International Journal of Innovative Technologies in Social Science

e-ISSN: 2544-9435

Scholarly Publisher
RS Global Sp. z O.O.
ISNI: 0000 0004 8495 2390

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Poland 00-773
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ARTICLE TITLE	FROM PREDICTION TO PREVENTION: THE ROLE OF AI IN TRANSFORMING CORONARY ARTERY DISEASE RISK ASSESSMENT
ARTICLE INFO	Natalia Kulicka, Kinga Knutelska, Tytus Tyralik, Maciej Karwat, Patrycja Jędrzejewska-Rzezak, Monika Czekalska, Aleksandra Winsyk, Joanna Węgrzecka, Paulina Gajniak, Klaudia Bilińska. (2025) From Prediction to Prevention: The Role of AI in Transforming Coronary Artery Disease Risk Assessment. *International Journal of Innovative Technologies in Social Science*. 3(47). doi: 10.31435/ijitss.3(47).2025.3589
DOI	https://doi.org/10.31435/ijitss.3(47).2025.3589
RECEIVED	14 July 2025
ACCEPTED	27 August 2025
PUBLISHED	01 September 2025
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FROM PREDICTION TO PREVENTION: THE ROLE OF AI IN TRANSFORMING CORONARY ARTERY DISEASE RISK ASSESSMENT

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ABSTRACT

Background: Artificial intelligence (AI) is reshaping the landscape of coronary artery disease (CAD) prevention through its ability to enhance risk prediction, early detection, and individualized interventions.
Objective: This narrative review examines the current role of AI-based models in CAD prevention, evaluating their predictive accuracy, clinical applications, and implementation challenges.
Methods: We synthesized evidence from recent systematic reviews, meta-analyses, and original studies on machine learning (ML) and deep learning (DL) techniques using multimodal data such as electronic health records (EHR), electrocardiograms (ECG), and imaging.
Key Findings: AI models consistently outperform traditional risk scores like Framingham and ASCVD in predictive performance, especially when multimodal data integration is applied. These models show particular promise in high-risk and complex populations. Additionally, AI tools contribute to clinical decision-making, including revascularization planning and precision phenotyping. However, critical limitations remain—most notably limited external validation, opacity in model explainability, and bias stemming from non-representative datasets.
Conclusions: While AI offers transformative potential in CAD prevention, responsible deployment requires addressing ethical, technical, and systemic challenges. Key strategies include improving model transparency, ensuring fairness across populations, and embedding AI tools seamlessly into clinical workflows. The success of future systems will depend on explainability, human-AI collaboration, and meaningful stakeholder engagement.

KEYWORDS

Artificial Intelligence, Coronary Artery Disease, Risk Prediction, Machine Learning, Multimodal Data Integration, Explainable AI

CITATION

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Introduction.

Coronary artery disease (CAD) remains the leading cause of death and disability worldwide, with nearly 7 million deaths and 129 million disability-adjusted life years (DALYs) attributed to it annually (Ralapanawa & Sivakanesan, 2021; Yazdani et al., 2023). The burden is particularly high in the Americas, Europe, and the Eastern Mediterranean, while in Africa and parts of Asia, stroke predominates as the leading cardiovascular condition (Victor et al., 2025). Despite advances in both treatment and prevention, CAD continues to exact a substantial clinical and economic toll, especially in low- and middle-income countries, where urbanization, dietary shifts, and sedentary behavior are driving a rise in incidence (Ralapanawa & Sivakanesan, 2021; Victor et al., 2025).

Socioeconomic disparities significantly shape CAD outcomes. Populations with lower socioeconomic status experience higher rates of premature cardiovascular death, compounded by limited access to healthcare, preventive services, and healthy lifestyle opportunities (Ralapanawa & Sivakanesan, 2021; Victor et al., 2025). As the global burden of CAD shifts toward less affluent regions, the need for scalable, equitable, and effective prevention strategies becomes more urgent.

Primary prevention efforts face persistent and multifaceted challenges. Modifiable risk factors—including hypertension, diabetes, dyslipidemia, obesity, smoking, and physical inactivity—remain highly prevalent across diverse populations (Al-Khlaiwi et al., 2024; Ralapanawa & Sivakanesan, 2021; Victor et al., 2025). At the same time, emerging contributors such as air and noise pollution, sleep disturbances, depression, and social isolation are increasingly recognized for their role in cardiovascular risk (Victor et al., 2025). In many settings, low levels of health literacy and limited education regarding prevention further complicate risk reduction, particularly among vulnerable groups (Hart, 2024; Victor et al., 2025).

Beyond individual-level factors, structural issues also hamper progress. Incomplete or inconsistent epidemiological data limit the ability to target interventions effectively, and variability in the adoption of evidence-based prevention guidelines across health systems weakens implementation (Ralapanawa & Sivakanesan, 2021). Together, these factors underscore the need for prevention strategies that are not only evidence-based but also context-sensitive.

Opportunities do exist. Digital and media-based education initiatives have shown promise in improving knowledge, behavior, and modifiable risk profiles (Hart, 2024). Region-specific programs that address local risk determinants and socioeconomic inequalities can enhance intervention effectiveness (Ralapanawa & Sivakanesan, 2021; Victor et al., 2025). Strengthening health systems—by investing in workforce capacity, increasing health literacy, and adopting life-course approaches to risk—offers a sustainable path toward burden reduction (Victor et al., 2025).

In this context, artificial intelligence (AI) emerges as a potentially transformative tool. Through its capacity to analyze large-scale health data, identify risk patterns, and support early, individualized intervention, AI may help overcome current limitations in CAD prevention. However, its integration into public health practice requires careful consideration of clinical relevance, validation, fairness, and ethical deployment. This paper explores the promise and limitations of AI in CAD prevention, with particular focus on predictive performance, equity, and policy implications.

Methodology

This narrative review was conducted using a structured search of three major academic databases: PubMed, Google Scholar, and Scopus. The aim was to identify recent, high-quality literature addressing the role of artificial intelligence in the prevention and risk prediction of coronary artery disease (CAD). The search focused exclusively on peer-reviewed articles published within the last five years (2020–2025), to ensure relevance to current clinical and technological standards.

Key search terms included combinations of: *"artificial intelligence," "machine learning," "deep learning," "coronary artery disease," "risk prediction," "cardiovascular prevention," "explainability,"* and *"clinical decision support."* Both systematic reviews and primary research articles were considered, including studies involving electrocardiograms (ECG), imaging (e.g., CCTA, MRI), and electronic health records (EHR).

Articles were selected based on their methodological quality, clinical relevance, and contribution to the understanding of AI-based predictive models. In total, 48 sources were included in the final synthesis. Special attention was given to studies with external validation, multimodal data integration, ethical implications, and implementation frameworks.

State of Knowledge

1. AI-Based Risk Prediction in CAD Prevention

Artificial intelligence (AI) has rapidly emerged as a transformative approach in coronary artery disease (CAD) risk prediction, leveraging multimodal data such as electronic health records (EHR), electrocardiograms (ECG), and cardiovascular imaging. Models built using machine learning (ML) and deep learning (DL) techniques have demonstrated promising predictive capabilities, particularly when these heterogeneous data sources are integrated.

In cardiac imaging, AI applications in modalities such as coronary CT angiography (CCTA), single-photon emission computed tomography (SPECT), and cardiac MRI have yielded encouraging results for both diagnostic and prognostic tasks. Deep learning approaches—especially convolutional neural networks—are frequently employed, achieving high sensitivity and specificity in identifying obstructive CAD or estimating future cardiovascular risk (Assadi et al., 2022; Baskaran et al., 2020; Cicek et al., n.d.; Jiang et al., 2020; Wang et al., 2022). Nevertheless, many of these studies are limited by small sample sizes and a lack of external validation, restricting their clinical generalizability.

Parallel advancements are evident in ECG-based AI modeling. Deep neural networks have demonstrated the capacity to detect CAD and acute coronary syndromes with performance metrics comparable to experienced clinicians (Alizadehsani et al., 2021; Bishop et al., 2024; Moreno-Sánchez et al., 2024). These systems can uncover subtle waveform patterns imperceptible to the human eye, offering novel diagnostic opportunities. However, concerns persist regarding the interpretability of DL models, potential algorithmic bias, and the opacity of decision-making processes.

EHR-derived models represent another active area of development. ML algorithms—particularly tree-based and ensemble methods—using routinely collected patient data (e.g., demographics, laboratory results, clinical history) have shown favorable performance in estimating CAD risk. Moreover, when EHR data are integrated with imaging or ECG features, the resulting multimodal models often outperform single-source models, highlighting the value of data fusion in risk stratification (Alizadehsani et al., 2021; Baskaran et al., 2020; Garavand et al., 2023).

Multimodal AI approaches—those that integrate data from electronic health records (EHR), imaging modalities, and electrocardiograms (ECG)—have been consistently shown to outperform unimodal models in the prediction of coronary artery disease (CAD). By leveraging diverse and complementary inputs, these systems are capable of identifying complex interactions and latent patterns that single-source models may overlook.

Several studies provide direct comparative evidence of this performance advantage. For instance, one multimodal nomogram developed for chronic CAD achieved a high C-index of 0.78–0.79, reflecting strong discriminatory ability and practical clinical relevance [17]. Another investigation demonstrated that removing imaging data from an integrated model significantly degraded its performance—lowering the AUC from 0.779 to 0.705—underscoring the critical role of multimodal inputs in maintaining predictive strength [1].

Systematic reviews further support these findings. Meta-analyses of multimodal machine learning applications in healthcare report an average 6.4% improvement in predictive accuracy over unimodal systems [1, 2]. These enhancements are largely attributed to the models' ability to synthesize heterogeneous clinical, imaging, and laboratory data into more nuanced risk estimates.

Beyond statistical performance, multimodal models also offer important benefits in clinical utility. Their ability to generate individualized and more robust risk assessments can enhance decision-making, reduce diagnostic uncertainty, and potentially lower the rate of unnecessary interventions [1–3].

Despite this momentum, several barriers continue to impede clinical translation. Key challenges include insufficient external validation, limited demographic and geographic diversity of training cohorts, and inconsistent reporting standards. These issues raise concerns about generalizability, fairness, and reproducibility (Carrasco-Ribelles et al., 2023; Suri, Bhagawati, Paul, Protogeron, et al., 2022; Wang et al., 2022). To overcome them, researchers emphasize the importance of using larger, more representative datasets and implementing standardized evaluation frameworks.

In summary, AI-based systems incorporating EHR, ECG, and imaging modalities are steadily advancing toward clinical relevance in CAD prediction and prevention. Deep learning is central to this progress, particularly in extracting complex patterns from high-dimensional data. Still, future efforts must focus on improving model transparency, equity, and robustness to ensure safe and effective deployment in real-world cardiovascular care.

2. Clinical Outcomes and Predictive Accuracy

Artificial intelligence (AI) models, particularly those based on machine learning (ML) and deep learning (DL), have demonstrated consistent advantages over traditional cardiovascular risk scores—such as Framingham or ASCVD—in predicting long-term coronary artery disease (CAD) outcomes. Meta-analyses and systematic reviews report that AI models typically achieve higher C-statistics, ranging from 0.77 to 0.84, compared to 0.73 to 0.76 for conventional scores, indicating improved discriminatory ability in predicting outcomes such as mortality and major adverse cardiac events (MACE) (Gupta et al., 2024; Nayebirad et al., 2025; Teshale et al., 2024; Tse et al., 2024).

These gains are especially evident in complex patient populations, including individuals undergoing percutaneous coronary intervention (PCI) or coronary artery bypass grafting (CABG), where standard models often underperform (Gupta et al., 2024; Nayebirad et al., 2025). Deep learning models designed for survival analysis—such as DeepSurv—and ensemble techniques like Random Survival Forests have shown particular promise in modeling time-to-event outcomes (W. Liu et al., 2023; Teshale et al., 2024).

For example, in a meta-analysis of 27 studies encompassing over 568, 000 patients, ML models outperformed conventional approaches with a pooled C-statistic of 0.82 (95% CI: 0.78–0.85), compared to 0.73 (95% CI: 0.70–0.75) for traditional methods (W. Liu et al., 2023). Similarly, AI approaches have shown superior accuracy in predicting post-PCI complications such as bleeding risk, short- and long-term mortality, and rehospitalization when compared to standard regression models (Teshale et al., 2024).

In addition to improving predictive performance metrics, AI-based risk stratification tools are increasingly being evaluated for their potential to support real-world clinical decision-making in coronary artery disease (CAD). Machine learning and deep learning algorithms can integrate diverse data sources—such as clinical characteristics, imaging results, and genetic profiles—to generate individualized risk assessments and identify patients who may benefit from intensified preventive or therapeutic strategies

(Alizadehsani et al., 2021; Mohsen et al., 2023; Singh et al., 2024; Suri, Bhagawati, Paul, Protogerou, et al., 2022). These capabilities position AI as a potential complement, or even alternative, to conventional tools in delivering more tailored and precise care.

More advanced applications have extended into procedural decision-making. For instance, AI-enabled tools such as the SYNTAX Score II 2020 leverage outcome prediction algorithms to guide the selection between percutaneous coronary intervention (PCI) and coronary artery bypass grafting (CABG), thereby facilitating more informed and personalized treatment planning (Takahashi et al., 2020). Additionally, AI has shown promise in enhancing patient phenotyping, which may support precision medicine approaches in CAD management and secondary prevention (Mohsen et al., 2023; Singh et al., 2024).

Nevertheless, despite these promising developments, current evidence for a direct impact of AI-guided predictions on clinical outcomes remains limited. The majority of studies to date have emphasized retrospective validation or improvements in statistical discrimination and reclassification, rather than demonstrating effectiveness in prospective clinical settings. Future research, including randomized controlled trials and implementation studies, will be essential to confirm the real-world utility and clinical benefit of AI-assisted decision-making in cardiovascular care.

Building on these predictive capabilities, recent efforts have focused on translating AI outputs into actionable clinical insights.

However, the clinical significance of these improvements remains a topic of discussion. While statistically significant, the magnitude of gain in discrimination is often modest—particularly when models are applied across broad, low-risk populations (Teshale et al., 2024; Tse et al., 2024). Furthermore, many AI models have not undergone robust external validation, which limits confidence in their generalizability beyond the development datasets (Cai et al., 2024; Gupta et al., 2024).

Another persistent limitation concerns interpretability. Particularly in deep learning architectures, the decision-making processes remain largely opaque, which may reduce clinical trust and hinder integration into workflows (Nayebirad et al., 2025; Teshale et al., 2024). Additionally, many models are trained on non-representative or demographically narrow datasets, increasing the risk of bias and restricting their real-world applicability (Cai et al., 2024; Nayebirad et al., 2025).

In summary, AI-based tools offer measurable improvements over conventional scores in CAD outcome prediction—especially in high-risk or procedurally complex subgroups. Yet, challenges around validation, transparency, and equitable performance must be addressed before these models can be responsibly integrated into clinical care.

3. Explainability, Trust, and Human-AI Collaboration

As artificial intelligence (AI) systems become increasingly embedded in cardiovascular disease (CVD) risk prediction, explainability and collaboration between humans and algorithms have emerged as essential pillars for successful clinical integration. Building clinician trust depends not only on the accuracy of AI models, but also on their interpretability, transparency, and alignment with real-world clinical workflows.

Clinicians are more likely to adopt AI-based tools when they understand how a model arrives at its conclusions. Explainable AI (XAI) methods—such as SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-Agnostic Explanations)—play a crucial role in rendering complex algorithms interpretable. These tools help identify which variables contributed to a given prediction, enhancing transparency and enabling clinicians to justify AI-supported decisions to patients, colleagues, and regulatory bodies [29–32].

Beyond transparency, explainability contributes to safety and accountability in clinical settings. By allowing practitioners to examine and challenge AI outputs, XAI helps identify potential errors or algorithmic biases, thereby reducing reliance on opaque"black-box" models and mitigating the risk of harm [29–32]. Moreover, as healthcare regulations increasingly emphasize ethical deployment, explainability is becoming a foundational requirement for approval and oversight of AI-driven clinical tools [1, 2].

Rather than replacing clinicians, AI should function as a decision support tool—enhancing human judgment without overriding it. Effective human-AI collaboration enables systems to provide actionable insights, such as highlighting influential features or calculating individualized risk scores, while preserving clinician autonomy in final decision-making [1, 2].

Engaging clinicians throughout the AI lifecycle—from development and validation to continuous monitoring—also ensures that models remain clinically meaningful and adaptable to dynamic healthcare environments. Such involvement fosters iterative improvement based on frontline feedback, improving both model performance and relevance [1, 2].

Finally, integration into clinical workflows is critical. AI tools must not only be accurate but also intuitive, with clear outputs that fit into time-constrained and high-stakes environments. Interpretable and seamlessly integrated systems are more likely to be used consistently and effectively in practice [1, 2].

4. Social and Ethical Considerations

The use of AI in preventing coronary artery disease (CAD) carries clear potential, but it also raises serious social and ethical questions. Among the most pressing concerns are bias in model design, unequal access to AI-driven care, and the challenge of ensuring transparency and fairness.

AI systems developed for CAD prediction often replicate or even amplify existing disparities tied to race, gender, or socioeconomic status. A recent review found evidence of racial or ethnic bias in 82% of cardiovascular AI studies (Cau et al., 2025; Suri, Bhagawati, Paul, Protogeron, et al., 2022). These discrepancies can translate into unequal risk assessments and, ultimately, unequal care. The problem often stems from unrepresentative training data, flawed measurement inputs, or design choices that don't account for variation across populations. Notably, even traditional scores like Framingham have known biases - and AI models may inherit or exacerbate them unless explicitly addressed (Cau et al., 2025; Chen et al., 2024; Garcha & Phillips, 2023; Suri, Bhagawati, Paul, Protogeron, et al., 2022).

Beyond model bias, concerns regarding equitable access remain critical. AI-based prevention tools—especially those relying on wearables, smartphones, or high-quality imaging—may be less accessible to low-income or digitally excluded populations. Without deliberate efforts to ensure inclusion, such tools risk widening existing health gaps rather than narrowing them (Al-Hwsali et al., 2023; Cau et al., 2025; Chen et al., 2024).

Efforts to address these challenges are increasingly reflected in the development of mitigation strategies aimed at improving the fairness and transparency of AI models. Approaches such as the implementation of fairness metrics, the use of demographically diverse training datasets, and the application of algorithmic audits are being investigated to systematically identify and reduce bias within predictive systems (Chen et al., 2024). Moreover, the integration of ethical principles during the design phase - commonly referred to as"ethics by design" - emphasizes the importance of embedding transparency, accountability, and inclusivity into model development from the outset (Al-Hwsali et al., 2023; Čartolovni et al., 2022; Morley et al., 2020).

In parallel, there is growing recognition of the need for regulatory frameworks that support ongoing monitoring, standardized evaluation, and independent oversight of AI systems in healthcare settings (Al-Hwsali et al., 2023; Čartolovni et al., 2022; Morley et al., 2020). These mechanisms are essential to ensure the responsible and equitable deployment of AI interventions, particularly in contexts such as CAD prevention where disparities in care can be inadvertently reinforced.

While most ethical debates focus on algorithmic bias and fairness in high-income countries, a crucial yet underexplored issue concerns global disparities in access to AI-powered cardiovascular care. In low- and middle-income countries (LMICs), limited infrastructure, inadequate digital literacy, and lack of regulatory oversight may prevent equitable implementation of even well-calibrated AI models. Studies suggest that without tailored deployment strategies, AI tools may reinforce existing global health inequalities by benefiting already well-resourced systems while neglecting underserved populations. Addressing this requires context-specific design, capacity building, and international collaboration to ensure that AI-driven CAD prevention does not become a privilege of the few, but a scalable and inclusive solution for all settings (Al-Hwsali et al., 2023; Čartolovni et al., 2022; Morley et al., 2020).

For AI to genuinely serve public health, it must be designed and implemented with equity in mind. That means using diverse, high-quality datasets, actively mitigating bias during development, and applying clear oversight to ensure fair outcomes. Without this foundation, even the most accurate systems may fail those who need them most.

5. Integration into Public Health Systems

Integrating AI-based tools for cardiovascular prevention into public healthcare systems holds substantial promise, but it also presents a set of complex challenges that must be addressed for widespread, equitable adoption. While AI has the capacity to enhance early detection, personalize risk stratification, and streamline preventive care, its implementation hinges on issues of data quality, model validation, interpretability, and systemic integration.

One of the primary barriers is the inconsistency and incompleteness of electronic health record (EHR) data. Many clinical datasets lack standardization in both format and content, which limits the robustness and reproducibility of AI models. Without common definitions for cardiovascular outcomes or harmonized data structures, comparing or validating models across institutions becomes difficult (T. Liu et al., 2025; Moazemi et al., 2023).

Generalizability is another concern. Numerous AI models are trained on narrowly defined or demographically limited datasets and rarely undergo rigorous external validation. As a result, their performance in real-world clinical settings—especially across diverse populations—remains uncertain (T. Liu et al., 2025; Moazemi et al., 2023). The lack of model interpretability further complicates clinical integration. When AI systems operate as"black boxes, " clinicians may hesitate to rely on their recommendations, which limits trust and adoption (T. Liu et al., 2025; Moazemi et al., 2023).

Ethical and regulatory considerations compound these challenges. Uneven model performance across racial, gender, or socioeconomic groups can inadvertently reinforce disparities in care. Transparent evaluation standards, robust auditing mechanisms, and clearly defined regulatory pathways are essential to address these concerns responsibly (Ahmed et al., 2025; T. Liu et al., 2025).

Successful integration of AI into healthcare workflows will also require substantial operational planning. Embedding AI tools into existing systems calls for interoperability with health IT infrastructure, targeted clinician training, and in some cases, redesigning clinical workflows. These efforts can be time- and resource-intensive, particularly in under-resourced settings (Aminizadeh et al., 2024; T. Liu et al., 2025; Olawade et al., 2024).

Despite these obstacles, the potential benefits are considerable. AI can offer more precise cardiovascular risk stratification by processing large-scale EHR and imaging data, improving upon traditional models (Ahmed et al., 2025; Elvas et al., 2025; T. Liu et al., 2025). Earlier detection enabled by AI could reduce the need for invasive diagnostics and lower costs while improving patient outcomes (Ahmed et al., 2025; Elvas et al., 2025). The capacity to tailor prevention strategies and therapy plans to individual profiles enhances not only clinical effectiveness but also patient engagement (Ahmed et al., 2025; Singh et al., 2024). Finally, integration with wearables and remote monitoring technologies opens the door to continuous risk assessment and early intervention outside of traditional care environments (Aminizadeh et al., 2024; Elvas et al., 2025).

To fully realize these benefits, future efforts must focus on improving data quality, validating models across diverse settings, ensuring transparency, and investing in clinical infrastructure that supports ethical and effective AI adoption.

6. Policy and Implementation Considerations

Deploying AI tools in cardiovascular disease prevention requires more than technological innovation - it demands careful planning, ethical foresight, and inclusive policy development. To ensure that these systems are safe, effective, and equitable in real-world use, several key areas must be addressed.

First, transparency is critical. AI models should be interpretable not only by developers but also by clinicians and, where appropriate, by patients. Decision pathways must be explainable, and any limitations or data dependencies clearly disclosed to support informed use (Goktas & Grzybowski, 2025; Siala & Wang, 2022).

Bias mitigation remains a central concern. Developers must ensure that models are trained on diverse, representative datasets and regularly audited for disparities in performance across demographic groups. Without this, AI could unintentionally reinforce existing health inequities rather than reduce them (Goktas & Grzybowski, 2025; Siala & Wang, 2022)

Equally important is the protection of data privacy and security. Strong safeguards are needed to protect sensitive health information, along with clear protocols for data ownership, access rights, and informed consent. Patients must be able to trust that their data is handled responsibly and transparently (Ahmed et al., 2025; Siala & Wang, 2022).

Validation and accountability go hand in hand. Before clinical deployment, AI models should undergo rigorous external validation to test their performance in independent, real-world settings. In parallel, mechanisms must be in place to assign responsibility in cases of algorithmic error or unintended harm (Cai et al., 2024; Siala & Wang, 2022).

Inclusive stakeholder engagement strengthens every phase of implementation. Involving patients, clinicians, and community representatives in the design, deployment, and evaluation of AI tools ensures that the systems reflect real clinical needs and social contexts. Clinician training and user support are also crucial to ensure effective uptake (Goktas & Grzybowski, 2025; Siala & Wang, 2022).

Robust and adaptive regulatory oversight will be essential. Regulatory frameworks must evolve in step with technological progress and should include measurable standards, real-time monitoring protocols, and pathways for corrective action when safety or efficacy is compromised (Goktas & Grzybowski, 2025; Siala & Wang, 2022).

Additional strategies support long-term impact. Human-centered design helps maintain patient autonomy and supports trust in AI-driven care (Siala & Wang, 2022). Global partnerships and sustainable development principles can promote broader access and scalability (Goktas & Grzybowski, 2025; Siala & Wang, 2022). And continuous monitoring ensures that AI systems remain responsive to new data, risks, and use cases over time (Goktas & Grzybowski, 2025).

Ultimately, responsible AI deployment in cardiovascular prevention depends on a foundation of transparency, fairness, and public accountability. These principles are not only ethical imperatives—they are practical necessities for building trust, ensuring effectiveness, and maximizing the social value of AI in healthcare.

7. Future Directions

As artificial intelligence continues to expand its role in preventive cardiology, several emerging directions offer the potential to significantly reshape risk prediction, monitoring, and personalized care for coronary artery disease (CAD). Among them, the integration of genetic data—particularly polygenic risk scores (PRS)—into AI-based models represents a promising yet nuanced area of development.

AI systems incorporating PRS and other genomic features have shown modest but consistent gains in predictive accuracy compared to traditional clinical models. These models are capable of processing complex genetic information and identifying patterns of risk that may not be apparent through standard statistical approaches (Khanna et al., 2023; Koyama et al., 2020; Singh et al., 2024). Meta-analyses indicate that the addition of PRS to clinical variables can improve discrimination metrics such as the C-index by approximately 1.5–1.6%, although the absolute gains are often limited (Agbaedeng et al., 2021; Rincón et al., 2023; Yun et al., 2022). The added value appears to be most notable in refining risk stratification for specific subgroups, particularly younger individuals or those with intermediate clinical risk (Rincón et al., 2023; Yun et al., 2022).

Despite its theoretical appeal, the clinical utility of AI-enhanced genetic modeling remains constrained by methodological heterogeneity, limited population diversity in genetic datasets, and the absence of standardized integration protocols. As such, the near-term impact may be confined to select applications, rather than broad-scale implementation.

In parallel with advances in genomics, the integration of physiological data from wearable devices represents another frontier in AI-driven CAD prevention. Smartwatches, fitness bands, and mobile ECG monitors now routinely collect real-time information such as heart rate, physical activity, sleep patterns, and even single-lead ECG signals. When analyzed using machine learning or deep learning algorithms, these data streams offer the potential to support early detection and continuous monitoring of cardiovascular risk.

Although most AI models for CAD risk prediction have historically relied on clinical, laboratory, and imaging data, recent studies have begun to explore the predictive value of wearable-derived metrics. Parameters such as heart rate variability, resting heart rate trends, and wearable ECG signals have shown promise, particularly when combined with demographic or electronic health record data(Alizadehsani et al., 2021; Garavand et al., 2023). Deep neural networks have demonstrated high accuracy in detecting related cardiovascular conditions, such as atrial fibrillation and hypertension, with area under the ROC curve (AUROC) values reaching up to 0.98 in some cases (Lee et al., 2022). While direct application to long-term CAD risk prediction is still emerging, the feasibility of this approach is supported by improving sensor fidelity and growing longitudinal datasets.

Notably, AI models trained on wearable data may still underperform compared to those built on in-hospital monitoring systems, primarily due to noise, data gaps, and variability in user adherence (Alizadehsani et al., 2021; Lee et al., 2022). However, the performance gap is narrowing as wearable technology matures and signal processing techniques evolve.

As wearable devices become more ubiquitous and data quality improves, their integration into AI pipelines for preventive cardiology may enable a shift toward proactive, decentralized, and highly personalized cardiovascular care.

Further innovations such as federated learning for privacy-preserving model training, and adaptive AI interventions tailored to real-time patient feedback, may also shape the next generation of prevention tools.

As the technological foundation for AI in CAD prevention continues to mature, there is growing consensus that innovation alone will not be sufficient. The long-term success of AI tools depends equally on the development of structured implementation frameworks that address not only technical performance, but also ethical, practical, and systemic concerns. Emerging policy recommendations consistently highlight the importance of transparency, fairness, and accountability throughout the AI lifecycle (Goktas & Grzybowski, 2025; Jacob et al., 2025).

To ensure safe and effective deployment, future systems will need to incorporate mechanisms for external validation, stakeholder engagement, and real-world performance monitoring. This includes rigorous testing across diverse populations, integration into clinical workflows, and adequate training for end users (Cai et al., 2024; Gama et al., 2022; Jacob et al., 2025). Moreover, the importance of including patients, clinicians, and policymakers in the design and evaluation process cannot be overstated; these perspectives are essential for building trust and ensuring clinical relevance (Goktas & Grzybowski, 2025; Jacob et al., 2025).

Ultimately, the next generation of AI-based preventive tools for CAD will be judged not only by their predictive accuracy, but by their ability to operate transparently, equitably, and responsibly within complex healthcare systems. Continued research, policy innovation, and interdisciplinary collaboration will be critical to realizing this potential at scale.

Conclusions

Artificial intelligence is steadily transforming the paradigm of coronary artery disease (CAD) prevention. By enabling earlier risk identification, more accurate stratification, and the design of personalized interventions, AI-based models have begun to exceed the capabilities of conventional risk prediction tools. In particular, the use of diverse data sources—ranging from electrocardiograms and imaging to electronic health records—has made it possible to generate more nuanced and individualized risk assessments.

Nonetheless, important barriers remain before these tools can be widely and responsibly implemented. Persistent issues such as algorithmic bias, insufficient external validation, and the opaque nature of many models continue to limit their integration into routine care. Broader concerns also persist around health equity, data governance, and the absence of comprehensive regulatory structures.

Addressing these challenges will require multi-level collaboration across technical, clinical, ethical, and policy domains. Transparent, explainable systems must be developed and rigorously evaluated across varied populations. Fairness and accountability should be embedded into the design process from the outset, and mechanisms for independent oversight must be strengthened. Equally vital is the active involvement of patients, practitioners, and public stakeholders in shaping how these tools are used.

In the end, the transformative potential of AI in preventive cardiology depends not only on its analytic accuracy, but on its capacity to promote more just, inclusive, and patient-aligned models of care. Realizing that potential will hinge on our collective ability to balance innovation with integrity and equity.

Acknowledgments

The author declares that no financial support, sponsorship, or external assistance was received during the preparation of this manuscript.

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