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STATE OF THE ART REVIEW
Digital health and innovation

Artificial intelligence to improve cardiovascular population health

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Abstract

With the advent of artificial intelligence (AI), novel opportunities arise to revolutionize healthcare delivery and improve population health. This review provides a state-of-the-art overview of recent advancements in AI technologies and their applications in enhancing cardiovascular health at the population level. From predictive analytics to personalized interventions, AI-driven approaches are increasingly being utilized to analyse vast amounts of healthcare data, uncover disease patterns, and optimize resource allocation. Furthermore, AI-enabled technologies such as wearable devices and remote monitoring systems facilitate continuous cardiac monitoring, early detection of diseases, and promise more timely interventions. Additionally, AI-powered systems aid healthcare professionals in clinical decision-making processes, thereby improving accuracy and treatment effectiveness. By using AI systems to augment existing data sources, such as registries and biobanks, completely new research questions can be addressed to identify novel mechanisms and pharmaceutical targets. Despite this remarkable potential of AI in enhancing population health, challenges related to legal issues, data privacy, algorithm bias, and ethical considerations must be addressed to ensure equitable access and improved outcomes for all individuals.

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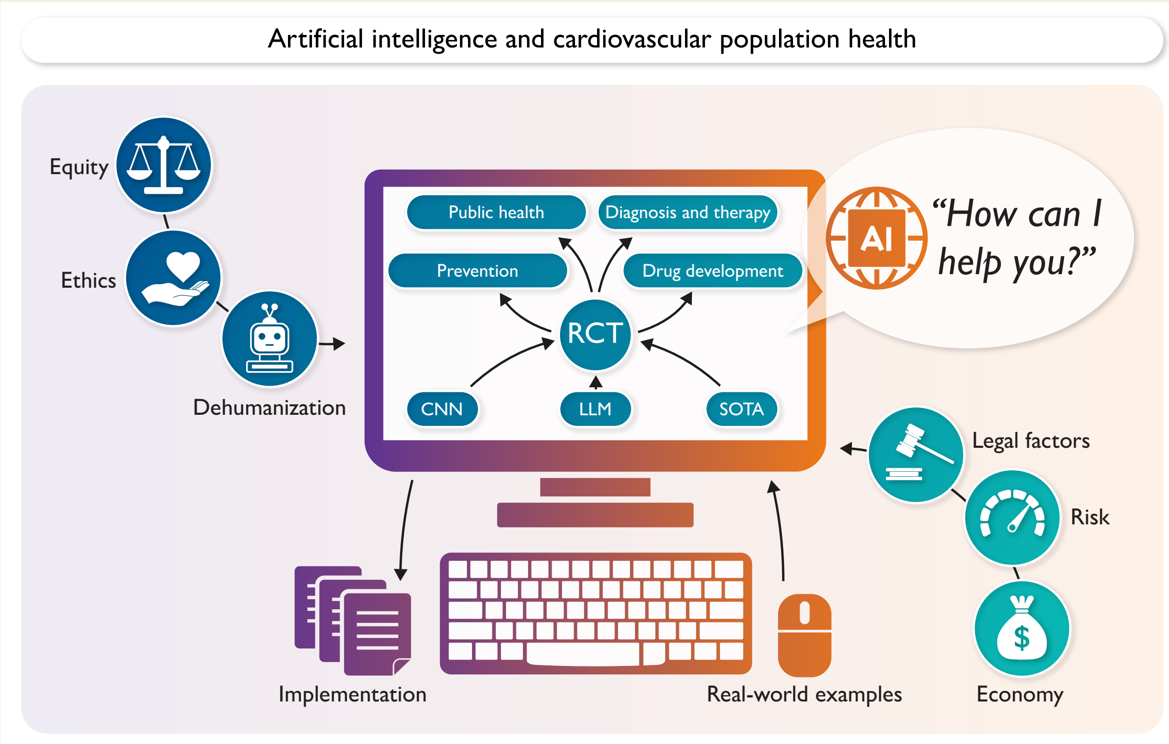
Graphical Abstract



This state-of-the-art review addresses the use of artificial intelligence (AI) in promoting public health. It details the impact of risk factors, metabolic and cardiovascular diseases on population health and shows available solutions and real-world examples of AI implementations to counteract them. The article dives deep into modern architectures of AI systems and analyses important factors contributing to a successful transformation of medicine and public health by AI. RCT, randomized controlled trial; CNN, convolutional neural network; LLM, large language model; SOTA, state-of-the-art.

Keywords Aritificial intelligence • Generative AI • EU AI Act • Prevention • Public health • Climate change • Wearable • Urban health

Population health and well-being at stakes

The Global Burden of Disease (GBD) study, involving more than 8000 collaborators worldwide, provides a comprehensive analysis of mortality and health-related factors across 204 countries and territories.[1] This extensive study enables the assessment of major cardiovascular health trends over time, offering critical insights to inform public policies, healthcare providers, and the health industry. It identifies key environmental, metabolic, and behavioural risks for cardiovascular diseases (CVDs), such as air pollution, high blood pressure, elevated cholesterol, smoking, high body mass index, and physical inactivity.[1] Through advanced statistical modelling, the causal relationship between these modifiable, non-genetic risk factors and causes of death, as well as disability-adjusted life years (DALYs)—which combine years of life lost to premature death and years lived with disability—can be quantified. *Table 1* summarizes the leading causes of mortality, highlighting ischaemic diseases, which are driven by various risk factors, as the most prominent contributors to global death numbers, thus positioning them as critical targets for preventive strategies using artificial intelligence (AI).

A large cross-sectional study of 514 971 individuals further underscores the relationship between population well-being and CVD mortality, independent of structural factors such as socioeconomic status and prevalent health metrics like hypertension, diabetes, obesity, and low physical activity.[2] Importantly, population well-being also mediates the impact of structural factors on CVD mortality, suggesting that improving overall well-being could enhance survival and reduce the burden of heart disease across populations.

To support the implementation of strategies aimed at reducing mortality and improving population health and thereby well-being, various stakeholders and cardiovascular medical societies, including the American Heart Association (AHA) and the European Society of Cardiology (ESC), advocate for the integration of AI.[3,4]

Predicting diseases and adverse outcomes in advance, by leveraging AI to recognize the numerous causally linked factors, including social determinants, is likely one of the most effective ways to improve population well-being.[5] Recent research highlights this potential to account for the complex and uneven/non-linear distribution of determinants, allowing for population-scale predictions and interventions.[6] The AHA endorses the use of data-driven population health interventions, emphasizing the need for interdisciplinary teams—including medical doctors, data scientists, and biostatisticians—to utilize AI in integrating data and developing predictive models to achieve optimal cardiovascular health.[7]

Table 1 Cardiovascular deaths by cause, globally 2021 (top 10)

Rank	Cause of death	Number of deaths in 2021	Number of DALYs
1	Ischaemic heart disease	9 440 000	185 000 000
2	Ischaemic stroke	3 870 000	70 200 000
3	Intracerebral haemorrhage	3 460 000	78 600 000
4	Hypertensive heart disease	1 410 000	24 900 000
5	Rheumatic heart disease	391 000	13 400 000
6	Atrial fibrillation and flutter	366 000	8 200 000
7	Subarachnoid haemorrhage	365 000	10 400 000
8	Cardiomyopathy	320 000	8 450 000
9	Other cardiovascular diseases	232 000	10 100 000
10	Aortic aneurysm	160 000	3 040 000

Modified from Vaduganathan *et al.*[1]

Artificial intelligence: a new era for preventive medicine

AI traces its roots back to the 1950s, pioneered by visionaries like Alan Turing and John McCarthy. In 1950, Turing introduced the 'Turing Test' to assess a machine's capacity for intelligent behaviour, while McCarthy's organization of the Dartmouth workshop in 1956 marked the official birth of AI as a formal discipline.[8] Early AI focused on symbolic reasoning and problem-solving, leading to advances in areas such as game-playing and theorem proving. Despite facing cycles of optimism and setbacks (referred to as 'AI winters'), the field has made significant strides, particularly with the rise of machine learning and deep learning in the 21st century. In 2024, the Nobel Prize in Physics was awarded to U.S. physicist John Hopfield and British-Canadian Geoffrey Hinton for their foundational work on machine learning. Additionally, the Nobel Prize in Chemistry honoured Google DeepMind researchers Demis Hassabis and John M. Jumper for developing AlphaFold, a deep-learning tool capable of predicting protein structures with unprecedented accuracy.

Artificial intelligence holds immense promise for preventive medicine, assisting clinicians in making data-driven decisions by providing rapid insights for diagnosis and treatment. It can enhance personalized care through tailored recommendations for medication, nutrition, weight management, and physical activity.[9] In medical research, AI enables the analysis of vast datasets and the development of innovative methodologies. One particularly transformative area is the use of generative AI, notably large language models (LLMs), which have the potential to revolutionize healthcare, medical education, and research.

Large language models, a subset of generative AI, are designed to process and generate human-like text by analyzing large bodies of language data. They use transformer architectures to understand the context and relationships between words, enabling them to generate coherent and contextually relevant responses. Trained on massive datasets such as books, articles, and websites, LLMs are capable of handling complex queries across various domains, from solving mathematical problems to writing computer code. Their capacity to generalize across topics makes them particularly useful in healthcare.

A recent study[10] compared responses from an LLM to those provided by verified physicians on a social media forum for patient questions (Reddit's r/AskDocs). Despite not being specifically trained for medical communication, ChatGPT provided more accurate and empathetic responses than the human physicians. Similarly, Eriksen *et al.*[11] found that GPT-4, an advanced LLM, outperformed (simulated) medical journal readers in diagnosing complex medical cases, successfully solving 57% of the challenges presented. Additionally, LLMs have been evaluated for their ability to provide preventive health advice. In a study by Sarraju *et al.*[12] experts deemed 84% of AI-generated answers regarding CVD prevention and risk factors as appropriate, highlighting AI's potential to assist in patient education and clinician communication on preventive strategies.

Artificial intelligence's real-world applications are already shaping the future of preventive healthcare. For instance, the National University Health System in Singapore has integrated AI into a real-time dashboard for cardiovascular risk management. The Endeavour AI system, paired with the Chronic Disease Management Program (https://medicine.nus.edu.sg/bisi/strategydevelopmentandtesting), allows clinicians to monitor cardiovascular risk factors down to the community level and adjust medical resources and educational programmes accordingly.[13]

Artificial intelligence has also shown superior capabilities in managing atherosclerotic CVD by analyzing risk markers from various imaging modalities, including electrocardiogram (ECG)-gated computed tomography (CT) scans, chest X-rays, and coronary angiography.[14] These AI-driven pathways synthesize vast amounts of risk and phenotype data, enabling a shift from traditional risk assessment algorithms to more sophisticated AI models that can help mitigate the risk and prevent the onset of conditions like ischaemic disease.[15] Scaled to a population level, screening methods must meet several essential criteria, including high sensitivity, specificity, reproducibility, early disease detection, cost-effectiveness, and clinical utility. AI has demonstrated significant potential to enhance such existing screening techniques, offering improvements across all these dimensions. For example, in detecting coronary artery disease (CAD) in high-risk populations, AI-enhanced cardiac CT, including spectral and photon-counting techniques can lower radiation doses, improve image quality even in high calcium score individuals, reduce the need for contrast agents, and shorten acquisition times.[16,17] In downstream applications of incident CAD or myocardial disease, AI can improve ischaemia detection or allow for molecular subtyping of disease using techniques such as magnetic resonance imaging, single-photon emission CT, or positron emission tomography imaging[18] By such AI-linked advances, high-risk plaque burden characterization by chemokine receptor tracers could be deployed to larger populations and predict those with the highest event rates and need for coronary interventions, addressing both effectiveness and resource allocation.[19] Recent randomized trials of certified AI radiology solutions have shown remarkable improvements in sensitivity and overall performance,[20] further underscoring its potential for scale effects. Another promising avenue is AI-enabled electrocardiography. Numerous studies have trained AI models, predominantly convolutional neural networks, on surface ECG data to detect conditions such as imminent atrial fibrillation, total coronary occlusion, heart failure, hypertrophic cardiomyopathy, or diastolic dysfunction. Given its affordability and widespread availability, ECG augmented by AI could deliver significant value in preventing major adverse cardiovascular events. The growing adoption of single-lead ECG recordings via smartwatches and other wearables adds a personalized dimension to early disease detection and prevention. AI algorithms also address challenges like inter- and intra-observer variability, enabling the automated quantification of diverse biological processes. This capability could introduce novel quantitative biomarkers into public health strategies, paving the way for innovative approaches to disease prevention and management.

In the following sections, we will explore recent developments in AI-driven strategies for addressing modifiable risk factors in cardiovascular health (*Graphical Abstract*).

Physical activity: addressing the growing challenge

Low physical activity is an escalating issue in Western societies, driven by modern lifestyles and increasingly sedentary work environments. Alarmingly, inadequate physical activity is linked to an estimated 397 000 cardiovascular deaths and 686 000 all-cause deaths annually.[1] Moreover, the GBD from insufficient physical activity is reflected in an all-cause DALYs rate of 193 per 100 000 individuals (95% confidence interval: 82.9–293.0 per 100 000). To address this public health challenge, national action plans are necessary to systematically gather reliable data on physical activity levels, track trends over time, and implement strategies to promote physical exercise.

While mobile technologies contribute to sedentary lifestyles by increasing 'screen time', they also offer potential solutions. Wearables and smart technologies, equipped with AI-driven features, can motivate individuals to engage in self-assessment, exercise planning, and tracking progress. These tools use integrated AI algorithms to process sensor data, providing users with meaningful and actionable insights. In countries like Germany and the USA, some health insurers support the use of smartwatches and digital health applications through initiatives like the Digital Supply Act (DiGA; https://diga.bfarm.de/de), which enables prescribing medical-grade exercise planning, rehabilitation, and prevention programmes for conditions such as diabetes, obesity, and smoking cessation.

AI is playing an increasingly central role in promoting physical activity and behavioural changes. As summarized by An *et al.*[21] neural networks, with their ability to model complex behaviours, outperform traditional linear statistical methods in predicting and influencing lifestyle interventions. AI can thus offer more personalized and effective strategies for improving physical activity. However, despite the potential of AI, challenges remain. A recent study by Dergaa *et al.*[22] evaluated OpenAI's GPT-4 LLM for personalized exercise prescription. While GPT-4 was able to generate safe general exercise recommendations, it lacked the precision needed to address individual health conditions and activity goals, often erring on the side of caution rather than optimizing the effectiveness of training. This limitation is partly because LLMs are not designed specifically for medical use. Other studies, such as those by Fuller *et al.*[23] have also identified similar limitations in AI applications for physical activity, noting that the field of physical activity research has not fully embraced advanced AI techniques. Researchers often focus on analyzing existing datasets instead of first generating precise, high-quality data, limiting the implementation of AI in real-world scenarios and large-scale evaluations.[24]

Despite these hurdles, there are examples of AI-driven physical activity interventions. For instance, the active dilated cardiomyopathy (DCM) study (NCT04359238; https://clinicaltrials.gov/study/NCT04359238), which investigates the effects of sports and exercise interventions in patients with DCM—a non-ischaemic form of heart failure and a leading cause of death in younger adults—illustrates the potential of AI in high-risk cohorts.[25] This randomized clinical trial uses personalized risk assessments to assign patients either to a structured exercise programme or to continue their usual activities. By integrating data from Apple Watch® sensors, the study collects and analyses detailed information on participants' activity levels, functional capacity, and adherence to exercise recommendations. This data will feed into AI models, refining them to improve future interventions. The transparent and secure nature of the data collection process ensures a user-friendly experience for patients while offering valuable insights for researchers.[26]

Obesity and diabetes

Recent reviews have summarized findings from 46 studies exploring AI's applications in obesity research and treatment.[27] AI offers the potential to identify distinct obesity endophenotypes—clusters with unique genetic, metabolic, and behavioural traits—that enhance our understanding of co-morbidities, treatment responses, and long-term outcomes. This ability to classify obesity into more precise subtypes has important implications for preventive strategies, as AI can identify genetic or phenotypic patterns that contribute to obesity risk and might be susceptible to differentiated treatment paradigms. Machine learning models are also effective at predicting such obesity categories by integrating demographic, laboratory, and lifestyle data.[28]

The integration of AI into existing care pathways is already yielding benefits in obesity management.[29] AI-powered apps have proven useful for weight loss, continuous weight monitoring, and patient engagement. Some of these applications are classified as medical devices, while others are consumer-focused tools without formal regulatory approval.

AI has made significant strides in the research and treatment of metabolic disorders like diabetes, also linked to obesity. From predicting the onset of diabetes and classifying its subtypes to managing modifiable risk factors and optimizing nutrition therapy, AI is currently transforming diabetes care. Many glucose monitoring devices and insulin pumps now incorporate AI algorithms to calculate optimal insulin doses or adjust oral anti-diabetic medication more precisely.[30] A review of 40 studies by Mohsen *et al.*[31] highlights AI's growing effectiveness in predicting the course of type 2 diabetes mellitus (T2DM). With the integration of wearable devices, non-invasive glucose monitoring is becoming more accurate, potentially replacing traditional blood glucose testing. This development promises to enhance the quality of life for the ∼425 million people living with diabetes worldwide, 90% of whom have T2DM.[32]

With a shortage of diabetes specialists, AI can help bridge the widening gap by providing patients with access to timely advice, resources, and professional monitoring. This can improve self-management of diabetes while reducing healthcare costs and enhancing the efficiency of resource utilization.[33]

Artificial intelligence for hypertension and lipid management

Hypertension remains a leading cause of morbidity and mortality globally. AI offers promising solutions for both the management and prediction of hypertension. Digital tools are well-suited to monitor blood pressure and improve adherence to treatment plans, while AI can go a step further by predicting the onset of hypertension and individual responses to specific antihypertensive medications.[34] This could revolutionize research on the aetiology of hypertension and accelerate the development of more targeted therapies.[35]

In addition, AI can integrate genomic and multi-omics data to help discover biomarkers and novel aetiological factors of hypertension. A study by Louca *et al.*[36] used multimodal data—including genetic, metabolic, laboratory, and demographic features—to predict systolic and diastolic blood pressure in ethnically diverse populations. This integration of data sources illustrates the potential for AI to enhance diagnosis and treatment outcomes.

AI has also demonstrated superior performance in diagnosing and managing hyperlipidaemia, particularly in predicting diagnostic markers using electronic health records.[37] AI algorithms have been shown to outperform traditional equations, such as the Friedewald equation, for estimating low-density lipoprotein cholesterol (LDL-C) levels, suggesting a role for AI in hospital labs and electronic health systems.[38] By automatically identifying patients with elevated cholesterol by digital surrogates, AI can support clinicians in decision-making, improving early detection and intervention potentially even without lab testing for cholesterol.

The developments are especially crucial for patients with familial hypercholesterolemia (FH), a genetic condition characterized by lifelong high LDL-C levels and a strongly elevated risk of CVD. AI-driven tools have significantly enhanced the process of diagnosing, stratifying risk, monitoring, and recommending treatment for FH.[39] Early intervention in these patients can dramatically reduce the risk of cardiovascular events, making AI a valuable asset in hyperlipidaemia care also in childhood.[40]

Together, these AI applications are driving advancements in the diagnosis, management, and treatment of chronic diseases, from obesity and diabetes to hypertension and hyperlipidaemia, offering more personalized and efficient care pathways for patients.

Can artificial intelligence stop tobacco and high alcohol use?

Despite the well-known health risks, tobacco smoking and vaping continue to be used by more than 1.3 billion people globally, according to the World Health Organization. The link between smoking and diseases like CAD and cancer is irrefutable, making smoking cessation a critical target in preventive health strategies. In Germany, the Digital Healthcare Act (2020) allows doctors to prescribe certified health apps that support patients in managing diseases or prevention strategies. Smoking cessation apps are among the most frequently prescribed, highlighting the potential of digital tools to overcome traditional barriers like scheduling difficulties, time constraints, and personal discomfort in clinical settings.

A recent systematic review and meta-analysis showed limited but promising evidence for the use of conversational AI in smoking cessation interventions.[41] Fu *et al.*[42] found that 22 of 74 recent studies leveraged machine learning technologies to assist individuals in quitting smoking, suggesting that AI could play an increasingly important role in behavioural health interventions.[42,43] These technologies can personalize smoking cessation plans, offer real-time feedback, and provide continuous monitoring, which may enhance the effectiveness of quitting attempts by catering to individual needs and habits.

Excessive alcohol consumption is responsible for an estimated 178 000 deaths annually in the United States. However, alcohol misuse can often go undetected in healthcare settings due to stigma and patient reluctance to disclose their drinking habits. AI has the potential to help overcome these barriers. For instance, natural language processing techniques can be used to analyse unstructured data in electronic health records and identify patterns indicative of alcohol-related health risks.[44] This AI-driven approach can supplement traditional screening methods by providing an additional layer of analysis that alerts healthcare providers to potential alcohol misuse, even if patients do not disclose it directly.[45] As with all such ‘mining’ approaches, consent and privacy protection are arguable opponents, which might be differently handled around the globe.

Climate change, urban health, and exposome modelling by artificial intelligence

Population health is profoundly shaped by environmental factors and the escalating impacts of climate change. The increase in heat waves, extreme weather events, and shifts in climate patterns requires preventive health strategies that also focus on climate change mitigation. To address these challenges, infrastructural advancements, innovative methodologies, and strong policymaking are essential to support region-specific research on the health impacts of climate change and develop tailored solutions, particularly for low-income regions that may be disproportionately affected.[46] Scalable digital solutions, including AI-driven technologies, offer a promising opportunity to address these issues by reaching larger populations with regionally appropriate interventions.

A comprehensive survey highlights key areas of climate change adaptation—earth systems, water resources, and agriculture—and the potential role of AI in supporting these efforts.[47] However, it is important to acknowledge the dual role of AI: while it can support environmental sustainability, AI is also used in industries like oil and gas exploitation, indirectly increasing carbon emissions.[48] Moreover, AI’s own energy demands are significant, with most of its energy consumption still derived from carbon-intensive sources.[49]

As urban populations continue to grow—it is estimated that by 2050, 75% of the global population will live in cities—there is an urgent need for studies that address urban health factors, including air quality, water access, healthcare availability, social disparities, housing conditions, and pollution (all forms including noise).[50] The ‘urban exposome’—a term referring to the total environmental exposures that urban populations face—will be a critical determinant of health and disease outcomes. AI is uniquely positioned to process the vast amounts of data required to model these exposures, combining various data sources in ways that traditional statistical methods cannot. This includes integrating the external environment (pollution, noise, etc.) with individuals' internal environments (genomic and epigenomic data) to better understand the complex interactions that shape health outcomes in modern cities.

Over the past three decades, there has been a global shift in morbidity and mortality from infectious diseases to non-communicable diseases like CVD. Air pollution remains a leading cause of global and cardiovascular mortality, with little improvement on the horizon.[51] Urban risk factors such as noise and light pollution also contribute significantly to CVD; in principle, these are preventable through technical interventions and regulatory measures.[52] AI can play a pivotal role in identifying the most cost-effective and resource-efficient solutions, prioritizing interventions that target the largest populations at risk or provide the most immediate results.

Despite the growing need to integrate environmental research, city planning, and prevention strategies, this area remains significantly underfunded. There is a pressing need for more attention from medical societies and lawmakers to address these gaps.[53] While organizations like the World Health Organization and the United Nations have launched initiatives to tackle some of these challenges, the specific impact of climate change on cardiovascular health seems still underappreciated. The urgency is compounded by the increasing number of children growing up in cities, exposed to the urban environment over their lifetimes, which may contribute to the rise in chronic disease, particularly CVD and its related mortality.

Artificial intelligence in drug development

In recent years, AI has become an indispensable tool in modern drug development, significantly influencing every stage of the translational pipeline for CVDs and related co-morbidities. During the COVID-19 pandemic, companies like BioNTech and Moderna utilized AI algorithms to optimize vaccine discovery, sequence optimization, and trial design, expediting the development of effective vaccines (https://www.pfizer.com/news/articles/how_a_novel_incubation_sandbox_helped_speed_up_data_analysis_in_pfizer_s_covid_19_vaccine_trial?utm_source=chatgpt.com). Artificial intelligence has also been instrumental in drug discovery and target modelling, with platforms like AlphaFold2 revolutionizing our understanding of protein structures. These advancements have facilitated the design of novel therapeutics, including biologics targeting key receptors involved in weight regulation, such as the glucagon receptor and glucagon-like peptide-1 receptor.[54] By training deep multi-task neural network models on existing peptide sequence data and their measured *in vitro* potency, AI-designed peptides have achieved up to sevenfold increased potency compared with traditional designs, highlighting AI's potential in optimizing established drug-target interactions. These developments hold promise for improving treatments for diabetes and obesity, potentially reducing cardiovascular risk, morbidity, and mortality associated with these metabolic disorders.

Beyond discovery, AI is employed in toxicity prediction, dosage estimations, pharmacodynamics, pharmacokinetics, trial design, and data interpretation from large-scale interventional studies.[55] The integration of AI with traditional molecular modelling strategies is anticipated to bring more candidates into clinical evaluation, conserve resources, and offer novel solutions to global health challenges such as heart failure.[56]

The convergence of AI and drug development signifies a transformative era in cardiovascular medicine, with AI-driven innovations poised to enhance therapeutic efficacy and patient outcomes also in preventive settings.

Healthcare delivery, implementation, and legal frameworks on advanced artificial intelligence systems

The introduction of ChatGPT in 2022 marked a major milestone in healthcare, as it was one of the first AI systems capable of addressing broad medical questions. Previous rule-based systems were typically limited to narrow and well-defined applications. The natural language capabilities of generative AI, such as ChatGPT, allow both physicians and patients to explore completely new possibilities in healthcare, which is being underlined by an increasing body of scientific evidence.[57] The new tools seamlessly integrate into existing workflows, alleviating the burden of fragmented information systems and the overwhelming amount of unstructured data, empowering healthcare professionals to make more informed clinical decisions.[58] Furthermore, healthcare organizations are increasingly focused on integrating AI innovations across culture, leadership, workforce, and clinical workflows.[59] This holds the promise of improving the precision, scalability, affordability, and transparency of medical services, leading to personalized yet population-scale healthcare.[60]

Artificial intelligence has the potential to extend beyond human decision-making, harnessing complex data from structured and unstructured sources such as cardiovascular imaging or ECGs. Gomes *et al.*[61] illustrated this by using AI to analyse vast population datasets like the UK Biobank. In their research, AI models were used to segment cardiac structures, assess blood flow, and link these AI-generated functional and structural parameters to genetic data, offering novel insights into CVD.[61] Similarly, Lehmann *et al.*[62] demonstrated how AI could analyse cardiac magnetic resonance imaging sequences, not just to diagnose conditions from a single image frame but also to predict haemodynamic patterns, offering new ways to classify complex conditions such as heart failure with preserved ejection fraction.[62]

The future of healthcare will likely see AI-driven systems combining multiple techniques to offer greater accuracy, generalization, and transparency. Multi-model AI systems, which coordinate and integrate outputs from several specialized models, will be essential in solving complex healthcare problems. Retrieval-Augmented Generation combines the generative capabilities of LLMs with external medical knowledge databases, enabling AI to provide real-time, contextually accurate responses with citation transparency. This can also include linkage to personal medical records and hospital information systems, allowing the transfer of clues from LLMs to the individual situation of a given patient. This approach helps clinicians validate AI-generated recommendations, enhancing trust and adoption in clinical practice. In a recent randomized AI trial, physicians were benchmarked against physicians who had access to LLMs. There was no significant difference between the two groups; however, LLMs without physicians scored higher (92% vs. 74%; $P = .03$), underlining that the human-AI interaction needs to be carefully studied, understood, and educated accordingly.[57,63] State-of-the-art (SOTA) models, which use cutting-edge techniques like transformer architectures and self-supervised learning, will further boost the performance and reliability of AI output on medical

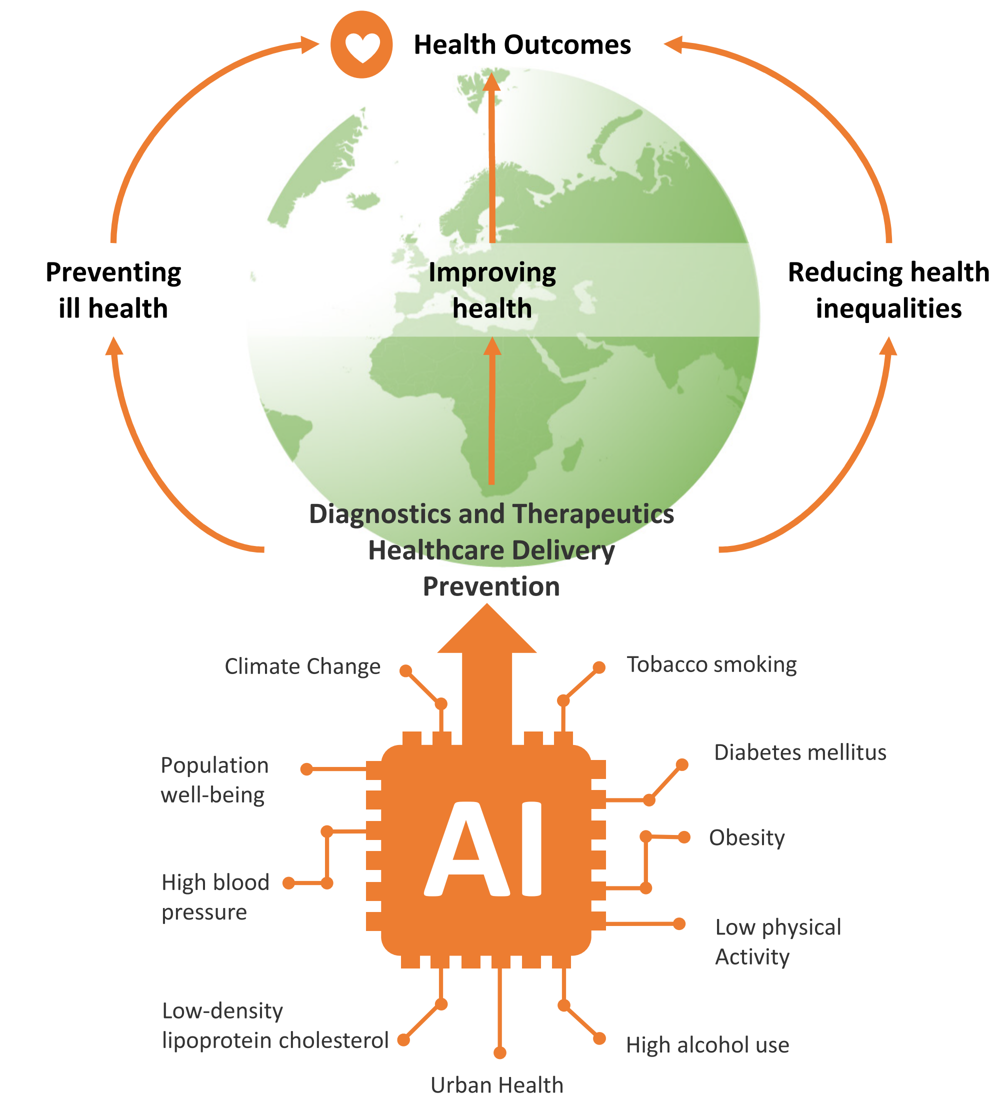


Figure 1 Artificial intelligence improves or enables preventive strategies for several risk factors, co-morbidities and cardiovascular diseases. The implementation of these artificial intelligence innovations into healthcare delivery, diagnostics, and therapeutics will require concerted national and European efforts to impact on reduction of ill health, improvement of health, and reduction of inequalities

topics. Transformer models, for instance, are the core technology of LLMs such as GPT. They learn the context of sequential data, which is highly similar to the human brain understanding voice, written text, or temporal vision. First published in 2017, transformers have revolutionized ML by focusing on attention and hence are architecturally different from recurrent neural networks. Without going into detail, the transformers take an input sentence, encode the individual words in their order and relation to each other, and transfer this matrix to a trained decoder that can, e.g. provide the translation to another language—in a semantically and grammatically correct order of words and means. These designs underline a deep understanding of brain physiology and highlight that AI algorithms are nowadays very diverse and more than simple collections of input data. These architectures further push AI's capabilities, offering unparalleled accuracy, reliability, and robustness in diverse applications. SOTA approaches ensure the most effective AI methods are chosen for specific healthcare challenges, aiming for precision and reproducibility.

Artificial intelligence's role in healthcare is already being tested in rigorous clinical settings. Randomized controlled trials (RCTs) are beginning to evaluate the real-world impact of AI-based interventions. One trial focusing on diabetes management showed that AI-driven insulin dosing was non-inferior to physician-led dosing in maintaining glucose levels within the target range, and no severe adverse events occurred in the AI group compared with three in the physician group.[64] Such trials represent a new frontier, benchmarking AI against best-practice care, and demonstrating that AI systems can perform at a comparable level, sometimes even exceeding human performance in terms of accuracy or safety. One promising technique for AI in this regard is causal learning, which focuses on uncovering cause-and-effect relationships from data, rather than just identifying correlations. This approach mirrors the objectives of RCTs, as both seek to identify the impact of interventions by controlling for confounding factors. While RCTs rely on randomization to achieve this, causal learning leverages statistical and machine learning methods to infer causality from observational data. This ability to extract robust, generalizable insights from 'naturally' randomized data opens up possibilities for AI to guide clinical decisions, even when conducting large-scale trials is impractical or too costly.

In all western economies, healthcare expenditures climbed to new heights. There are several reasons for the increased costs, including the ageing populations with consecutively increased disease prevalence, the failure to introduce effective prevention, rising safety demands, environmental impacts, a rise in the frequency of utilization of health care services, and increases in prices of diagnostics and therapeutics. It will be the question if AI produces more costs by pricey software solutions or rather will economically be a necessity due to increases in quality and efficiency. A recent paper investigated 200 AI healthcare studies with a primary focus on costs. While several broader assumptions had to be made, in all scenarios AI is saving considerable costs already in the first year of introduction and with an increasing margin over time.[65] Some projections indicate that AI might annually save between $200 and $360 billion in the US alone.[66] Another study comes to the conclusion that broad AI implementation could decrease hospital stays by 25%, having a profound impact on resources.[67] On top of this estimation, the positive impacts on prevention, as summarized in this article, will further increase the potential of AI in the economy of healthcare.

The U.S. Food and Drug Administration authorized 950 AI/ML-enabled medical devices as of August 2024. With the availability of certified AI products, the implementation into routine care has accelerated in recent months. There are several examples from leading healthcare providers on how the implementation already affects outcomes in real world. For instance, Mid and South Essex NHS Foundation Trust supports a population of 1.2 million in Great Britain (https://www.nhsconfed.org/publications/ai-healthcare). Although medical resources are nowadays limited, as much as 8% of patients did not attend (DNA) their appointment at the hospital due to various reasons. During a 6-month trial with an AI model to detect and prevent DNA, 1910 additional patient visits and 377 less DNAs were recorded. The provider calculated that an additional 80 000 patients can be seen in the hospital when the system is completely rolled out. On the same note, Cleveland Clinic could use AI to optimize patient scheduling and reduce wait times around 10%.[68] In the University of Heidelberg, several AI systems have been evaluated and integrated into routine processes, diagnostics, and decision support, e.g. as simply as by introducing an AI phone agent for patients. Around the world, several hospitals now routinely use LLMs to support documentation processes.[69] The Eppendorf University of Hamburg started implementation of an AI model called ARGO to support this documentation process and simultaneously use the AI-curated data to support clinical decision-making—fully compliant with the strict GDPR privacy regulations.

As AI becomes increasingly integrated into healthcare systems, there is a growing need for ethical, legal, and regulatory oversight to ensure safety and trust. Several frameworks exist to provide guidance in properly designing and evaluating AI systems regarding bias, trust, access, inequity, and ethical standards (e.g. https://future-ai.eu; https://algorithmwatch.org). Ethics will not only involve the developers, commercial entities, and physicians; it also is central for the acceptance by patients and populations. A recent survey by Carta Healthcare found that nearly all US patients had touchpoints with medical AI solutions, yet only a minority (38%) do trust it.[70] The standing principles of beneficence and non-maleficence ensure that medical treatments, but also AI technologies, benefit patients and do not cause harm, whether through error, bias, or misuse.[71] Consent and transparency are additional pillars that need to be proactively pursued in AI solutions. The risk of dehumanization of medicine is another factor that needs careful thinking and societies' discourse. It will also be important to study the ethics of withholding potent AI solutions once they demonstrate their superiority to current standards, either due to conservatism, fear, or financial reasons.

On 13 March 2024, the European Parliament enacted the Artificial Intelligence Act (AI Act), the world's first comprehensive legal framework governing AI. This framework complements existing regulations such as the U.S. Executive Order on AI (Biden administration, 2023, which was just recently revoked by the suceeding administration) and includes provisions specifically for high-risk AI applications in healthcare. The AI Act introduces stricter requirements for training data, transparency, human oversight, and accountability, going beyond existing regulations like the Medical Device Regulation (MDR). It mandates the use of notified bodies for AI evaluation, the logging of data and results, and post-market surveillance, particularly for AI systems classified as high-risk due to their use in diagnosis or treatment. Although this legislation is pioneering, it could slow down the rapid implementation of AI in healthcare due to increased regulatory burdens and additional costs.

Established frameworks, as outlined above, ensure that accountability is clearly defined for AI medical products, encompassing the range of stakeholders. These frameworks include the regulatory provisions enforced by AI/MDR-notified bodies and the responsibilities of producers, such as providing adequate warnings, precautions, contraindications, limitations, and ensuring software security. They address both pre-market and post-market investigations, as well as the labelling requirements for the intended use of the product. Similar to pharmaceuticals, healthcare professionals are required to adhere to the certified use of AI-based products and may be held liable for medical malpractice or negligence if they fail to do so. Additionally, healthcare organizations are responsible for implementing safeguards, including oversight, staff training, regular updates, and system maintenance. Notably, there is a growing consideration that even the failure to adopt a superior AI-enabled solution, when available, could potentially expose an organization to liability, highlighting the evolving legal and ethical landscape surrounding AI in healthcare.

In summary, AI is transforming healthcare delivery, and its influence will continue to grow, especially in the areas of preventive medicine and population health (*Figure 1*). The pace of AI implementation is rapidly accelerating, but careful and balanced regulation is essential to ensure 'healthy AI' systems that are both effective and safe. While it may take years to fully predict the impact of AI on population health outcomes, the ability to scale (AI-powered) healthcare solutions to thousands or even millions of people has never been more within reach. This presents an unprecedented opportunity to revolutionize healthcare.

Supplementary data

Supplementary data are not available at *European Heart Journal* online.

Declarations

Disclosure of Interest

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Data availability

No data were generated or analysed for or in support of this paper.

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