across the CKM continuum can be conceptualized as a four-stage clinical pipeline (Figure 1). The foundational stages—multimodal data ingestion (Stage 1) and computational risk identification (Stage 2)—are supported by a robust body of evidence demonstrating the capacity of machine learning models to extract actionable predictive signals from standard diagnostic testing, continuous telemetry, and opportunistic imaging. The next frontier is represented by clinical intervention and impact on clinical outcomes—Stages 3 and 4.

While AI models demonstrate remarkable accuracy in retrospective diagnostic classification, a critical gap remains between retrospective discrimination (eg, high area under the receiver operating characteristic curve or C-index metrics) and prospective clinical implication in terms of both applicability and utility. Demonstrating that algorithmic alerts actively alter physician behavior, guide actionable clinical pathways, and improve long-term outcomes without triggering system-wide alert fatigue remains the field's central mandate.

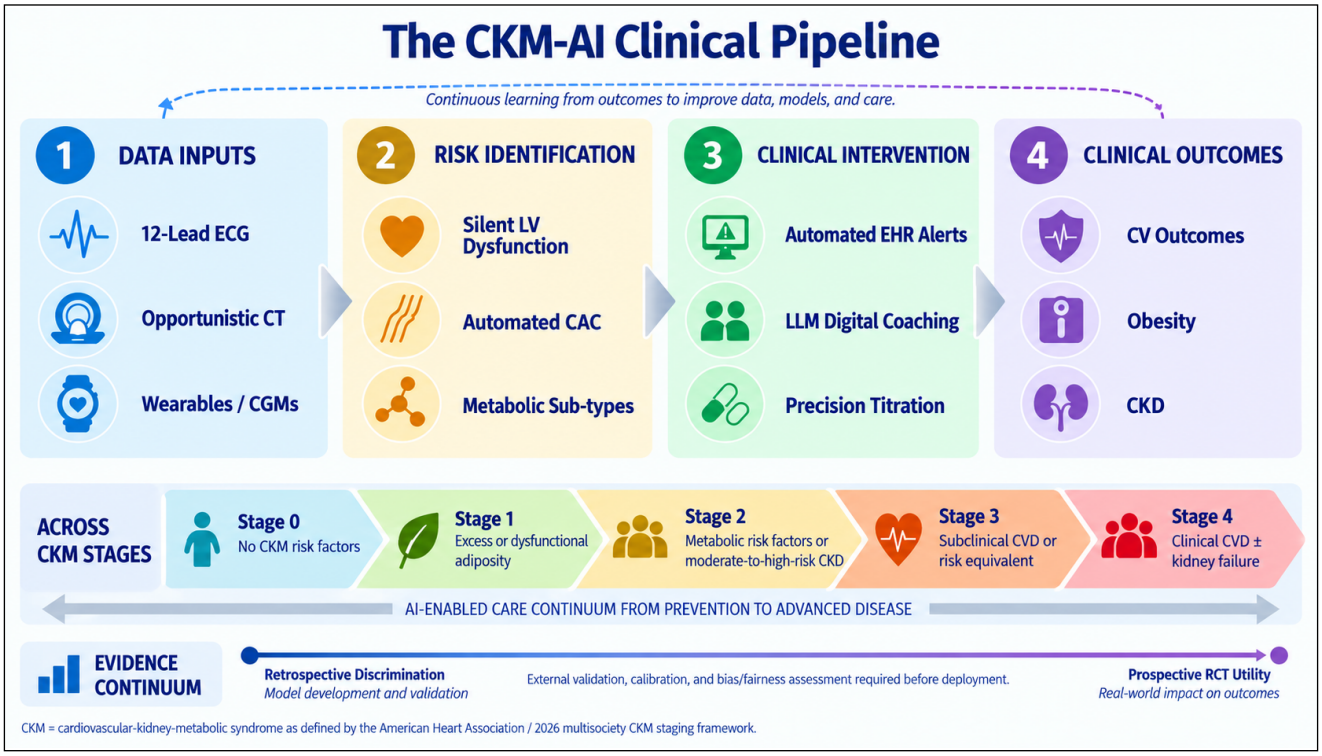


Figure 1 The chronic kidney disease-artificial intelligence clinical pipeline.

AI ENHANCED RISK PREDICTION TOOLS: HARNESSING IMAGING AND LARGE DATASETS

RISK PREDICTION FROM THE ELECTROCARDIOGRAM

AI-enabled electrocardiography was developed primarily to help clinicians detect subclinical or early-stage heart conditions before symptoms fully manifest. This includes predicting the onset of arrhythmia (eg, atrial fibrillation), the development of heart failure or diastolic dysfunction, or the early diagnosis of hypertrophic cardiomyopathy. These advanced tools are increasingly available at the point of care and on consumer devices such as smartwatches.[2]

This technology is supported by a growing body of real-world clinical evidence. For example, in a large, cluster-randomized primary care trial, using an AI-electrocardiogram (ECG) screening tool led to a 32% relative increase in the odds of a new diagnosis of left ventricular systolic dysfunction (LVSD) without causing an unnecessary surge in echocardiography referrals.[3] Recent studies are pushing this technology even further, moving from tracking single conditions to creating comprehensive risk-prediction platforms. A prime example is the AIRE (Artificial intelligence-enabled electrocardiogram for mortality and cardiovascular risk estimation) platform, which was trained on over 1.1 million ECGs from nearly 190,000 patients and validated across five international patient groups. Instead of analyzing a single disease, the AIRE platform can analyze a single, routine ECG tracing to generate a personalized survival curve for the patient. From that single input, it can simultaneously predict a patient's risk for all-cause mortality, future ventricular arrhythmias, atherosclerotic vascular disease, and heart failure.[4]

Other large-scale models demonstrate similar promise. An AI model trained on more than 10 million ECGs demonstrated a high average accuracy score of 0.93 across eight different cardiovascular diseases.[5] Interestingly, the specific features the model learned to identify in these tracings mapped directly onto 24 genetic regions, eight of which had never been linked to ECG patterns before. Another model built on nearly 2.8 million tracings, externally validated, successfully predicted a patient's 1-year risk for a major adverse cardiovascular event (MACE) with high accuracy, ultimately outperforming the traditional Framingham Risk Score when projecting a patient's 5-year risk profile.[6]

The most important takeaway from this research challenges our original assumptions about how these tools work. An analysis of more than 233,000 individuals was designed to determine whether these AI algorithms simply identify specific isolated conditions or also function as broader indicators of cardiovascular health. Each model was strongly associated with a wide variety of cardiovascular traits in addition to its target. The authors concluded that we should stop viewing AI-ECG as a simple "yes or no" diagnostic test and instead treat it as a comprehensive, general biomarker for overall cardiovascular health.[7]

Taken together, these data show that the field is moving away from multiple narrow tools and toward using a routine surface ECG as a single, powerful risk signal. However, clinicians should interpret these findings with healthy caution. The impressive accuracy metrics published so far are overwhelmingly retrospective, derived from existing historical datasets. True prospective evidence—where these models are actively deployed in clinics to guide and change patient care—is currently limited to a single randomized trial.[3]

Furthermore, the clinical actionability of an AI-ECG high-risk flag in an asymptomatic patient remains undefined. Addressing this requires moving beyond post-hoc explainability, which reconstructs a rationale after the fact and may diverge from the model's actual computation, towards intrinsically interpretable architectures—concept-bottleneck or two-stage designs in which the prediction is routed through explicit, clinically named physiological features. The explanation then becomes a structural property of the model, auditable and correctable rather than merely illustrative.

RISK PREDICTION FROM CARDIAC AND OPPORTUNISTIC IMAGING

Medical imaging represents a rich and important source of data for AI models. Dedicated cardiac scans can be analyzed with AI-enhanced technology to extract deep biological information that a standard human reading could not access. Additionally, AI can work "opportunistically," automatically scanning routine imaging—like a chest computed tomography (CT) or a mammogram that was ordered for an entirely different medical reason—to find hidden cardiovascular warning signs. For safe clinical adoption, both approaches must meet the same strict screening standards: They must be sensitive, specific, highly reproducible, and cost-effective.

AI ENHANCEMENT OF CLINICALLY INDICATED CARDIAC IMAGING

Cardiac CT, whether coronary CT angiography or functional perfusion imaging, is increasingly the first-line test for suspected coronary disease, and AI now extracts far more information from each acquisition than the visual read alone—quantifying inflammation, adiposity, chamber geometry and myocardial mass from images already obtained for diagnostic purposes.[8]

In the ORFAN (Oxford Risk Factors And Non-invasive imaging) study, which followed 40,091 patients undergoing clinically indicated coronary CT angiography (CCTA), most events occurred in individuals without obstructive coronary disease.[9] By using an AI model to measure coronary inflammation (via the fat attenuation index metric), the system identified individuals with high inflammation who faced a nearly 30-fold higher risk for cardiac death. This risk was entirely independent of traditional risk factors or the physical extent of their coronary disease, leading researchers to propose this AI-risk classifier as a powerful alternative to traditional risk calculators.[9] Similarly, analyzing the characteristics of epicardial fat from routine heart scans allowed an AI model to accurately predict which patients would develop incident heart failure before any clinical symptoms appeared.[10] Furthermore, a fully automated, quantitative CCTA model diagnosed restricted blood flow (ischemia) more accurately than traditional fractional flow reserve (FFR-CT) or standard perfusion imaging.[11] AI has also refined functional imaging. When applied to hybrid myocardial perfusion scans, automated measurements of left ventricular mass and chamber volumes improved accurate patient risk reclassification by 23%.[12] Taken together, these data points to a new understanding of standard scan as a rich source of hidden biomarkers rather than a single, isolated anatomical or functional representation.[13]

OPPORTUNISTIC IMAGING

A large clinical opportunity lies in utilizing routine scans that were never originally ordered to answer a cardiovascular question. The potential volume here is massive: roughly 15 to 19 million non-gated chest CTs are performed every year in the United States alone.[14] Measuring coronary artery calcium (CAC) is a proven, direct method to assess a patient's burden of atherosclerosis. It consistently outperforms traditional clinical risk scores when predicting future events, and it has been endorsed by the latest American College of Cardiology (ACC)/American Heart Association (AHA) guidelines as a powerful tool to help guide clinical decision-making in tailoring the choice of treatment for cholesterol lowering.[14] Yet, despite more than 17 million individuals being eligible for this screening, its clinical use remains limited. Historically, this limitation is because finding and measuring calcium on non-dedicated routine scans has required tedious, manual, and highly subjective effort by a radiologist. The valuable data already existed within health system databases, but it was extremely hard to access.

AI solves this operational bottleneck directly. The topic has been the subject of a recent AHA scientific statement,[14] and its full review is beyond the scope of the current work. Fully automated software pipelines can now precisely calculate coronary calcium, heart chamber volumes, and left ventricular mass from a routine chest CT in 18 seconds, with a failure rate of only 0.1%.[15] It can also map and segment epicardial fat in under 2 seconds, a task that typically requires 15 minutes of manual effort by an expert observer.[16] These findings confirm that certified AI tools can provide meaningful improvements in screening sensitivity while simultaneously allowing for reduced radiation exposure during CT scans by harvesting preexisting data.

Importantly, these automated measurements carry independent prognostic weight. Automated measurements of CAC, left atrial volume, and left ventricular mass index successfully predicted all-cause and cardiovascular mortality, outperforming standard expert readings in classifying patient risk. In fact, an AI interpretation of calcium scans outperformed the traditional, manually calculated Agatston score in predicting cardiovascular events over a 15-year period in the MESA study.[17]

The opportunities go beyond chest imaging. An AI model analyzing routine head CTs obtained in the emergency department predicted future cardiovascular disease more accurately than the now recommended clinical PREVENT equations.[18] Routine screening or surveillance imaging can be harvested similarly. For example, evaluating the heart and aorta on routine lung cancer screening CTs successfully flagged high-risk patients who were completely missed by standard clinical risk scores.[19] Similarly, an AI model designed to quantify breast arterial calcium on routine screening mammograms independently predicted future cardiovascular events better than standard clinical scores across two large groups of women, providing vital heart health data at absolutely no additional radiation cost.[20]

Results from retinal eye imaging, despite an abundance of data, have been more mixed. In patients with type 2 diabetes (T2D) for example, a deep learning model analyzing retinal photos predicted major cardiovascular events comparably to standard risk equations.[21] However, a massive evaluation using the UK Biobank database found that adding retinal images did not improve cardiovascular risk prediction beyond what we can already measure with standard primary prevention scores.[22] This serves as an important reminder for clinicians: Simply matching the performance of an existing test is not equivalent to adding true clinical value.

Imaging the Exposome and Environmental Risk

The final conceptual frontier of AI application extends beyond the human body entirely. In an innovative study of 64,230 patients, an AI model was applied to satellite imagery of the built environment surrounding where those patients lived.[23] The model generated a localized risk score that was strongly associated with a higher risk

of heart attacks and strokes, completely independent of the patient's personal calcium score or traditional medical risk factors (showing a more than 2-fold increase in risk).[23] This approach essentially allows us to "image" a patient's environmental exposure (the exposome) rather than just their anatomy, thus turning community and environmental factors into clear targets for AI-driven prevention.

However, a vital cautionary lesson emerged from this study: When the researchers adjusted the model to account for a standard social vulnerability index, the strong link between satellite images and heart events disappeared. This suggests that the AI model wasn't uncovering a hidden environmental hazard but was highlighting neighborhood poverty and economic deprivation.

Downstream Pathways for Opportunistic Flags

When applied carefully, opportunistic imaging holds considerable promise for detecting presymptomatic disease early and could prove cost-saving for health systems.[24] Yet substantial implementation hurdles remain. When an automated chest CT pipeline flags incidental CAC, clear protocols are required to assign ownership of the finding, identify and notify the appropriate provider, and initiate the appropriate guideline-directed treatment without burdening radiology workflows. Bringing these processes up to scale is a further roadblock. Noncardiac chest CT is performed far more often than dedicated calcium scoring, so systematic automated reporting would greatly expand the detection of subclinical atherosclerosis; however, in the era of personalized medicine, each finding should rightfully carry a subsequent onus of risk discussions, laboratory tests, referrals, and in some pathways further imaging.

Once these are multiplied across the volume of scans acquired for unrelated indications, they can constitute a substantial and largely unbudgeted demand on services already operating at capacity. There is promise here too, however, with AI assisted pathways for the management of patient centered care. A pattern recurs across the technologies reviewed here: AI performs well at identifying risk retrospectively, in historical data, but evidence that acting on these automated findings improves long-term outcomes remains extremely limited.

ADDRESSING CVD RISK FACTORS WITH AI IN THE NEW CKM FRAMEWORK

Below, we review the active applications of AI in CKM Stage 0 (absence of risk factors), Stage 1 (excess or dysfunctional adipose tissue), and Stage 2 (metabolic risk factors and chronic kidney disease); subsequent sections within this issue will provide targeted insights into more advanced stages.

LIFESTYLE

The primordial prevention in CVD relies on lifestyle recommendations, as summarized by AHA's "life's essential eight." As is the case for "health maintenance" in the absence of negative symptoms, patient buy-in, engagement, and positive motivation are essential to promote healthy and positive habits. The initial baseline iteration of digital health involved the objective quantification and tracking of continuous physical activity metrics, sleep architecture, and daily behavioral habits—domains in which commercial wearable devices inherently excel.[25] Providing personalized insight on each individual's patterns and habits in continuous feedback served as the first historic phase of digital lifestyle medicine, relying primarily on patient self-reflection as the core triggering mechanism for behavioral modification. Automated text messaging represented the second historic iteration of this technology.

Today, advanced AI is playing an increasingly central role in promoting physical activity and behavioral changes. While simple step-counting or manual logging represents passive digital health, AI integration occurs when machine learning models analyze continuous multi-sensor telemetry to adaptively modify intervention goals. With the progression of generative AI into conversational technology and highly articulate chatbots, scalable, personalized digital coaching has become a clinical reality. While coaching is regarded as an effective mechanism to promote and sustain healthy behaviors, provider availability and cost remain significant barriers to its large-scale deployment. New conversational technologies could represent a solution to these barriers, extending support to a much larger and diverse population, although not completely eliminating the digital divide.

In young adults and individuals at risk of metabolic syndrome, the use of wearables to provide feedback increased physical activity and improved some metabolic syndrome measures. PH-LLM, a version of the Gemini LLM, performed similarly to human experts for fitness-related tasks and provided personalized sleep and exercise insights.[26-28] These interventions appeared most useful when monitoring data was paired with elaboration and translation into specific goals with detailed feedback and accountability.[29] Notably, in some countries, including the United States and Germany, these digital health applications—when paired with validated wearable devices—are already embedded into formalized medical prescription services or insurance payer's plans to govern exercise planning, cardiovascular rehabilitation, and structured primary prevention programs.[2]

OBESITY

Stage 1 CKM is defined by excessive/dysfunctional adipose tissue. As the medical community embarks on the task of

addressing obesity as a chronic disease on its own and as the powerful precursor to comorbid conditions, AI offers the distinct potential to help understand its phenotypes—in terms of genetic, metabolic, behavioral and social determinants—and guide prevention and treatment strategies, including selection of medications.[2,30,31] For example, machine learning models have been applied to redefine the classification of obesity beyond static body mass index (BMI) and basic anthropometric measures. These models identified three distinct metabolic profiles differentially associated with cardiometabolic risk in patients with obesity in the Di@bet.es cohort in Spain.[32]

Large-scale open-science initiatives like the UK Biobank have been harnessed to map the patterns of multimorbidity development and disease trajectories in individuals with overweight and obesity.[33] Furthermore, utilizing real-world clinical data extracted from the nationwide All of Us Research Program, a recent study showed strong potential for LLM technology to predict weight loss outcomes after GLP-1 receptor agonist initiation and to identify key features associated with treatment response.[34] The clinical application of these predictive datasets could significantly refine clinical decision-making, optimize drug allocation, and deliver highly customized treatment protocols. Likewise, AI integration of data extracted from imaging, able to track the trajectory of key parameters beyond weight on the scale (visceral fat, epicardial fat, muscle mass), could allow true personalization of the obesity treatment journey.

On a consumer level, mobile apps that encourage positive health behavior have been proliferating in the obesity space. As an example, an exclusively AI-led lifestyle intervention based on the Diabetes Prevention Program (DPP) was noninferior to referral to a human-led DPP in achieving recommended thresholds for weight loss, hemoglobin A1c reduction, and weekly physical activity among adults with prediabetes and overweight or obesity.[35] The overall evidence for these tools improving health outcomes (still only measured as weight loss in the main portion of the literature) over sufficient time frames to be clinically meaningful is limited.[36] Although a large meta-analysis reported positive outcomes specifically for mobile device-based intervention compared to purely static, web-based platforms—indicating that the inherent portability and real-time feedback loops of smartphone software provide a distinct operational edge—the long-term outcome remains underwhelming because adherence tends to fade over time.[37] This is a limitation that digital technologies undoubtedly share with intensive in-person multidisciplinary programs, and an area of active research, in which these apps are being paired with specific behavioral theories to target habit formation.[36]

HYPERTENSION

AI can be effectively deployed to enhance both the diagnosis and longitudinal management of hypertension (HTN), and its transformative applications in the field have recently been reviewed.[38] Current cuffless technology—in the form of AI-powered photoplethysmography systems as well as specialized bioimpedance sensors—for the measurement of blood pressure (BP) has not been extensively validated and thus cannot yet be recommended for diagnosis of HTN or daily monitoring of BP values.[38] However, they hold the promise of a more reliable, discomfort-free experience. The seamless acquisition of continuous monitoring data can significantly improve the clinical detection of occult HTN while offering a highly personalized, complete assessment of BP burden.[39]

A recent meta-analysis indicated that digital health interventions—in the form of apps, text messages or web-based approaches that share BP values with patients—can have a small but significant effect on reducing systolic BP in hypertensive patients.[40] Furthermore, machine learning approaches could provide unexpected clinical insights, prompting the preventive cardiology community to reconsider long-held conventions regarding resource allocation and strategic therapeutic focus. For example, AI was utilized to map personalized antihypertensive treatment responses at the individual patient level, utilizing data models trained on the landmark SPRINT and ACCORD clinical trials. The results highlighted how the absolute risk reduction achieved via aggressive, intensive BP titration was frequently independent of the baseline estimated risk of atherosclerotic cardiovascular disease (ASCVD).[40]

HYPERLIPIDEMIA

AI algorithms can estimate low-density lipoprotein cholesterol levels with precision that significantly outperforms standard, widely used clinical estimation equations. Machine learning models can be embedded in EHRs for automatic identification of patients with hyperlipidemia by "digital surrogates" without relying on actual lab tests.[41] This automated capability can drastically enhance early, population-wide screening for advanced ASCVD risk, a benefit that is particularly impactful for underinsured, rural, or vulnerable populations who face structural barriers to routine preventative laboratory testing.[42] Natural language processing applied to clinical notes can identify reasons for statin non-use in high-risk populations, providing an important tool to address gaps in care and design appropriate strategies to mitigate them.[43]

TYPE 2 DIABETES MELLITUS

The widespread clinical adoption of continuous glucose monitoring (CGM) technology has fundamentally

enhanced patient quality of life and long-term metabolic outcomes. AI is uniquely equipped to handle and process these dense data, evaluate advanced indexes such as glycemic variability and time-in-range patterns, and then predict response to environmental factors as well as suggest proactive strategies to improve blood sugar control.[44] Moreover, modern machine learning frameworks can integrate CGM streams with multisensor inputs from commercial wearables, including real-time accelerometry and continuous heart rate monitoring, to power closed-loop behavioral feedback systems and digital coaching platforms.[30,31,45,46] Chatbots have entered the type 2 diabetes (T2D) arena too.

In a pilot study in economically disadvantaged communities, patients with T2D were randomly assigned to a human coach or a "conversational agent," with both cohorts communicating exclusively via text messages. The study reported positive experiences in both arms. Although human coaches demonstrated a superior capacity to convey genuine clinical empathy and naturally "branch out" to address unexpected nonclinical barriers to patient care, the chatbot's absolute consistency in following its preprogrammed, evidence-based script frequently translated into a greater sense of patient autonomy and empowerment.[47] To further elucidate the AI potential in guiding treatment, a large randomized controlled trial is currently underway to assess the effectiveness of a fully AI-based system (MELISSA) that integrates CGM data with personalized insulin dose recommendations and dietary recommendations. Although focused on type 1 diabetes, the trial will enroll an exploratory cohort of patients with T2D in multiple insulin dosing protocols, representing an important step forward for algorithmic clinical triage.[48]

CHRONIC KIDNEY DISEASE

Identification and aggressive treatment of patients at risk for chronic kidney disease (CKD) is pivotal in the CKM continuum, especially given the modern therapeutic availability of cardio- and nephro-protective medications that can fundamentally alter long-term multiorgan disease trajectories. AI has been increasingly harnessed to parse through massive, longitudinal EHR datasets, effectively highlighting a substantial and systemic underutilization of UACR testing within current cardiology practices—a missed opportunity for prevention.[49] Moreover, AI algorithms can determine the likelihood and rate of progression of CKD based on different available biomarkers, simulate CKD progression, and model individual treatment responses based on dense longitudinal data through "digital twin approaches."[50] This computational triage could allow preventive clinicians to proactively initiate organ-protective therapies—such as SGLT2 inhibitors and nonsteroidal mineralocorticoid receptor antagonists—effectively delaying the cardiorenal disease progression. Renal digital twins and EHR gap-analyzers rely on dense longitudinal data. However, algorithmic execution depends heavily on the specifics of each healthcare system. Models trained on single-center EHR architectures frequently experience a significant drop in their performance when deployed across different health systems and as such are not necessarily ready for clinical primetime.

ALGORITHMIC FAIRNESS, HEALTH EQUITY, AND IMPLEMENTATION BARRIERS

As AI applications expand across the CKM spectrum, systemic implementation barriers must be addressed to ensure technologies do not exacerbate health disparities.

1. **Dataset Shift and External Validation:** Algorithms trained on homogenous datasets from tertiary academic centers frequently do not perform as well once applied to diverse community populations.
2. **Algorithmic Bias and Social Determinants:** Models trained on historical EHR data inherit past clinical practice patterns, and when those patterns include underdiagnosis or undertreatment of marginalized groups, the models can reinforce these disparities—perpetuating bias and stigmatization rather than correcting it.
3. **The Digital Divide:** Wearable-based AI models and continuous digital therapeutics depend on access to smartphones, stable internet, and digital literacy. Health systems must design accessible AI solutions to reach underserved CKM Stage 2 and 3 populations.
4. **Physician Alert Fatigue and System Readiness:** Integrating automated opportunistic screening and EHR alerts into clinical workflows risks overwhelming providers. AI implementation strategies must establish clear governance, define clinical responsibility for automated findings, and set high-specificity operational thresholds.

CONCLUSION

The integration of AI into preventive cardiology offers a powerful mechanism to operationalize the new CKM framework, turning dense clinical, imaging, and lifestyle data into precise, actionable interventions. However,

as the field transitions from retrospective discovery to real-world clinical application, a vital word of caution is required: Our enthusiasm for automated efficiency must not outpace rigorous, prospective clinical validation. While opportunistic screening and deep learning algorithms isolate hidden structural and physiological risk factors, the utility of AI in preventive cardiology rests on its capacity to modify clinical trajectories. Within the newly established CKM framework, this requires moving beyond abstract risk scoring to actively manage individual metabolic and renal drivers across successive stages of disease. Moving forward, we hope the ultimate goal of cardiovascular AI is not to replace clinical judgment but to enhance it—serving as an intelligent partner that handles cognitive and administrative burdens so that clinicians can focus on what matters most: delivering highly personalized, empathetic care to patients across all stages of cardiovascular risk.

KEY POINTS

- Artificial intelligence (AI) models demonstrate excellent retrospective accuracy in diagnostic classification, but prospective evidence for improved patient outcomes and clinical utility remains limited.
- AI-electrocardiogram is emerging as a comprehensive biomarker for cardiovascular health, moving beyond single disease detection.
- The cardiovascular-kidney-metabolic framework can integrate AI-driven multimodal data to personalize risk prediction and management across metabolic, renal, and cardiovascular systems.
- AI extends risk assessment beyond traditional clinical data, quantifying environmental exposomic factors and lifestyle determinants to advance preventative cardiology.

ARTIFICIAL INTELLIGENCE ASSISTANCE AND AUTHOR RESPONSIBILITY

The authors used a large language model assistant (Claude, Anthropic) in three well-defined ways during the preparation of this review. First, we iteratively codeveloped with the model a custom Python pipeline for PubMed retrieval and post-hoc filtering against a curated Scimago Q1 journal corpus, with an optional SJR threshold; this quality-filtering approach is not natively available in PubMed and would not have been practical to implement at the required level of methodological rigor without AI-assisted coding. Second, the same pipeline was designed to produce a structured spreadsheet output, containing full abstracts, per-record metadata, and a Selection field, in order to facilitate manual screening by the authors. Third, the model assisted in language review, refining the English wording of the manuscript, in particular for the sections drafted by CM. The identification, screening, selection, and interpretation of every reference cited in this review, as well as all conclusions drawn, were performed exclusively by the authors, who take full responsibility for the content.

COMPETING INTERESTS

The authors have no competing interests to declare.

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