European Commission

Joint Research Centre

Artificial Intelligence in Cardiovascular Care

Navigating the Gap Between Technical Progress and Clinical Impact

Comte, V., Camara, O., Bijnens, B., Fraser, A., Meersmans, K., Zani, A., Bertolini, L., Ruiz Serra, V., Stilianakis, N., Griesinger, C.B., Panidis, D., Amato, O., Hatzaras, K., Mestre Gascon, A., Zanca, F., Bernaux, M., Oliveira, A., Ceresa, M., Querci, M., Wiesenthal, T.

2026

The Joint Research Centre: EU Science Hub
https://joint-research-centre.ec.europa.eu

JRC146049
EUR 40690

PDF ISBN 978-92-68-38945-4 ISSN 1831-9424 doi:10.2760/4314186 KJ-01-26-159-EN-N

Luxembourg: Publications Office of the European Union, 2026

How to cite this report: Comte, V., Camara, O., Bijnens, B., Fraser, A., Meersmans, K. et al., *Artificial Intelligence in Cardiovascular Care - Navigating the Gap Between Technical Progress and Clinical Impact,* Publications Office of the European Union, Luxembourg, 2026, https://data.europa.eu/doi/10.2760/4314186, JRC146049.

Contents

Abstract

Cardiovascular disease remains the leading cause of death in the European Union, claiming over 1.7 million lives each year and imposing a substantial economic burden on health systems and societies. One in five of these deaths is considered preventable. As Europe's population ages, this burden is projected to intensify, impacting citizens' life and placing growing pressure on health systems already facing workforce shortages and constrained budgets. Artificial Intelligence (AI) presents an opportunity to change this trajectory.

This report examines the current state of AI across the cardiovascular care continuum, from prevention and early risk prediction through detection, diagnosis, personalised treatment, and health system optimisation. It assesses the maturity and evidence base of key applications, identifies the barriers to wider adoption, and proposes policy priorities for the European Union.

The evidence reviewed points to real progress in a number of domains. AI-assisted echocardiography, automated ECG interpretation, CT-derived fractional flow reserve, and AI-supported stroke triage are among the applications with the strongest validation and the clearest demonstrated benefit in routine clinical practice. Other applications, including wearable-based risk detection, AI-guided screening for undiagnosed atrial fibrillation, and machine learning approaches to personalised treatment selection, show considerable promise but require more rigorous prospective evaluation before broad deployment can be recommended.

Across the field, a persistent gap exists between technical performance and demonstrated clinical impact. Most AI tools have been evaluated on accuracy metrics rather than on whether their use improves patient outcomes, and independent external validation remains limited. Adoption is uneven, concentrated in well-resourced academic centres, while smaller hospitals and less affluent health systems often lack the infrastructure, workforce capacity, and financing mechanisms needed to implement and sustain these tools. Consumer-facing AI is already shaping how millions of Europeans engage with their cardiovascular health, often operating outside traditional clinical governance structures and raising new regulatory and public health challenges that require urgent policy attention.

The EU has built a strong regulatory and data governance foundation through the AI Act, the Medical Devices Regulation, and the reform of the EU Pharmaceutical Legislation. In addition, the European Health Data Space Regulation provides the framework for secure and privacy-preserving access to health data across Member States, supporting the development, validation and scaling of AI applications in cardiovascular care. Realising the potential of AI in cardiovascular care will require translating these frameworks into practical support for validation, implementation, and equitable access. Key priorities include strengthening post-market surveillance, investing in data infrastructure and workforce readiness, directing implementation support toward under-resourced settings, and requiring demonstration of clinical utility rather than technical performance alone as the standard for adoption.

Cardiovascular care offers a compelling domain in which to establish the conditions for responsible AI deployment: the disease burden justifies investment, clinical pathways are well-defined, and rich data streams support evidence generation. Lessons learned here will be transferable across the broader landscape of non-communicable diseases that account for most of the health burden in Europe.

Acknowledgements

The authors would like to thank the participants of two expert workshops whose contributions significantly enriched this report. Both workshops brought together stakeholders from diverse backgrounds, including clinicians, researchers, industry representatives, and policymakers.

The first workshop was held at the Milan Innovation District (MIND) on 28 November 2025. The authors are grateful to:

Edoardo Conte[1], Antonio Rossi[1], Matteo Briguglio[1], Federico Penestrì[1], Giuseppe Banfi[1], Jose F. Rodriguez Matas[2], Luca Mainardi[2], Valentina Corino[2], Francesco Regazzoni[2], David Asturiol (JRC.F.1), Luigi Calzolai (JRC.F.2), Dimitris Panidis (JRC.F.2), Sara Bridio (JRC.F.3).

The second workshop was held at Universitat Pompeu Fabra on 5 December 2025. The authors are grateful to:

Carme Buisan[3], Miguel A. González Ballester[3], Gemma Piella[3], Marta Sitges[4], Xènia Acebes[5], Leticia Fernández[6], Anna Benavent[7], Abdel Hakim Moustafa[5], and Carlos Albors Lucas[8].

Authors

Valentin Comte (JRC.F.7), Oscar Camara Rey[3], Bart Bijnens[3], Alan Fraser[9], Karen Meermans (JRC.F.7), Alessandro Zani (JRC.F.7), Lorenzo Bertolini (JRC.F.7), Victoria Ruiz Serra (JRC.F.7), Nikolaos Stilianakis (JRC.F.7), Claudius Griesinger (JRC.F.2), Dimitrios Panidis (JRC.F.2), Ottavia Amato (JRC.F.1), Kyriacos Hatzaras (CNECT.A.6), Antoni Mestre Gascon (CNECT.A.6), Federica Zanca (EISMEA), Melodie Bernaux (SANTE.B.1), Andreia Oliveira (SANTE.B.1), Mario Ceresa (JRC.F.7), Maddalena Querci (JRC.F.7), Tobias Wiesenthal (JRC.F.7).

[1] Ospedale Galeazzi Sant'Ambrogio, Milan, Italy.

[2] Politecnico di Milano, Milan, Italy.

[3] Universitat Pompeu Fabra, Barcelona, Spain.

[4] Hospital Clínic, Barcelona, Spain.

[5] Hospital de la Santa Creu i Sant Pau, Barcelona, Spain.

[6] Hospital de la Mutua, Terrassa, Spain.

[7] Parc Tauli Healthcare Consortium, Sabadell, Spain.

[8] Virtest Technologies, Barcelona, Spain.

[9] Cardiff University, United Kingdom.

Executive Summary

Policy Context

Cardiovascular disease (CVD) claims **1.7 million** lives in Europe every year [1], **more than any other disease**. 62 million Europeans currently live with CVD, and due to an **ageing population**, this number could reach **more than 100 million by 2050**.

Artificial intelligence presents an opportunity to change this trajectory. AI can enable life-long health management, allowing it to **identify individuals at risk** before symptoms appear, **accelerate time-critical diagnoses**, support more **personalised treatment** decisions, and **help health systems allocate resources more effectively**. Some applications are already in clinical use; many more are in development. The question for policymakers is no longer whether AI will play a role in cardiovascular care, but **how to enable its integration in day-to-day healthcare provision and how to ensure it delivers real benefits for patients and health systems**: safely, equitably, and at scale.

The **EU Safe Hearts Plan**, launched in December 2025, places AI and digital innovation at the heart of future care delivery. It is underpinned by enabling instruments including the **AI Act**, the **Medical Device Regulation**, the **European Health Data Space**, and targeted funding through Horizon Europe, Digital Europe and EU4Health, together positioning Europe to lead in the responsible deployment of AI in cardiovascular care.

Key Conclusions

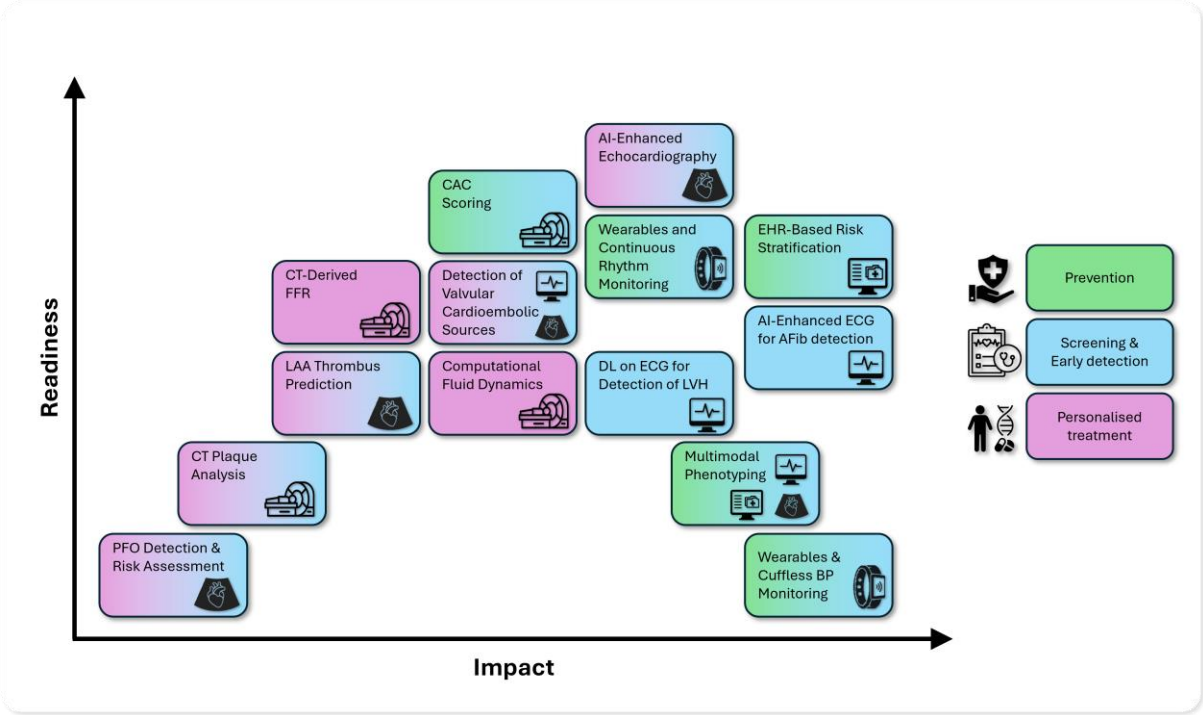
AI has clear potential to improve cardiovascular care, but the gap between technical performance and demonstrated clinical impact remains wide. Most tools have been evaluated on accuracy metrics rather than on **patient outcomes**, **care efficiency**, or **workflow integration**. Technical clearance provides important safeguards but does not guarantee real-world clinical value, and greater emphasis on demonstration of **clinical utility** would strengthen the pathway from regulatory approval to meaningful **patient benefit**.

For this report, **14 high-potential AI applications** were identified and assessed by experts against two dimensions: their **readiness** for clinical use, reflecting the maturity of the evidence base and the degree to which tools have been validated in real-world settings, and their **potential impact**, reflecting the benefits these tools could deliver if widely adopted in clinical practice. These insights help identify where investment is needed and where the evidence base must first be strengthened before broader deployment can be recommended (Figure 1). Translating this potential into population-level benefit will require coordinated action across five priorities:

- **Putting clinical evidence first**. Funding should prioritise independent validation and head-to-head comparisons between competing tools, not just technical performance. The measure of success should be whether AI improves patient outcomes, care experience, and sustainable costs.
- **Investing in infrastructure**. Many hospitals lack the infrastructure needed to deploy AI. Without targeted investment, AI risks widening rather than narrowing disparities in cardiovascular care across Europe.

- **Simplifying regulation**. The regulatory burden of navigating multiple overlapping frameworks falls disproportionately on the small companies and start-ups that develop many cardiovascular AI tools. The proposed revision of the Medical Devices Regulation and the In Vitro Diagnostic Medical Devices Regulation, alongside the Digital Omnibus, aim to streamline compliance, and further efforts are needed to reduce duplication without compromising safety.
- **Building workforce capacity**. AI literacy must be integrated into medical education at all levels. Sustained investment is also needed in the technical roles required to implement and maintain AI tools within healthcare organisations.
- **Clarifying the role of consumer AI**. Millions of Europeans already use smartwatches and health apps that generate cardiovascular data. Clear guidance is needed on what these tools can reliably do, how their data should reach clinicians, and how to manage the demand generated by alerts and self-diagnoses.

Figure 1: Expert assessment of 14 high-potential AI applications in cardiovascular care, mapped against their readiness for clinical use and their potential population health impact. Applications are colour-coded by domain: prevention (green), screening and early detection (blue), and personalised treatment (pink).



Source: own elaboration.

Main Findings

AI is already being used at every stage of cardiovascular care, but its **maturity** varies considerably. Some tools are **approved and deployed** in hundreds of hospitals across Europe; others show promising results in research settings but are **not yet ready** for widespread clinical use.

In **prevention**, AI has the potential to identify people at **risk of heart disease before symptoms appear**. It can detect early signs of heart muscle thickening from a routine electrocardiogram far more reliably than traditional methods, and this finding **predicts future cardiovascular deaths**.

AI can also automatically measure calcium deposits in the coronary arteries, a well-established marker of future heart attack risk, including from scans originally performed for other purposes such as lung cancer screening. Smartwatches and health apps can flag potential heart rhythm problems and offer a new pathway to medical attention for people who might not otherwise seek it. However, any alert requires confirmation by a clinician before a diagnosis is made or treatment started, as **false positives are common**. Clearer pathways for integrating these tools into clinical care are needed to ensure they add value rather than overload already stretched healthcare services.

In **diagnosis**, AI has made the most visible progress. It can assess heart function from ultrasound scans **as accurately as specialist** cardiologists while **cutting analysis time by more than half**. It can also help non-specialist healthcare workers to perform heart scans with minimal training, improving access to cardiac care in settings that lack specialists. AI can also **detect hidden atrial fibrillation**, a common cause of stroke, from a standard electrocardiogram recorded during normal heart rhythm, although evidence that it actually reduces stroke rates is still needed.

For **treatment decisions**, AI can help analyse Computed Tomography (CT) scans of the coronary arteries to assess whether a **narrowing is restricting blood flow**, helping clinicians decide who needs a procedure and who can be safely managed with medication alone. Beyond this, AI models show promise in identifying patients who may safely avoid semi-invasive imaging before certain procedures, and **multimodal approaches** combining electrocardiogram, echocardiography, and clinical data are being applied to distinguish between conditions that look similar but carry different clinical implications.

Significant challenges remain. Most AI tools have been tested on technical accuracy rather than on patient outcomes, and regulatory approval does not guarantee real-world benefit. Greater investment is needed in local implementation studies that allow institutions to assess whether a tool performs reliably in their specific setting. Without deliberate efforts to support smaller hospitals, primary care, and less-affluent regions, AI risks amplifying rather than reducing existing inequalities in cardiovascular care. Ultimately, the measure of success should be whether AI improves outcomes for patients, enhances the experience of care, supports healthcare professionals, and helps healthcare systems operate more sustainably.

Related Joint Research Centre Work

This report is part of a **broader corpus of JRC studies on AI in healthcare**, ranging from technical assessments of **AI in medical imaging** [2] and **interpretability methods for cardiovascular applications** [3], to the **opportunities and risks of generative AI in healthcare** [4] and frameworks for operationalising **trustworthy AI in clinical settings** [5]. These provide complementary perspectives on the conditions for responsible AI deployment: the technical foundations, the transparency requirements, the emerging capabilities, and the governance structures needed to ensure benefit-risk balance in high-risk applications. Looking forward, horizon scanning [6] extends this work into the future, identifying trends such as **multimodal data integration**, **digital twins**, and **synthetic data generation** that may reshape cardiovascular care in the coming years.

Quick Guide

This report is structured in four main parts. Section 1 sets out the broader context, examining the scale of the cardiovascular disease burden in Europe and the rationale for deploying AI in cardiovascular care. Section 2 describes how AI is being deployed from prevention and early detection to personalised treatment and health system optimisation, with illustrative EU-funded projects at each

stage. Section 3 examines the key challenges to implementation, covering regulation, data infrastructure, clinical evidence, and workforce readiness. Section 4 examines AI applications in depth across three major cardiovascular disease subtypes, with an expert assessment of 14 high-potential applications mapped against their readiness and potential impact. Section 5 presents conclusions, five policy priorities, and a forward-looking perspective.

1 Introduction

Cardiovascular disease (CVD) remains the leading cause of mortality and disability in the European Union, with wide-ranging consequences for individuals, healthcare systems, and the economy. Reducing this burden is a core objective of the EU Cardiovascular Health Plan, which places strong emphasis on prevention, early detection, and equitable access to high-quality care. Within this policy context, this report examines how artificial intelligence (AI) can support these goals, from risk stratification to timely diagnosis, and identifies key opportunities and challenges for implementation.

CVD also represents a particularly suitable entry point for examining the use of AI in healthcare more broadly. Cardiology is a clinically mature and technologically advanced field, characterised by well-defined care pathways, widespread use of digital imaging and monitoring technologies, and the availability of large, longitudinal, and multi-modal datasets. Rich datasets already exist across hospitals, regional health systems, and national registries, though they largely remain in silos with limited interoperability or cross-border accessibility. The European Health Data Space[10] (EHDS) offers a pathway to unlock this potential by enabling secure secondary use and interoperability across Member States. These features make cardiovascular care an ideal demonstrator for the development and deployment of trustworthy AI under the EHDS framework. Lessons learned in this domain are expected to be transferable to other non-communicable diseases (NCDs), supporting the broader objectives of the EU Cardiovascular Health Plan and informing future AI-enabled health strategies.

CVD is a major public health challenge across the European Union, representing both the leading cause of death and a significant economic burden. In 2021 alone, CVDs were responsible for 1.7 million deaths in the EU, accounting for 32.4 percent of all deaths, and affecting around 62 million people [1]. This is considerably higher than cancer, the second leading cause of death, which accounted for 21.6 percent.. Strikingly, around one in five of these deaths could have been avoided (Figure 2), whether through primary prevention of acute cardiovascular events or improved management of chronic cardiovascular conditions. This highlights not only the scale of the challenge but also a clear opportunity to reduce avoidable mortality across Europe[11].

Beyond mortality, CVD is a leading cause of long-term disability, premature retirement, and work absenteeism, with a marked impact on quality of life and life expectancy. The economic burden is substantial. In 2021, CVD was estimated to cost the European Union around 282 billion euro annually[1] [7] [8], corresponding to approximately 2% of GDP[12], largely due to productivity losses and reduced economic output. This sustained burden places significant pressure on national health systems and undermines the EU's broader economic resilience. Population ageing is expected to further exacerbate these challenges. The share of people aged 65 and over is projected to increase from 22% to 29% [1] in the EU and from 10% to 16%[13] globally by 2050. This demographic transition will have profound consequences for CVD burden: globally, the total number of people living with CVD is projected to increase by 90% between 2025 and 2050, accompanied by a 73.4% rise in crude cardiovascular mortality and a 54.7% increase in crude disability-adjusted life years [8].

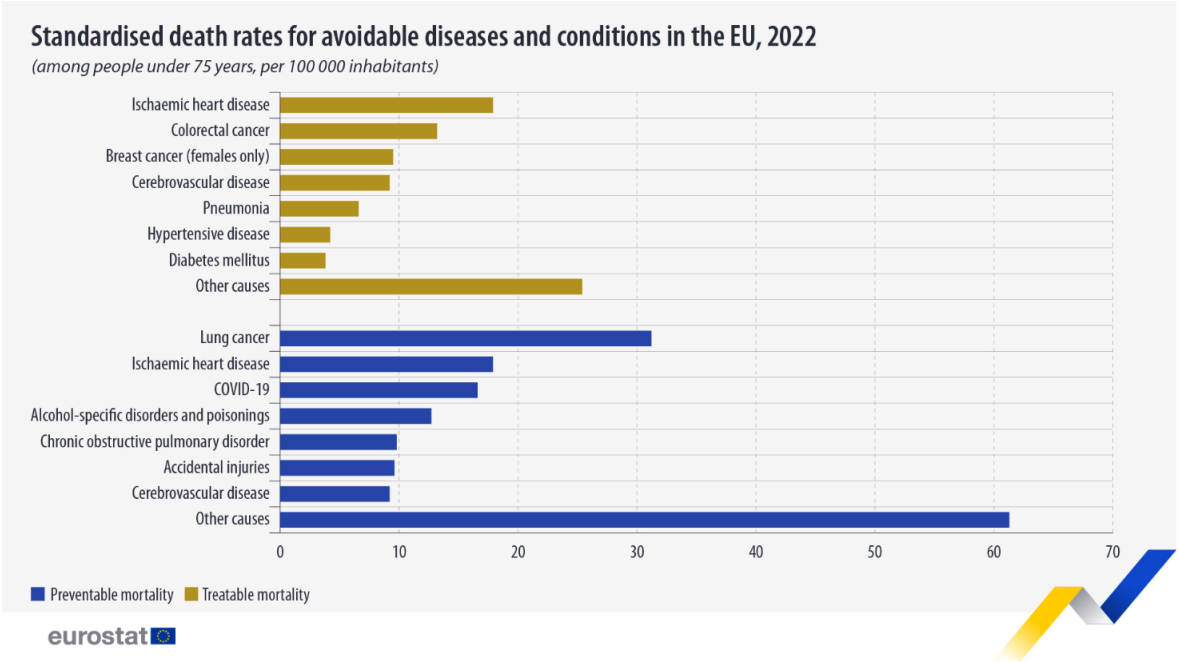
[10] Regulation - EU - 2025/327 - EN - EUR-Lex

[11] 1.1 million deaths linked to avoidable conditions - News articles - Eurostat

[12] On per capita basis, CVD-related costs averaged EUR 630 per EU citizen.

[13] Chart: Aging Populations | Statista

Figure 2: Standardised death rates for avoidable diseases and conditions in the EU, 2022.



Source: [1.1 million deaths linked to avoidable conditions - News articles - Eurostat]

Addressing a challenge of this magnitude requires a strategic and coordinated response. AI's capacity for large-scale data analysis and predictive modelling offers new tools across the care continuum: from early risk identification and population-level stratification to optimised clinical workflows and personalised treatment pathways tailored to individual patient profiles. In particular, AI offers opportunities to strengthen prevention and early detection of CVD, which remain central priorities for reducing avoidable mortality across Europe. At the health system level, AI can support more efficient resource allocation and help identify underserved groups who may benefit most from preventive interventions. Realising this potential will require robust data foundations, appropriate clinical validation, and effective integration into care pathways, which are central considerations for the policy and implementation issues discussed in this report. This creates a strong rationale for policy attention to AI tools that can support earlier, more targeted, and more scalable cardiovascular care, both at the individual and health system level.

2 The Deployment of AI Across the Cardiovascular Care Continuum

AI has the potential to transform cardiovascular care by enhancing the ability to prevent, detect, treat, and manage disease. Cardiovascular conditions arise from a complex interplay of genetic, metabolic, behavioural, and environmental factors, and their early stages are often clinically silent. Traditional risk models capture only a fraction of this complexity, and diagnosis frequently occurs only after disease has progressed. AI offers a different approach: by integrating large, heterogeneous datasets—imaging, electrocardiography, electronic health records (EHRs), wearables, and increasingly genomic and proteomic data—it can identify patterns invisible to conventional analysis, enabling earlier intervention and more personalised care.

The maturity of AI applications varies considerably across the care pathway. Diagnostic tools are the most advanced: CE-marked systems for Electrocardiogram (ECG) interpretation, echocardiography analysis, coronary physiology assessment, and acute stroke triage are already deployed in hospitals across Europe. Prevention and continuous monitoring are at an earlier stage, with wearable devices generating cardiovascular data at scale but systematic integration into clinical workflows being still limited. AI for personalised treatment selection and clinical decision support is largely experimental, concentrated in research settings and specialised centres. At the health system level, AI is beginning to support hospital operations and emergency response, though large-scale deployment remains uncommon. The EU is investing to advance these capabilities across the care continuum. Through Horizon 2020 and Horizon Europe, the European Commission has funded projects spanning prevention, early detection, personalised treatment, and health system optimisation (Table 1). The European Innovation Council (EIC) complements these efforts by supporting a portfolio of high-risk, high-impact research projects and deep-tech startups developing next-generation diagnostic, imaging, and decision-support technologies for CVD. These projects explore areas such as advanced cardiovascular imaging analysis, predictive modelling for risk stratification, and AI-assisted clinical workflows. By supporting both early-stage research and the scale-up of innovative companies, the EIC contributes to strengthening Europe's capacity to translate cutting-edge AI research into clinically deployable solutions.

The following sections examine these applications in detail, organised across four domains: prevention and risk prediction, early detection and risk stratification, personalised treatment and clinical decision support, and healthcare system optimisation.

Table 1: Illustrative projects related to AI for cardiovascular health (co-)funded under Horizon Europe[14] for research and innovation.

Focus Area	Project	Programme & Budget	Duration	Key Application
Prevention & Risk Prediction	VASCUL-AID[15]	Horizon Europe €6.4M	2023–29	AI platform integrating imaging, genomics, proteomics, and wearable lifestyle data to predict cardiovascular event risk and vascular disease progression
	SHIELD[16]	Horizon Europe €6.5M	2024–28	AI-based personalised risk scores and prevention strategies for CVD and diabetes, delivered via mobile app with behaviour change interventions
	CARAMEL[17]	Horizon Europe €12M	2024-29	AI-based multimodal risk stratification for cardiovascular disease in women aged 40–60, with specific attention to sex- and gender-specific risk factors during the menopausal transition
	AI-POD[18]	Horizon Europe €5.3M	2023-27	AI tools integrating clinical, laboratory, and imaging data to predict obesity-related vascular disease risk and support clinical decision-making
Early Detection & Risk Stratification	STRATIFYHF[19]	Horizon Europe €4.5M	2023–27	AI-based decision support system for heart failure risk stratification, early diagnosis, and disease progression prediction in primary and secondary care
	iCARE4CVD[20]	Horizon Europe €9.9M EU contribution	2023–28	AI-based modelling using data from >1 million patients for early diagnosis, risk stratification, and prediction of treatment response across the CVD spectrum
	AI4HF[21]	Horizon Europe €5.9M	2023-27	Trustworthy AI for personalised heart failure risk assessment and management; integrates cardiac imaging, biomarkers, ECG, and clinical data with federated learning across 3 continents

[14] Except for the Healthcare System Optimisation category, for which Horizon 2020 projects are provided as examples.

[15] VASCUL-AID: Developing Trustworthy AI-Driven Tools to Predict Vascular Disease Risk and Progression

[16] SHIELD: Strategic Health Initiatives for Effective Disease Prevention

[17] CARAMEL: CArdiovascular Risk Assessment in MEnopausaL women via multimodal data analysis enabling personalized prevention strategies

[18] AI-POD: Trustworthy AI Tools for the Prediction of Obesity Related Vascular Diseases

[19] STRATIFYHF: Artificial intelligence-based decision support system for risk stratification and early detection of heart failure in primary and secondary care

[20] iCARE4CVD: Individualised Care from Early Risk of Cardiovascular Disease to Establish Heart Failure

[21] AI4HF: Trustworthy Artificial Intelligence for Personalised Risk Assessment in Chronic Heart Failure

	CVDLINK[22]	Horizon Europe €9.7M	2024-27	Privacy-by-design federated platform integrating real-world data sources for AI-driven diagnosis, prognosis, and risk assessment across seven cardiovascular conditions
	ThrombUS+[23]	Horizon Europe €8.1M EU Contribution	2024-27	Wearable AI-powered device for continuous point-of-care monitoring, risk estimation, and prevention of deep vein thrombosis in high-risk patients
	RealCare[24]	Horizon Europe €8.4M EU Contribution	2023-28	Next-generation point-of-care systems for real-time biomarker detection in cancer and cardiac diseases, integrating AI data processing with portable biosensor technologies
Personalised Treatment & Clinical Decision Support	GEMINI[25]	Horizon Europe €10M	2023–29	Multi-scale digital twins of ischaemic and haemorrhagic stroke patients to support treatment selection
	NextGen[26]	Horizon Europe €7.6M	2024–28	AI tools for genome-centric multimodal data integration to personalise cardiovascular therapies
	Euro-HeartPath[27]	Horizon Europe €15M EU contribution	2025–30	18 pathfinder studies on AI-powered diagnostics, digital health tools, and robotics for heart failure, atrial fibrillation, and coronary disease
	SMASH-HCM[28]	Horizon Europe €8.5M	2024-27	Hybrid digital twin platform integrating biophysical models and data-driven analytics for personalised stratification and management of hypertrophic cardiomyopathy
	TARGET[29]	Horizon Europe €7M	2024-28	Virtual twin models and AI decision-support tools for the full pathway of atrial fibrillation-related stroke, from prevention and acute management to rehabilitation
	GRACE[30]	Horizon Europe €12M EU contribution	2025-29	AI and digital solutions to improve the clinical management pathway for cardiovascular disease, fostering multidisciplinary care

[22] CVDLINK: A federated paradigm of real-world data sources utilization for the empowerment of diagnosis, prognosis and risk assessment of cardiovascular conditions

[23] ThrombUS+: Wearable Continuous Point-of-Care Monitoring, Risk Estimation and Prevention for Deep Vein Thrombosis

[24] RealCare: Real-time biomarker detection systems for rapid medical decision-making in cancer and cardiac diseases

[25] Towards GEMINI: A Generation of Multi-scale Digital Twins of Ischaemic and Haemorrhagic Stroke Patients

[26] NextGen: Next Generation Tools for Genome-Centric Multimodal Data Integration in Personalised Cardiovascular Medicine

[27] EuroHeartPath: Leading Innovation in Cardiovascular Pathways for Improved Patient Outcomes

[28] SMASH-HCM: Stratification, Management, and Guidance of Hypertrophic Cardiomyopathy Patients using Hybrid Digital Twin Solutions

[29] TARGET: Health virtual twins for the personalised management of stroke related to atrial fibrillation

[30] GRACE: bridGing gaps in caRdiAC health managEment

				coordination and personalised early intervention
Healthcare System Optimisation	AICCELERATE[31]	Horizon 2020 €9.2M EU contribution	2021–24	Smart Hospital Care Pathway Engine for AI-driven patient flow management in emergency and surgical units
	HosmartAI[32]	Horizon 2020 €10M EU contribution	2021–24	Open integration platform for AI and robotics in hospital operations, with pilots covering cardiovascular disease, cancer, and rehabilitation

Source: cordis.europa.eu.

2.1 Prevention and Proactive Health Management

The indicators used to assess the risk of heart disease and stroke span multiple, complementary dimensions of cardiovascular care. They include non-modifiable factors such as age, sex, and genetic predisposition; modifiable risk factors that are routinely monitored and targeted through prevention and clinical management; standard clinical assessments that provide direct information on the structural, functional, and electrical status of the heart and vasculature; and a growing set of advanced and emerging biomarkers that offer more granular insight into underlying pathophysiological processes. Together, these indicators capture the multifactorial nature of CVD and the interplay between biological, behavioural, and environmental determinants. Table 2 summarises these categories and illustrates how different types of indicators contribute to cardiovascular risk assessment, diagnosis, and ongoing monitoring across the care continuum.

Table 2: Categories of cardiovascular risk indicators and their clinical applications[33].

Type of indicator	Representative examples	Role in cardiovascular care
Non-modifiable factors	Age, sex, genetic predisposition, family history	Baseline cardiovascular risk and lifetime susceptibility
Modifiable risk factors	Blood pressure, dyslipidaemia, diabetes mellitus, smoking, obesity, physical inactivity, diet, depression, chronic stress, sleep disorders	Primary targets for prevention, risk reduction, and long-term management
Standard clinical assessments	Electrocardiography (ECG), echocardiography, cardiac stress testing, ambulatory blood pressure monitoring, Holter monitoring, carotid ultrasound	Detection, staging, and monitoring of structural, functional, and electrical abnormalities
Lab tests and emerging biomarkers	High sensitivity C reactive protein, interleukin 6, TNF α, lipoprotein(a), NT proBNP, high sensitivity troponin I, cystatin C, ICAM, VCAM[34]	Deeper characterisation of pathophysiology, residual risk, and disease progression

Source: own elaboration.

[31] AICCELERATE: A Smart Hospital Care Pathway Engine

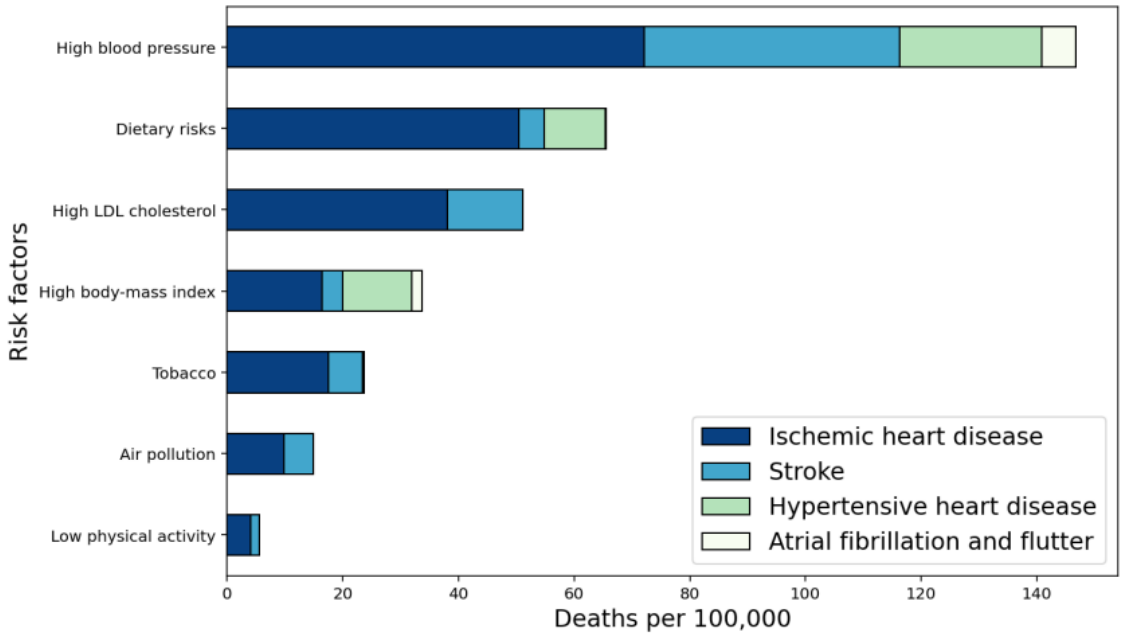
[32] HosmartAI: Hospital Smart development based on AI

[33] Own elaboration based on expert input.

[34] ICAM: intercellular adhesion molecule; VCAM: vascular cell adhesion molecule

Unlike non-modifiable factors (age, genetics, family history), the major modifiable risk factors are well-established and can be effectively addressed through lifestyle modifications and medical interventions. Therefore, early identification and intervention targeting modifiable risk factors represents a possibly very effective strategy for reducing CVD burden. The scale of this opportunity is substantial. In the EU, high blood pressure accounts for over 140 deaths per 100,000 population from ischaemic heart disease (IHD), stroke, hypertensive heart disease (HHD), and atrial fibrillation (AF) combined, more than any other modifiable risk factor. Dietary risks and high LDL cholesterol follow, each contributing significantly to cardiovascular mortality, while tobacco use, high body-mass index, air pollution, and physical inactivity add further to the burden (Figure 3). These are precisely the factors that AI-enabled continuous monitoring and early intervention could help address at scale.

Figure 3: Cardiovascular disease mortality attributable to modifiable risk factors in the EU.



Source: Global Burden of Disease (GBD)

The integration of AI and wearable technologies is beginning to reshape preventive medicine by enabling continuous monitoring and early identification of risk factors [9]. Wearable devices can continuously monitor physiological parameters such as heart rate, blood pressure, and sleep [10]. While these devices generate a vast amount of data, AI is required to efficiently extract value from this information and provide meaningful insights for early detection and lifestyle modification [9]. This represents a fundamental shift from a reactive, clinic-based model to a continuous, proactive, and patient-driven one. AI's ability to interpret this data is the key to empowering both patients and clinicians in preventive care, helping to mark a shift from reactive treatment to proactive health management [11] [12].

Beyond wearables, AI-powered conversational tools and symptom checkers are also emerging as a means for citizens to engage with their own health data. Large language model (LLM)-based applications and symptom assessment platforms allow individuals to input data from wearables, clinical reports, or self-reported symptoms and receive personalised guidance or a preliminary health assessment. While these tools are not intended to replace clinical judgement, they may serve as a first or second opinion for persons seeking to understand their cardiovascular risk or interpret monitoring data. However, the reliability, safety, and regulatory status of such tools vary considerably,

and their integration into formal care pathways remains limited. In terms of maturity, the use of AI and wearables for cardiovascular prevention is still at an early stage of clinical adoption. While consumer devices are widely available and several have received CE-marking, their systematic use in clinical workflows remains the exception rather than the norm. Most wearable-generated data is not yet integrated into EHRs, and evidence on the impact of these technologies on long-term cardiovascular outcomes is still emerging.

EU-funded initiatives are working to bridge this gap. VASCUL-AID (Horizon Europe, €6.4 million, 2023–2029) is developing an AI-driven platform that integrates imaging, genomic, and proteomic data with lifestyle information from wearables to predict cardiovascular event risk and disease progression in patients with abdominal aortic aneurysm and peripheral arterial disease. SHIELD (Horizon Europe, €6.5 million, 2024–2028) uses AI to create personalised risk scores and prevention strategies for CVD and diabetes, delivering behaviour change goals, lifestyle recommendations, and health literacy content via a mobile app. CARAMEL (Horizon Europe, €12 million, 2024–2029) is addressing a significant gap in risk assessment for women aged 40 to 60 by developing AI-based multimodal models that account for sex- and gender-specific risk factors during the menopausal transition, a period when cardiovascular risk increases markedly but is frequently overlooked in clinical practice. AI-POD (Horizon Europe, €5.3 million, 2023–27) is developing AI tools that integrate clinical, laboratory, and imaging data to predict vascular disease risk in patients with obesity, a population in which standard risk scores perform poorly. These projects illustrate how continuous monitoring, AI-based risk stratification, and digital interventions can support a shift from reactive treatment to proactive health management.

2.2 Early Detection and Risk Stratification

Among the domains of cardiovascular care, detection and risk stratification are where AI has made its most visible and clinically validated progress. Current diagnostic practice tends to favour high specificity, reflecting the need to keep healthcare manageable and affordable: tests are designed to confirm disease reliably before triggering treatment or intervention. AI does not simply invert this logic, but rather opens the possibility of more sequential approaches, where highly specific models continue to drive immediate clinical action while more sensitive tools identify individuals warranting closer monitoring or earlier preventive intervention. This staged model, where risk stratification precedes rather than replaces definitive diagnosis, remains underdeveloped in AI research and is only beginning to be reflected in clinical guidelines.

By leveraging large-scale, multimodal datasets such as imaging, electrocardiography, wearable sensor data, and structured and unstructured information from patient medical records, AI models can detect subclinical disease, stratify individual risk, and identify patients who may benefit from earlier or more intensive intervention. Deep learning (DL) algorithms are increasingly applied to cardiac imaging modalities such as computed tomography (CT), particularly coronary CT angiography (CCTA), and cardiac Magnetic Resonance Imaging (MRI) to identify early atherosclerotic changes or functional abnormalities. AI-enhanced ECG analysis can uncover subtle conduction patterns or electrical instability indicative of early myocardial damage and ventricular remodelling[35], before clinical symptoms emerge. Similarly, machine learning (ML) applied to longitudinal EHR data can forecast

[35] Structural and functional changes in the heart muscle that result from sustained stress or injury, such as hypertrophy or fibrosis.

the onset of hypertension, treatment resistance, or the transition to heart failure (HF) with greater accuracy than traditional risk models [13][14]. Beyond supervised prediction, unsupervised learning techniques are also being explored to identify novel patient phenotypes based on the integration of clinical, imaging, and molecular data. These approaches can map patients into a latent space representing distinct risk profiles, enabling more granular stratification and potentially revealing subgroups that respond differently to treatment. Such phenotyping methods are an active area of research, though not yet widely adopted in clinical practice.

It is important to note that early detection remains challenging, as most imaging and other diagnostic tools are still predominantly used when patients already present with symptoms, though some modalities such as ECG are increasingly applied in screening contexts, including in athletes and high-risk populations. The most mature AI applications in this domain are in diagnosis, particularly AI-powered feature extraction tools that support radiologists in interpreting cardiac imaging. Several such tools have received regulatory clearance in Europe and the US, and are increasingly used to accelerate interpretation, reduce workload, and improve consistency. These tools are designed to augment rather than replace clinical judgement, and human oversight remains essential at critical decision points. These advances enable more precise and dynamic risk stratification, moving beyond population-level predictions toward continuous, personalised assessment of cardiovascular health. Moreover, the integration of AI with opportunistic imaging and remote monitoring tools facilitates early detection in routine care and outside clinical settings. By capturing early physiological and structural signals of disease, AI-driven approaches hold strong potential to reduce late diagnoses, guide preventive therapies, and improve long-term cardiovascular outcomes across diverse populations.

However, several limitations must be addressed before these tools can be reliably deployed at scale. AI algorithms trained on data from a single imaging manufacturer, hospital, or patient population often suffer from poor generalisation when applied in different settings. Ensuring robust performance across diverse scanners, clinical environments, and demographic groups is essential to avoid biased or unreliable predictions. Addressing these challenges will require diverse, representative training datasets and rigorous external validation across multiple sites and populations.

EU-funded initiatives are advancing these capabilities. STRATIFYHF (Horizon Europe, €4.5 million, 2023–2027) is developing an AI-based decision support system for HF that integrates clinical, imaging, biomarker, and wearable data to enable risk stratification, early diagnosis, and disease progression prediction in both primary and secondary care settings. iCARE4CVD (Innovative Health Initiative, €9.9 million, 2023–2028) is applying AI to data from over one million patients to classify individuals into clinically meaningful subgroups, stratify risk, and predict individual treatment response across the full spectrum of CVD from early risk to established HF. AI4HF (Horizon Europe, €5.9 million, 2023–2027) is developing trustworthy AI for personalised HF risk assessment, integrating cardiac imaging, biomarkers, ECG, and clinical data through federated learning across multiple continents to ensure broader generalisability. CVDLINK (Horizon Europe, €9.7 million, 2024–2027) is building a privacy-by-design federated platform that integrates real-world data sources across seven European countries to develop and validate AI tools for diagnosis, prognosis, and risk assessment across seven cardiovascular conditions. ThrombUS+ (Horizon Europe, €8.1 million EU contribution, 2024–2027) is taking a different approach, developing a wearable AI-powered device for continuous point-of-care monitoring of deep vein thrombosis in high-risk patients, including those recovering from surgery or undergoing cancer treatment. These projects collectively exemplify the shift toward more granular, personalised risk assessment and underscore the need for diverse,

representative datasets and rigorous external validation to ensure reliable performance across different clinical settings and populations.

2.3 Personalised Treatment and Clinical Decision Support

AI is reshaping clinical decision-making by enabling more personalised and timely treatment strategies. Many cardiovascular AI applications go beyond data-driven pattern recognition by grounding predictions in physiological measurements and mechanisms, an approach sometimes described as physiology-driven AI and closely related to the concept of computational modelling and digital twins (DTs) of the cardiovascular system [15]. In conditions such as IHD, stroke, and HHD, AI models could identify which patients are most likely to benefit from specific interventions, optimise drug selection and device settings, and anticipate individual therapeutic response or adverse effects [16]. In IHD, CT-derived fractional flow reserve (CT-FFR) exemplifies physiology-driven AI: computational fluid dynamics models, accelerated by AI-based segmentation of coronary anatomy from CT images, derive functional blood flow information to guide revascularisation decisions. It is worth noting, however, that in many current implementations, the AI contribution is primarily in automated image segmentation, rather than in the functional modelling itself; more transformative applications, such as AI-based surrogates of fluid simulations or AI-informed device design, remain largely investigational. Similarly, AI-assisted planning tools for structural heart interventions such as left atrial appendage (LAA) occluder implantation use automated extraction and characterisation of patient-specific anatomy to determine optimal device size and implantation position for each individual's geometry. In stroke care, automated lesion detection supports time-critical reperfusion decisions. Machine learning models analysing EHRs are also improving the management of hypertension by predicting treatment resistance and supporting medication adjustment [17].

Several EU-funded initiatives are advancing these applications. GEMINI (Horizon Europe, €10 million, 2023–2029) is creating multi-scale DTs of ischaemic and haemorrhagic stroke patients to support treatment selection. NextGen (Horizon Europe, €7.6 million, 2024–2028) is developing AI tools for genome-centric multimodal data integration to personalise cardiovascular therapies. TARGET (Horizon Europe, €7 million, 2024–2028) is building virtual twin models and AI decision-support tools for the full pathway of AF-related stroke, from prevention and acute management through to rehabilitation. SMASH-HCM (Horizon Europe, €8.5 million, 2024–2027) is developing a hybrid DT platform that integrates biophysical models and data-driven analytics for personalised stratification and management of hypertrophic cardiomyopathy, one of the leading causes of sudden cardiac death in young people. EuroHeartPath (Innovative Health Initiative, €15 million EU contribution, 2025–2030) is conducting 18 pathfinder studies on AI-powered diagnostics, digital health tools, and robotics to optimise detection, diagnosis, and treatment of HF, AF, and coronary disease. GRACE (Innovative Health Initiative, €12 million EU contribution, 2025–2029) takes a systems-level perspective, using AI and digital solutions to improve the end-to-end clinical management pathway for CVD, fostering multidisciplinary care coordination and earlier personalised intervention. Collectively, these efforts aim to enhance clinical decision support, reduce unnecessary interventions, and promote more equitable cardiovascular care across Europe.

2.4 Healthcare System Optimisation

AI's capacity to analyse real-time and historical health data makes it a powerful tool for improving the responsiveness, efficiency, and resilience of healthcare systems. In the hospital setting, AI combined with lean management methodologies can optimise clinical workflows, forecast patient

admissions, anticipate peaks in care demand, and help allocate limited resources such as beds, staff, and critical care units. For cardiovascular care, this capability holds clear relevance: acute events such as myocardial infarctions, strokes, and hypertensive crises require rapid intervention and coordinated emergency response. AI can help optimise the functioning of cardiac care networks by forecasting surges, supporting triage decisions, and informing ambulance dispatch or catheterisation laboratory (cath-lab) activation based on incoming data streams. An emerging approach is the use of DTs of hospitals, which create virtual replicas of physical facilities to simulate patient flows, test operational scenarios, and optimise resource allocation with minimal risk. The Cortex initiative at Hospital Sant Joan de Déu in Barcelona[36] exemplifies this approach: a command centre that provides real-time visibility into bed occupancy, surgical schedules, intensive care unit (ICU) capacity, and patient monitoring across the hospital. By comparing individual patient data against hundreds of similar cases using AI, the system can anticipate complications and support proactive decision-making, including earlier transfer of stable cardiac patients from intensive care to general wards.

EU-funded initiatives are advancing these capabilities more broadly. AICCELERATE (Horizon 2020, €9.2 million, 2021–2024) developed a Smart Hospital Care Pathway Engine that uses AI to optimise patient flow management in emergency and surgical units, tested across five European hospitals including Hospital Sant Joan de Déu. HosmartAI (Horizon 2020, €10 million, 2021–2024) created an open integration platform for deploying AI and robotics across hospital operations, with eight large-scale pilots covering areas including CVD, cancer diagnostics, and rehabilitation. Looking ahead, the EU4Health flagship initiative on AI and health data for cardiovascular health (EU4H-2026-SANTE-PJ-04, €20 million) will support the validation and scale-up of mature AI applications for risk prediction, early detection, personalised prevention, treatment, and rehabilitation across the cardiovascular care continuum, while building a trusted European health data ecosystem. Beyond hospitals, AI also shows promise for improving emergency medical services. AI4EMS[37] (Horizon 2020, €1.5 EU contribution, 2018-2020) explored AI to assist ambulance call handlers in identifying out-of-hospital cardiac arrests, reducing delays in care. More broadly, projects using AI to model emergency department admissions and ICU occupancy show that data-driven systems can support proactive planning and mitigate bottlenecks[38]. Despite this, there is limited evidence of large-scale deployment focused specifically on cardiovascular emergencies. Given the high burden and time-sensitivity of these events, this is an area where further investment would be both strategic and impactful. A comparable gap exists in primary care. Beyond the emerging use of automatic transcription tools to reduce documentation burden, AI applications aimed at optimising resource allocation, triaging cardiovascular risk in patient lists, or prioritising referrals remain limited in primary care settings. This is a significant omission given that primary care is where cardiovascular risk is most commonly first identified and where earlier, more systematic intervention could prevent a substantial share of hospitalisations and adverse events.

AI can also support healthcare professionals directly. Clinical documentation is a major contributor to burnout, and this burden has been identified as a key driver of staff attrition [18]. AI-powered

[36] Liquid Hospital | SJD Barcelona Children's Hospital

[37] Artificial Intelligence for Emergency Medical Services: a smart digital assistant for faster and more accurate cardiac arrest recognition during emergency calls | H2020 | CORDIS | European Commission

[38] Prediction of emergency department presentations for acute coronary syndrome using a machine learning approach | Scientific Reports

ambient documentation tools, which automatically generate clinical notes from consultations, have shown consistent reductions in documentation time and clinician workload in early studies [19][20]. Beyond documentation, AI can improve how clinicians access and synthesise medical knowledge, helping them retrieve relevant evidence, guidelines, and patient-specific recommendations at the point of care [21]. The European Commission has recognised this potential: the 2025 Horizon Europe work programme includes a dedicated call (GenAI4EU, HORIZON-HLTH-2025-01-CARE-01) for the development of generative AI virtual assistant solutions to support healthcare professionals, covering use cases from clinical decision support to information retrieval.

By integrating predictive AI into hospital operations and regional emergency planning, health systems can move from reactive crisis management to anticipatory, data-informed responses. This not only improves patient outcomes but also addresses chronic systemic pressures, such as workforce shortages and ICU overcrowding, by allowing more intelligent deployment of available resources. The same logic applies to primary care, where AI-supported resource optimisation could help manage growing patient lists, reduce unnecessary referrals, and ensure that cardiovascular risk is identified and acted upon earlier. Such process optimisation is essential if Europe is to sustain its public-oriented healthcare systems, which represent distinctive EU values of universal access and solidarity, and which face growing demographic and financial pressures.

3 Path to Implementation: Challenges and Mitigation Strategies

While AI holds substantial promise for cardiovascular care, significant barriers remain between technological potential and widespread clinical adoption. These barriers span regulatory complexity, data infrastructure, evidence generation, trust, and organisational readiness. They are deeply interconnected. In practice, the implementation of AI in cardiovascular care follows a multi-stage pathway. Early-stage innovation typically emerges from academic research and startup ecosystems, where algorithms are developed and technically validated. Subsequent phases involve pre-clinical and clinical validation, regulatory approval, health technology assessment, and integration into clinical workflows. Barriers arise at every stage, and understanding where they occur is essential to addressing them effectively.

Through a combination of regulatory frameworks, data governance instruments, funding programmes, and implementation support, the EU has constructed a strategic response that maps onto each stage of this pathway. This section examines these challenges and the corresponding mitigation strategies across five interconnected domains: regulatory harmonisation, data availability and infrastructure, transparency and validation, evidence and clinical utility, and trust and readiness.

3.1 Regulatory Harmonisation in the EU Landscape

A recognised barrier to AI deployment in cardiovascular care is the complexity of navigating multiple intersecting regulatory frameworks. The EU regulatory landscape for healthcare AI comprises both cross-sector legislation, including the AI Act and the Product Liability Directive, and healthcare-specific regulations including the Medical Devices Regulation (MDR), the In Vitro Diagnostic Regulation (IVDR), the Health Technology Assessment Regulation (HTAR), and the EHDS. These frameworks govern different but overlapping aspects of AI-enabled medical technologies: algorithmic risk and transparency, product safety and clinical performance, liability for harm, clinical value assessment, and data access and governance. Developers and healthcare institutions must navigate these requirements in concert, and clear guidance on their interplay is essential. A key difficulty, however, lies less in the content of these regulations than in how to navigate them in practice. Unlike the FDA, which offers structured early dialogue between developers and regulators, the EU system has historically relied on notified bodies to implement regulatory requirements, without a comparable mechanism for pre-submission engagement. Inconsistent interpretation of MDR requirements across notified bodies further compounds this uncertainty. The Commission has recognised this gap: its December 2025 proposal to revise the MDR and IVDR (COM(2025) 1023 final) introduces a formal legal basis for structured pre- and post-submission dialogue between manufacturers and notified bodies, as well as a new breakthrough device designation providing priority review and early regulatory engagement for innovative technologies (MDCG 2025-9).

3.1.1 The AI Act

The AI Act (Regulation (EU) 2024/1689) establishes a risk-based approach to AI governance, classifying systems into risk categories and imposing correspondingly proportional obligations. Most healthcare AI applications — diagnostic tools, clinical decision support systems, patient monitoring — fall under the high-risk category, where "the stakes for life and health are particularly high" and "increasingly sophisticated diagnostic systems and systems supporting human decisions should be reliable and accurate." The high-risk classification triggers a comprehensive set of pre-market and post-market obligations that apply throughout the product lifecycle, from data governance and technical documentation to transparency, human oversight, robustness, and post-market surveillance. High-risk systems face strict requirements across the AI value chain, with distinct obligations

for providers (risk management, robustness, conformity assessment) and deployers (human oversight, monitoring, incident reporting, fundamental rights impact assessment). This distribution of responsibility is particularly significant in healthcare, where the same AI tool may be developed by a technology company, procured by a hospital, and used by a clinician, with each actor carrying distinct legal obligations. The AI Act applies jointly with sectoral legislation such as the MDR and IVDR. For AI systems that qualify as medical devices, both frameworks apply: the MDR/IVDR governs clinical safety and performance, while the AI Act addresses AI-specific risks including transparency, human oversight, and algorithmic robustness. This articulation reflects the framework currently in force; as noted above, the Commission proposal (COM(2025) 1023) may affect how these obligations interact. Table 3 summarises how these requirements align across key compliance areas.

Table 3: Summary of AI Act requirements for medical AI systems and their relationship with existing regulatory frameworks.

Compliance Area	**AI Act Requirements**	**MDR/IVDR & EHDS Interplay**
Data Governance	Training, validation, and testing datasets must be relevant, representative, and appropriately documented.	EHDS establishes the legal and interoperability framework for lawful data access; actual availability depends on Member State implementation.
Transparency	Record-keeping, traceability, and clear instructions for use including capabilities, limitations, and intended purpose.	MDCG 2025-6 enables integration of AI Act transparency obligations into existing MDR/IVDR documentation processes.
Human Oversight	Systems must enable users to understand outputs, override recommendations, and intervene when necessary.	Complements MDR/IVDR emphasis on clinical user responsibility; reinforces AI as decision-support rather than autonomous decision-maker.
Risk Management	Lifecycle risk management addressing health, safety, and fundamental rights, including AI-specific risks.	Extends existing MDR/IVDR risk management (ISO 14971) to cover algorithmic bias, data drift, and cybersecurity.
Post-Market Surveillance	Ongoing performance monitoring; serious incident reporting to competent authorities.	Extends MDR/IVDR vigilance obligations to include AI-specific monitoring (drift detection, bias emergence).
Conformity Assessment	High-risk AI requires conformity assessment; medical devices can use existing MDR/IVDR notified body procedures.	Single assessment pathway for AI Act and MDR/IVDR compliance reduces duplication.

Source: own elaboration.

3.1.2 Medical Devices and In Vitro Diagnostic Regulations

AI systems that meet the definition of a medical device—software intended for diagnosis, prevention, monitoring, prediction, prognosis, treatment, or alleviation of disease—fall under the MDR or IVDR. Both regulations employ risk-based classification systems, with higher-risk devices requiring conformity assessment by independent notified bodies. The MDR and IVDR mandate rigorous clinical evidence, continuous post-market surveillance, and traceability through the Eudamed database and unique device identification system. For AI-based medical devices, conformity assessment must address both traditional device requirements and AI-specific considerations. MDCG 2025-6, jointly adopted by the Medical Device Coordination Group and the AI Board, provides guidance on integrating AI Act obligations into existing MDR/IVDR quality management systems. This supports a more integrated conformity assessment approach across both frameworks and aims to reduce duplication and administrative burden.

3.1.3 The Digital Omnibus Package

The EU is actively working to streamline this regulatory landscape. The Digital Omnibus package (November 2025) represents the Commission's most significant effort to reduce complexity, responding to concerns in the Draghi Report about innovation barriers. Key measures relevant to healthcare AI include:

- Postponed application of certain high-risk AI provisions, linked to the availability of harmonised standards, common specifications, or guidelines: once the Commission confirms their availability, the high-risk rules will apply six months later for Annex III systems and twelve months later for systems embedded into regulated products (Annex I), with fixed long-stop dates of 2 December 2027 and 2 August 2028 respectively.
- Extended transitional periods for general-purpose AI transparency requirements.
- Expanded regulatory sandbox provisions, including at EU level.
- Extension to small mid-cap enterprises of simplified compliance measures currently available to small and medium-sized enterprises (SMEs).
- New legal basis (Article 4a) for processing sensitive personal data for bias detection and correction.
- Streamlined conformity assessment enabling single application and assessment under both AI Act and MDR/IVDR / Further clarification of the interplay between the AI Act and the MDR/IVDR, confirming that medical device manufacturers can rely on the MDR/IVDR conformity assessment procedure to demonstrate compliance with both frameworks.
- A shift in AI literacy obligations, requiring the Commission and the Member States to foster AI literacy, instead of enforcing an unspecified obligation on providers and deployers, while training obligations for high-risk deployers remain.
- Non-legislative support measures including an AI Act single information portal and service desk to assist developers and deployers in navigating compliance requirements.

The Commission emphasises that "simplification does not mean softening standards." The package aims to reduce administrative burdens by at least 25% for all businesses (35% for SMEs) by 2029. MedTech Europe has welcomed the intent to streamline legislation while noting that concerns about unclear and duplicative concepts remain to be addressed.

3.1.4 Regulatory Sandboxes

Further support comes from AI regulatory sandboxes, controlled environments where developers can test innovative AI systems under regulatory supervision before market deployment. Under Article 57 of the AI Act, all Member States must establish at least one operational sandbox by 2 August 2026. For healthcare AI, sandboxes offer opportunities to receive direct regulatory guidance during development, test algorithms with real-world clinical data, and obtain documented engagement informing future compliance. SMEs and startups receive priority access and free participation. In December 2025, the Commission released a draft Implementing Regulation[39] detailing sandbox operation, including provisions for sandbox plans, documentation, and exit reports. The Commission has also proposed an EU-level sandbox under the AI Office's competence, with strengthened cross-border cooperation between national sandboxes.

3.2 Data Availability and Infrastructures

The development and validation of AI for cardiovascular care depends fundamentally on access to large, diverse, and high-quality health datasets. Training algorithms to detect early disease, stratify risk, or predict treatment response requires data that spans populations, institutions, and clinical contexts. Yet, health data in Europe remains highly fragmented, siloed within hospitals, regions, and Member States, often stored in incompatible formats, and subject to inconsistent interpretations of data protection rules. This fragmentation is a structural barrier to AI development: without access to representative data, algorithms risk poor generalisability, embedded bias, and limited clinical utility.

3.2.1 Fragmentation of Health Data in the EU

EHRs across Member States use different terminologies, coding systems, and data structures, making cross-border data aggregation for AI development exceptionally difficult. Even within institutions, inconsistent data curation, annotation practices, and incomplete longitudinal follow-up limit the utility of existing records for training and validating AI models. Differences in governance practices, institutional capacity, and interpretations of data protection requirements can create uncertainty for health data sharing across institutions and Member States and often result in overly cautious approaches that impede legitimate data use, even when institutions wish to collaborate.

Work to overcome these challenges began before the introduction of the EHDS. Work on a European EHR exchange format (xEHR) has been underway through a series of EU-supported initiatives, establishing common standards for the cross-border exchange of priority data categories. The EHDS Regulation now provides the legal basis for scaling this work. Under Article 15, the Commission is required to adopt implementing acts specifying the technical architecture of the xEHR by March 2027.

The challenge extends to routine clinical practice. In many hospitals, clinicians lack simple, secure, and efficient tools for exchanging clinical information with colleagues across departments or institutions. In time-critical situations, medical images, ECG tracings, and other clinical data must be shared rapidly, yet institutional IT systems often fail to support this need effectively. In practice,

[39] https://digital-strategy.ec.europa.eu/en/consultations/commission-seeks-feedback-draft-implementing-act-establish-ai-regulatory-sandboxes-under-ai-act

clinicians sometimes rely on informal communication channels to exchange medical information rapidly in time-critical situations, highlighting the need for secure, interoperable clinical communication tools. That such workarounds remain widespread reflects the gap between what clinicians need and what institutional IT systems currently provide. Addressing this gap is a prerequisite not only for AI-enabled care coordination but for safe and efficient clinical practice more broadly.

Beyond access, data quality poses a distinct challenge. High-quality AI development depends on data consistently coded using international terminologies such as SNOMED-CT for clinical terms and ICD-10 for diagnoses, with structured fields for procedures, medications, laboratory values, and outcomes. Cardiovascular care generates particularly complex data spanning imaging, electrophysiology, biomarkers, and longitudinal clinical observations, all of which must be harmonised for effective AI use. In practice, much clinical data remains in unstructured formats: free-text clinical notes, scanned documents, dictated reports, and inconsistently coded entries that require significant processing before use in AI training or validation. Furthermore, training data that underrepresents certain populations, whether by age, sex, ethnicity, socioeconomic status, geographic region, or comorbidity profile, risks producing models that perform poorly or inequitably when deployed in diverse clinical settings.

3.2.2 The European Health Data Space

The EHDS, which entered into force in March 2025, represents the EU's most ambitious effort to address data fragmentation. The regulation establishes a legal, governance, and interoperability framework for health data exchange across Member States, with provisions for both primary use (facilitating individuals' access and control over their personal health data with seamless cross-border sharing) and secondary use (enabling authorised researchers, public health authorities, and AI developers to apply for access to health data for research, innovation, regulatory, and policy purposes under strict privacy and security standards).

For AI development, the secondary use provisions are particularly significant. The EHDS creates a legal basis under which authorised actors can apply for access to electronic health data for purposes including training, testing, and validating AI systems. Central to this framework is HealthData@EU, a decentralised EU-wide infrastructure that connects Health Data Access Bodies (HDABs) established in each Member State. Each HDAB is responsible for processing and assessing secondary use applications against defined criteria, issuing data permits, ensuring data is provided in anonymised or pseudonymised form where appropriate, and maintaining secure processing environments. HDABs must also establish and maintain national dataset catalogues and inform the public about data uses.
The regulation mandates interoperability standards, including the European EHR exchange format, to reduce technical barriers to cross-border data access. The TEHDAS2 Joint Action is developing technical specifications and guidelines to ensure health data can be accessed securely across borders, while the SHAIPED project, funded under the Digital Europe Programme and starting in March 2025, pilots the development, validation, and deployment of AI models using the HealthData@EU infrastructure, specifically supporting HDABs in establishing AI pathways for medical device development.

For cardiovascular AI, this framework opens significant opportunities. Large-scale registries, imaging archives, and longitudinal EHRs could become accessible for algorithm training and external validation through authorised access pathways, enabling models to be tested across diverse populations and healthcare settings. Cross-border access would support research into rarer cardiovascular

conditions and improve the representativeness of training datasets. The ability to link clinical, imaging, and genomic data under appropriate governance could accelerate precision approaches to cardiovascular risk prediction and treatment selection.

The EHDS establishes rights, obligations, and governance structures; it does not itself make data available. Actual data availability depends on implementation by Member States and data holders. Implementation is phased: most provisions on secondary use under Chapter IV apply from March 2029, while specific categories of data, such as genomic and other omics data, are subject to application from March 2031. Within the first two years, Member States must establish their HDABs and digital health authorities. These timelines govern the legal and governance framework; national and institutional initiatives may enable earlier access under existing legal bases.

3.2.3 European Health Data Infrastructures

The Commission has invested substantially in European health data infrastructures that go beyond governance frameworks, providing the actual computing capacity, federated data access, and interoperability tools needed to develop and validate AI in health. Several of these are directly relevant to cardiovascular AI and are already operational or in active deployment.

The Virtual Human Twins (VHT) Initiative[40] is a flagship under the Apply AI Strategy, with over €100 million in Commission investment. It supports the development of patient-specific computational models integrating clinical, imaging, and physiological data across scales of human anatomy. Dedicated Horizon Europe research and innovation actions focus on integrated, multi-scale computational models of patient pathophysiology for personalised disease management, with cardiovascular applications among the primary use cases. A state-of-the-art Advanced VHT Platform, funded under the Digital Europe Programme and launched in June 2025, provides shared infrastructure for the integration, validation, and scaling of these models, offering researchers and clinicians access to supercomputing capacity, synthetic data, and open-source specifications in a secure, privacy-preserving environment.

The INDICATE project[41], co-funded under the Digital Europe Programme, deploys a pan-European federated infrastructure for intensive care unit data. It supports the development and clinical evaluation of machine learning models for the early detection of organ failure, including cardiovascular, based on time-series patient data collected across participating institutions, with an explicit focus on accounting for regional, sex, and minority differences in model development and validation.

In the genomics domain, the 1+ Million Genomes initiative and its implementation vehicle, the Genomic Data Infrastructure project, are building a federated, secure European infrastructure for genomic and corresponding clinical data across 20 Member States. The Genome of Europe project[42], co-funded under the Digital Europe Programme with 49 partners across 27 countries, is establishing a pan-European reference database of at least 100,000 representative genomes. Its Common and

[40] https://digital-strategy.ec.europa.eu/en/policies/virtual-human-twins: Horizon Europe WP23-24 topic: Integrated, multi-scale computational models of patient patho-physiology for personalised disease management

[41] https://indicate-europe.eu/use-cases/early-detection-of-organ-failure/

[42] https://framework.onemilliongenomes.eu/common-complex-diseases

Complex Diseases use case focuses on decision-support tools based on polygenic risk scores, with direct applications to cardiovascular risk prediction and personalised prevention.

3.2.4 Computing Infrastructures: AI Factories

Building on these data infrastructures, the EU is also investing in the computing capacity needed to put them to use. The AI Factories initiative, part of the AI Continent Action Plan launched in April 2025, builds on the existing network of EuroHPC supercomputers to create dynamic ecosystems integrating AI-optimised supercomputing, data resources, programming facilities, and human capital. Nineteen AI Factories have been launched under the EuroHPC Joint Undertaking, with 17 focusing on healthcare among other topics. These facilities give startups, SMEs, researchers, and industry access to supercomputing resources for training, developing, and improving AI models.

Several AI Factories have explicit healthcare focus areas. Finland's LUMI AI Factory concentrates on manufacturing, health, life science, and communication technologies. Italy's IT4LIA focuses on agritech, cybersecurity, healthcare, and education. Spain's BSC AI Factory, built around the MareNostrum 5 supercomputer, emphasises health, climate, agriculture, and energy applications. Health data infrastructures funded through the DIGITAL Programme will link with these AI Factories, advancing the objectives of both the Apply AI Strategy and the EHDS.

The Data Labs initiative, to be established as part of the AI Factories, will bring together and federate data from different factories covering the same sectors, linking to Common European Data Spaces including health. These labs will offer services including data cleaning, enrichment, standardisation, and interoperability tools, helping to bridge the gap between raw health data and AI-ready datasets.

3.2.5 Federated Approaches and Early Implementation

Until the EHDS governance framework is fully operational, data access for AI development will continue to depend on institutional capacity, bilateral agreements, and federated approaches that allow algorithms to be trained across sites without centralising sensitive data.

Projects such as AI4HF and iCARE4CVD are already demonstrating how federated learning can enable multi-site collaboration under current constraints. A comparable model is emerging in cancer imaging through EUCAIM[43], the European Federation for Cancer Images, which has built a federated infrastructure connecting over 88 imaging datasets across nine cancer types and is in the process of transitioning to a permanent European Digital Infrastructure Consortium[44] (EDIC) with planned integration into the HealthData@EU framework. While focused on oncology, EUCAIM illustrates the governance and technical architecture that federated cardiovascular imaging infrastructures could adopt. These approaches will remain relevant even as the EHDS matures, offering a complementary pathway for privacy-preserving AI development.

[43] Home - Cancer Image Europe

[44] European Digital Infrastructure Consortium - EDIC | Shaping Europe's digital future

In parallel, forthcoming EU-level actions under EU4Health will support early implementation in priority domains. The cardiovascular flagship action aims to anticipate the application of Chapter IV by facilitating the federation, standardisation, and reuse of high-quality cardiovascular datasets for AI development and validation, in alignment with the EHDS governance model.

3.2.6 Building Capacity Across the Ecosystem

Realising the potential of these frameworks requires substantial investment that goes well beyond institutional readiness. Data preparation, federated AI development, and the deployment of AI tools in clinical settings each demand different forms of capacity, technical, organisational, and human, that must be built in parallel and at scale across the entire ecosystem.

At the institutional level, preparing data for access under the EHDS framework, or for use in federated AI development, demands not only technical systems for data extraction, formatting, and secure transmission, but also dedicated professionals who can bridge clinical practice and data science. Biomedical engineers, clinical informaticians, health data managers, and data scientists are essential to ensure data is curated correctly, quality-controlled, and catalogued in interoperable formats. Many institutions currently lack this capacity, and building it will require sustained investment in workforce development, training, and infrastructure.

Beyond individual institutions, capacity gaps also exist at the level of health systems, regional networks, and national ecosystems. Change management, clinical engagement, and the practical integration of AI tools into care workflows are as important as technical infrastructure, yet they receive comparatively little attention in funding and policy discussions. AI tools that are technically sound but poorly integrated into clinical practice will not deliver value, regardless of the sophistication of the underlying data infrastructure.

LLMs and other AI tools are increasingly explored to assist with retrospective standardisation of EHRs, offering potential to extract structured information from legacy data at scale. However, these approaches introduce their own validation requirements and cannot substitute for prospective data quality improvements embedded in clinical workflows. Ensuring balanced, representative datasets will also require deliberate curation strategies, prospective collection designs, and targeted efforts to include underrepresented groups.

3.3 Transparency and Validation

3.3.1 Transparency Challenges

A particular challenge for cardiovascular AI is ensuring adequate transparency. Many AI systems operate as 'black boxes' where relationships between inputs and outputs are not readily interpretable. Clinicians are reluctant to act on recommendations they cannot verify, and transparency toward patients is important for maintaining trust in decisions affecting their care. This opacity can conflict with evidence-based medicine, which relies on clinicians understanding the basis of recommendations they act upon. Cases have emerged where models based their predictions on artefacts such as imaging equipment identifiers rather than clinically relevant features, errors only uncovered through subsequent explainability analysis.

The challenge extends beyond algorithmic interpretability to disclosure practices. Many commercially available AI tools lack adequate information regarding training and validation datasets,

making it difficult to assess robustness, potential biases, and generalisability. Key questions, such as which populations were included, how ground truth labels were established, and what performance was achieved in external validation, often remain unanswered. Healthcare professionals do not need to understand complex computational processes, but they do need to know what features influenced a decision, the model's confidence level, and conditions under which performance may degrade [3].

The absence of standardised benchmark datasets further limits an objective comparison between tools. Without agreed-upon benchmarks reflecting diverse European populations, performance claims cannot be independently verified, complicating procurement decisions and slowing evidence generation. This makes it difficult for healthcare institutions to compare products, for regulators to assess submissions, and for clinicians to know which tools they can trust. The AI Act addresses this directly, requiring providers of high-risk AI systems to ensure transparency through record-keeping, traceability, and clear instructions covering capabilities, limitations, and intended purpose, while deployers must be able to understand outputs and intervene when necessary. There is scope to build on these obligations by developing standardised disclosure formats that translate regulatory requirements into practical guidance for developers and clinicians alike.

3.3.2 Testing and Experimentation Facilities

A structural barrier to validation is the limited availability of environments in which AI tools can be rigorously tested before clinical deployment. Real-world or simulated settings where AI systems can be evaluated for safety, usability, and integration with care pathways remain scarce across most Member States.

The EU has taken steps to address this. The Testing and Experimentation Facilities (TEFs) for AI, including the health-focused TEF-Health, provide shared infrastructure for validating AI solutions across Member States, offering access to realistic datasets, interoperability testing, and simulated clinical environments. TEF-Health enables developers to test AI systems against diverse patient populations and clinical scenarios before seeking regulatory approval or clinical deployment, helping to identify performance gaps, biases, or integration challenges early in the development cycle.

Complementing this, the European Digital Infrastructure Consortium for Digital Twins in Healthcare (EDITH) focuses on advancing DT and biophysical modelling capabilities. These virtual representations of patients and physiological systems offer a pathway for testing AI algorithms in silico, reducing reliance on costly and time-consuming clinical trials for initial validation while maintaining rigorous safety standards.

3.3.3 Toward Standardised Benchmarks

Addressing validation gaps will require regulatory emphasis on disclosure, industry commitment to transparent reporting, and investment in shared benchmark datasets. The EU4Health Cardiovascular Flagship Action could play a catalytic role by developing reference datasets and validation frameworks for cardiovascular AI, establishing benchmarks that reflect the diversity of European populations and enabling objective comparison between tools.

Such benchmarks would serve multiple purposes: supporting regulatory assessment by providing standardised performance metrics, enabling healthcare institutions to make informed procurement decisions, facilitating post-market surveillance by establishing baselines against which real-world

performance can be compared, and accelerating research by providing common datasets for algorithm development and comparison.

3.4 Evidence and Clinical Utility

3.4.1 The Evidence Gap

A common challenge in healthcare AI is the disconnect between model performance and clinical utility. While rapid advances have produced models with impressive technical performance, their readiness for clinical use in cardiovascular care remains uneven. Many AI systems demonstrate strong results on retrospective datasets or narrowly defined tasks, yet provide limited support for real-world clinical decision-making. A recent review found that only 11 randomised controlled trials of AI in cardiology had been conducted through late 2024, despite more than 100 FDA-cleared applications already on the market [22]. Similarly, another systematic review found that of nearly 500 AI models for cardiovascular risk prediction, none had undergone independent external validation [23]. These findings underscore that strong performance in controlled settings does not guarantee clinical utility.

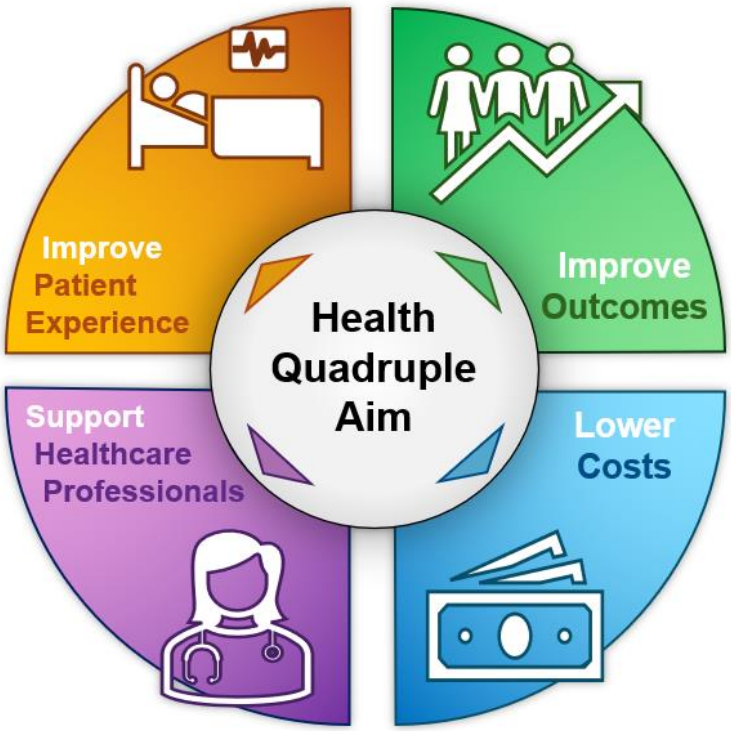
Part of this gap reflects a mismatch between how AI models are designed and how clinical decisions are made. Clinical reasoning in cardiovascular medicine typically relies on probabilistic judgement, longitudinal observation, and contextual information, often involving the balancing of competing risks and benefits rather than applying binary rules or fixed thresholds. AI models trained on simplified labels or proxy endpoints, and producing categorical classifications without calibrated uncertainty, may fail to reflect this complexity. Their outputs can be technically correct yet clinically difficult to interpret or act upon, and may even contribute to disagreement between clinicians and AI recommendations rather than supporting informed decision-making.

Moreover, models are typically optimised to maximise predictive accuracy on a defined outcome, yet clinical value depends on whether acting on predictions improves patient outcomes, integrates into care pathways, and does so without unintended harms or excessive resource use. A model that accurately predicts risk but does not change management, or that triggers interventions with marginal benefit and significant burden, may offer little real-world value despite strong technical performance.

The Healthcare Quadruple Aim [24] provides a useful lens for assessing whether technical innovation translates into meaningful system-level value (Figure 4). The framework organises health system improvement around four objectives: improving population health, enhancing patient experience, reducing costs, and supporting the wellbeing of healthcare professionals. Progress along one dimension should not come at the expense of the others. An AI system may improve clinical outcomes by detecting disease earlier, yet increase clinician workload because of poor user interface design, excessive alerts, or time-consuming data entry requirements. Conversely, a tool may enhance patient experience through personalised communication or remote monitoring, while being too costly or resource-intensive to scale sustainably. Highly accurate models may erode professional autonomy or trust if their outputs are opaque or difficult to integrate into clinical reasoning, undermining clinician wellbeing and adoption despite technical success. Applying the Quadruple Aim shifts the focus from isolated performance metrics to balanced value creation: successful clinical AI should improve outcomes without degrading care experience, reduce costs without increasing professional burden, and support clinicians rather than displacing or overwhelming them.

Beyond technical performance and clinical accuracy, economic value plays a critical role in determining whether AI tools are adopted into routine care. Health systems and reimbursement bodies must assess not only whether AI improves diagnostic performance, but also whether it reduces costs, improves workflow efficiency, or enables earlier detection that reduces downstream expenditure. Yet the economic evidence base remains thin: three recent systematic reviews found that studies with rigorous quantification of economic outcomes represent only a small fraction of the published literature, and that existing cost-effectiveness analyses rely predominantly on modelling assumptions rather than prospective real-world data [25] [26] [27]. Strengthening this evidence base through prospective studies designed alongside clinical validation is essential to close the gap between demonstrated clinical benefit and sustainable adoption.

Figure 4: The Healthcare Quadruple Aim.



Source: own elaboration.

3.4.2 Pre-Market Validation

The evidence base for many commercially available AI tools remains thin. While regulatory approval requires demonstration of safety and performance, the clinical evidence supporting CE-marked AI devices varies considerably in quality and scope [28]. Many tools receive approval based on retrospective validation studies using datasets from a limited number of centres, without prospective evaluation in diverse clinical settings or demonstration of impact on patient outcomes. External validation across different populations, imaging equipment, and care pathways is often absent or limited. Rigorous clinical validation does not necessarily require randomised controlled trials; equivalence studies, prospective registries, and real-world evaluation designs can all provide meaningful evidence of clinical utility. This creates uncertainty for healthcare institutions seeking to adopt AI tools: without robust evidence of clinical effectiveness and generalisability, procurement decisions become difficult, and the risk of deploying systems that underperform in local settings remains

high. The absence of head-to-head comparisons between competing tools further complicates decision-making, leaving institutions reliant on manufacturer claims rather than independent evidence.

3.4.3 Post-Market Evidence

Evidence generation remains a critical bottleneck. While numerous AI tools have reached regulatory approval or are close to deployment, robust evidence demonstrating improved patient outcomes is still limited. In many cases, validation focuses on technical performance rather than clinical impact, workflow integration, or downstream consequences. This creates a risk of premature deployment of systems that are not yet mature enough to support clinical decision-making in routine care.

The consequences of inadequate pre-market evaluation are becoming apparent. A recent analysis of 950 FDA-cleared AI-enabled medical devices found that 6.3% had been subject to recalls, with 43% of these recalls occurring within the first year of market authorisation, roughly double the rate observed for conventional devices [29]. Most recalled devices lacked pre-market clinical validation, and the most common causes were diagnostic or measurement errors. While this study examined FDA-cleared devices, similar patterns may emerge in Europe as AI deployment scales; the findings underscore the need for more rigorous pre-market evaluation and for post-market surveillance systems capable of detecting performance degradation, emerging biases, or unintended clinical consequences.

Post-market evidence generation is equally important but often neglected. AI systems may perform differently in real-world deployment than in controlled validation studies, due to differences in patient populations, data quality, workflow integration, or user behaviour. Continuous monitoring of performance, detection of drift, and assessment of clinical impact are essential to ensure that AI tools continue to deliver value after deployment. A further complication is that AI tools are rarely static: models are continuously retrained on new data, updated, and improved after deployment, meaning that published validation evidence may no longer reflect the performance of a tool currently in use. Version control, change documentation, and the threshold for re-evaluation after significant updates remain poorly standardised, creating gaps between what has been validated and what is actually being applied in clinical settings. The AI Act and MDR/IVDR impose post-market surveillance obligations on providers: monitoring performance, detecting serious incidents, reporting to competent authorities, and for AI systems specifically, tracking algorithmic drift and bias emergence. Yet systematic frameworks for post-market evidence generation remain underdeveloped, and many institutions lack the capacity to conduct ongoing evaluation. The EU4Health Cardiovascular Flagship Action includes provisions for validating AI applications across the care continuum, with potential to generate real-world evidence on clinical impact and health system effects.

3.4.4 Closing the Gap

Addressing the disconnect between model performance and clinical utility will require a shift in how AI tools are developed, evaluated, and monitored: greater emphasis on prospective validation in diverse settings, evaluation against the Quadruple Aim rather than technical metrics alone, attention to workflow integration and clinician acceptance, and systematic post-market evidence generation. Building this evidence base is essential for earning the trust of clinicians, patients, and health systems that will ultimately determine whether AI realises its potential to improve cardiovascular care.

3.5 Trust and Readiness

The successful adoption of AI in cardiovascular care depends not only on regulatory approval and technical performance, but on the willingness of clinicians, patients, and healthcare organisations to trust and use these tools in practice, and on the capacity of health systems to integrate, finance, and sustain them. Significant barriers remain across each of these dimensions.

3.5.1 Trust and Acceptance

Trust remains a significant barrier to AI adoption. Many clinicians are cautious about relying on AI-generated recommendations, particularly when the reasoning behind outputs is opaque, when outputs do not fit naturally into existing information flows and clinical workflows, or when systems have not been validated in similar settings. Concerns about accountability, specifically who bears responsibility when an AI-supported decision leads to harm, further contribute to hesitancy.

Patient acceptance is similarly uneven. While some patients welcome AI-assisted care as a route to faster or more precise diagnosis, surveys indicate a significant trust gap: although patients may be comfortable with AI freeing up clinician time, only around 29% report that they would trust AI for basic health advice[45]. Transparent communication about how AI is used, what role it plays in clinical decisions, and how human judgement remains central is essential to maintaining trust in the therapeutic relationship.

These trust deficits point to a deeper challenge: the core obstacle to AI adoption in cardiovascular care is often not technological capability, but the quality and design of human oversight across the full AI lifecycle. "Human-in-the-loop" is not a single safeguard but a set of distinct and interdependent roles, spanning the point of care, the governance of deployment, and the ongoing monitoring of models after deployment. Failure in any one of these domains undermines safety and accountability. Crucially, these practices are shaped by health system structures, reimbursement models, regulatory frameworks, and cultural priorities, and cannot be universally standardised. AI systems developed in one context may embed assumptions about resources and acceptable interventions that do not translate to other settings, a particularly important consideration for the diverse health systems of EU Member States [30]. When these conditions are not met, even technically strong AI systems may fail to gain acceptance or deliver value in practice.

Part of the problem lies in the disconnect between developers and clinical end-users. Many AI tools are designed by teams with limited exposure to the realities of healthcare delivery, resulting in systems that perform well in research settings but prove difficult to use in routine care. Bridging this divide requires closer collaboration throughout the development lifecycle, with clinicians involved as active partners in problem definition, dataset curation, and validation design. Effective oversight must be treated as a design specification that is deliberately adapted to local contexts, rather than exported as a universal model.

[45] KFF Health Misinformation Tracking Poll: Artificial Intelligence and Health Information | KFF

3.5.2 Consumer-Facing AI

The rapid uptake of patient-facing AI tools, including consumer wearables and general-purpose AI chatbots, is creating new pressures on cardiovascular care services. While these technologies can support earlier awareness of potential health issues, many are developed for commercial rather than medical purposes, and their evidence base often lags behind their widespread use.

Consumer wearables capable of detecting arrhythmias such as AF are increasingly recognised in clinical practice. The 2024 ESC guidelines incorporate consumer wearables into the AF detection pathway, and many clinicians are already advising at-risk patients to use them, with some initiating anticoagulation based on smartwatch-detected AF episodes [12] [31]. However, the guidelines emphasise that any alert requires confirmation by a competent clinician before a diagnosis is established or treatment initiated. The clinical value of these alerts is highly dependent on patient selection: false positives are more common in younger or low-risk populations where the pre-test probability of AF is low, while evidence suggests that positive predictive value improves substantially in older or higher-risk individuals [32] [33]. The converse problem of false negatives also deserves attention, as patients may not appreciate the inherent limitations of these devices, for instance that they are not designed to detect conditions such as myocardial infarction, potentially leading to false reassurance. In practice, alerts frequently generate false positives, leading to unnecessary patient anxiety, avoidable consultations, and specialist referrals, contributing to strain on already resource-constrained health services. At the same time, patients increasingly arrive at consultations with self-generated diagnoses or risk assessments derived from LLMs or other AI systems. Most patients lack medical training and may struggle to interpret probabilistic outputs, uncertainty, or contextual limitations. AI-generated information can therefore be misunderstood or overinterpreted, amplifying perceived risk rather than supporting informed decision-making.

These developments highlight the importance of improving public awareness of what consumer AI tools can and cannot do, providing guidance on appropriate use, and developing pathways for integrating validated patient-facing technologies into clinical care without overwhelming health services.

3.5.3 Financing and Institutional Capacity

Widespread AI adoption is further slowed by organisational and economic factors. Many healthcare institutions face limited budgets for digital innovation [34], and the business case for AI investment remains weak: most Member States lack reimbursement pathways for AI tools, leaving adoption largely dependent on hospital budgets or national innovation funds [35] [36]. Innovators face parallel pressures: initial MDR certification is estimated to cost €200,000–600,000 per product, with industry surveys reporting significant R&D capacity diverted from innovation to regulatory compliance and more than half of companies considering or initiating product withdrawals from the European market[46]. These requirements exist to ensure patient safety, but the burden falls disproportionately on start-ups and small companies, precisely the profile of many cardiovascular AI innovators.

At the same time, private investment is playing an important role in accelerating the development of AI-enabled healthcare technologies. Recent analyses indicate that digital health investment in

[46] https://www.snitem.fr/wp-content/uploads/2025/01/SNITEM_236.pdf

Europe reached approximately €4.8 billion[47], while healthcare AI funding in the United States reached €6 billion in 2024[48]. Despite this growing investment, only a small proportion of startups targeting health systems progress beyond early funding stages [37]. This reflects a persistent "valley of death" between technological innovation and clinical deployment, driven by the long timelines required for clinical validation, regulatory approval, and health system adoption. While clinical and regulatory development often takes 8–12 years [38] [39], venture capital investors typically expect returns within 5–7 years[49], creating structural tensions between innovation cycles and investment horizons.

Beyond financing, these challenges are compounded by uneven capacity across the healthcare landscape. Larger academic centres may have access to clinical informatics teams, data scientists, and dedicated digital health units capable of evaluating, deploying, and monitoring AI tools. Smaller hospitals, primary care networks, and health systems in less-resourced regions often lack this infrastructure. Similar disparities exist at national level, where differences in digital maturity, regulatory capacity, and healthcare funding mean that some Member States are far better positioned to adopt AI than others. Without deliberate efforts to address these gaps*, e.g. supporting piloting and evidence generation across several types of healthcare settings*, and the benefits of AI risk being unevenly distributed, potentially amplifying existing inequalities in cardiovascular care across Europe.

3.5.4 Workforce Readiness and Digital Skills

Addressing these disparities will require investment in workforce readiness, which remains a critical gap. Digital skills education and training across the EU are often insufficient, with particular shortfalls in advanced areas such as AI [40]. Most healthcare professionals have not been trained to work with AI in clinical settings, and medical curricula do not yet systematically prepare clinicians to evaluate AI outputs or recognise when such tools may fail. Beyond clinical training, hospitals also need biomedical engineers and data scientists working within clinical operations rather than exclusively in academic or research institutions, positioned within data management and governance structures to ensure AI tools are properly implemented, monitored, and maintained.

Building this capacity will require coordinated action across undergraduate and postgraduate training, continuing professional development, and the development of governance structures within healthcare organisations to oversee AI adoption responsibly. The EU is supporting these efforts through the DIGITAL and EU4Health programmes, which fund advanced training and upskilling initiatives in digital health and AI, co-designed with higher education institutions, research organisations, and industry. The Apply AI Strategy, launched in October 2025, includes provisions to strengthen the EU workforce to be AI-ready across sectors, with healthcare identified as a priority domain. A European Network of Expertise on AI Deployment in Healthcare is planned for establishment in late 2027 to consolidate guidelines and best practices.

These initiatives reflect a recognition that sustainable AI adoption requires not only technological infrastructure and regulatory clarity, but a workforce equipped to use these tools effectively and

[47] 2024 Europe Digital Health Funding Propelled to Record Highs by Mega Deals and AI - Galen Growth

[48] https://www.svb.com/trends-insights/reports/healthcare-investments-and-exits/healthcare-investments-and-exits-annual-2024/

[49] Based on experience reported by innovation ecosystem partners engaged through the European Innovation Council.

critically. Without parallel investment in human capacity, the potential of AI in cardiovascular care will remain unrealised. Beyond regulatory approval and technical validation, the uptake of AI tools in clinical practice will also depend on health system factors such as procurement processes, integration into clinical workflows, and national reimbursement arrangements. In the absence of clear pathways on these fronts, even well-validated tools are unlikely to move beyond pilots into routine care.

4 Use Cases on Major CVD subtypes

This section examines AI applications across three major CVD subtypes: IHD, cardioembolic stroke and AF, and HHD. These conditions together account for the majority of cardiovascular deaths and disability in Europe. For each subtype, the report reviews the epidemiological context and identifies the AI applications with the greatest potential for clinical impact.

A panel composed of three AI experts and one cardiologist assessed these 14 high-potential applications against two dimensions: their current readiness for clinical use, based on the maturity of the evidence base and the degree of real-world validation, and their potential impact on population health, reflecting the benefits these tools could deliver if widely adopted. The results are summarised in Figure 17, which maps each application on a readiness-impact matrix and provides an at-a-glance overview of where the field currently stands.

4.1 Ischemic Heart Disease

4.1.1 Epidemiology and Risk Factors

IHD remains the leading cause of cardiovascular mortality in Europe, despite continuous advances in prevention, diagnosis, and treatment. According to the *ESC Cardiovascular Statistics 2021* [41], IHD accounted for roughly 1.6 million deaths across the WHO European Region in 2019, representing nearly half of all cardiovascular deaths. However, this burden is distributed unevenly: Central and Eastern European Member States exhibit age-standardised mortality rates more than triple those observed in Western Europe (Figure 5), reflecting persistent gaps in prevention, diagnosis, and access to specialist care [42].

Demographically, IHD incidence increases sharply with age and remains consistently higher among men, although the gap narrows after menopause. In women, the disease often presents with atypical symptoms and is underdiagnosed or diagnosed later, contributing to worse post-infarction outcomes. As the European population ages, the absolute number of IHD cases is expected to rise, even as age-adjusted mortality declines.

Across Europe, the main modifiable determinants of IHD mortality include high systolic blood pressure, elevated LDL cholesterol, hyperglycaemia, obesity, tobacco use, unhealthy diet, and physical inactivity. These factors frequently cluster in metabolic syndrome, a condition marked by insulin resistance, abdominal obesity, and chronic inflammation that sharply increases cardiovascular risk. The persistence of sedentary lifestyles, especially among younger and working-age populations, continues to drive this trend. According to Global Burden of Disease (GBD)[50] 2021 estimates, these risks account for the majority of IHD-related deaths [43]. Figure 5 (right panel) highlights high blood pressure and poor diet as the leading contributors, followed by hyperglycaemia, obesity, and tobacco use.

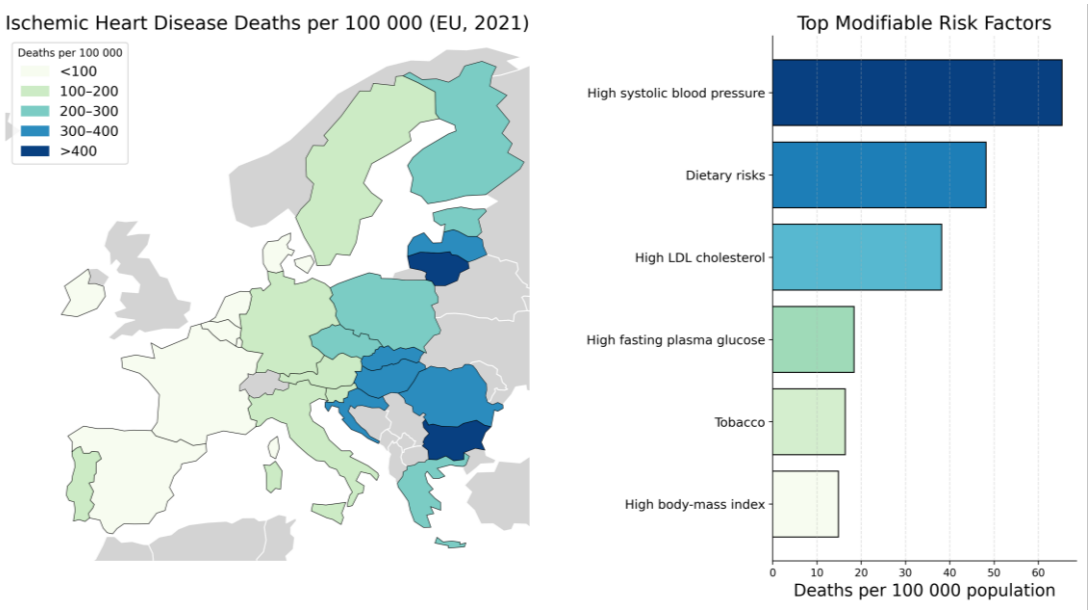
Additional exposures such as air pollution and alcohol consumption contribute indirectly by promoting hypertension and vascular dysfunction, further compounding the effects of primary metabolic

[50] *Global Burden of Disease (GBD)*

risk factors. Taken together, these patterns underscore the need for integrated prevention strategies targeting both behavioural risk factors and their systemic drivers [44].

Early detection and accurate risk stratification remain critical to reducing IHD mortality. More than half of IHD deaths occur in individuals without a prior diagnosis [45], revealing the limitations of current clinical risk models such as SCORE2 [46], which are based on population averages and often poorly calibrated for specific subgroups. Imaging biomarkers have become increasingly valuable for detecting subclinical disease. Coronary artery calcium (CAC) scoring, CT coronary angiography, and cardiac MRI markers of ischemia and ventricular remodelling enable quantification of structural and functional changes that precede overt disease [47] [48]. The use of AI in these modalities now allows automated, reproducible analysis, facilitating opportunistic risk assessment from non-cardiac CT scans and enabling large-scale screening initiatives [49], including in settings where specialist expertise is limited.

Figure 5: Ischemic heart disease deaths per 100,000 in the EU (left) and the main modifiable risks factors (right).



Source: Global Burden of Disease (GBD).

Complementing imaging, ECG and wearable sensors are emerging as scalable tools for continuous and remote cardiovascular monitoring. The integration of AI algorithms with ECG and photoplethysmography data supports the early identification of subtle conduction abnormalities, silent ischemia, and arrhythmic events that may signal underlying myocardial injury. Arrhythmias are not a primary cause of IHD but a frequent manifestation of it, arising from ischemia-induced electrical instability and post-infarction remodelling. Detecting these patterns early, particularly through wearable or home-based ECG monitoring, provides a pathway to identifying high-risk individuals before clinical symptoms appear [50] [51].

AI applications extend across the full cardiovascular care continuum. Beyond risk stratification and early detection, AI supports clinical decision-making by integrating imaging, laboratory, and clinical data; guides personalised treatment selection; and enables continuous disease monitoring and follow-up. By combining population-level risk information with individual physiological and imaging biomarkers, these technologies can enhance risk prediction, support targeted prevention, and inform more equitable health strategies across the EU. Such advances align with ongoing European

initiatives, including the *EHDS* and the *EU Non-Communicable Diseases Initiative*[51], which seek to harness digital innovation to reduce premature cardiovascular mortality and narrow the health gap between Member States.

4.1.2 High-Potential AI Applications

AI-Enhanced Echocardiography

Echocardiography is the most widely used cardiac imaging modality, offering real-time assessment of cardiac structure and function without ionising radiation. Unlike CT or MRI, ultrasound equipment is easily portable, relatively inexpensive, and widely deployed across healthcare settings, including primary care and resource-limited environments. However, echocardiographic assessment has traditionally been operator-dependent and time-consuming, with significant inter-observer variability that can affect diagnostic consistency.

AI is transforming echocardiography across multiple dimensions. Many of these developments are already on the roadmap of major imaging vendors, driven by competitive pressure and the demonstrable value of automation, meaning that AI-enhanced echocardiography is increasingly a clinical reality rather than a future opportunity. The most established application is automated measurement of left ventricular ejection fraction (LVEF), the single most important echocardiographic parameter for clinical decision-making in HF, myocardial infarction, valvular disease, and arrhythmias [52]. DL models can automatically trace endocardial borders and calculate LVEF with minimal user intervention, achieving accuracy comparable to expert cardiologists while reducing processing time by up to 77% [53]. A blinded randomised trial demonstrated that AI assessment of LVEF was superior to sonographer assessment, with fewer studies requiring substantial correction by cardiologists [54]. Beyond ejection fraction, AI can automate measurement of chamber volumes, wall thickness, Doppler parameters, and global longitudinal strain, reducing examination time and eliminating inter-observer variability [52] (Figure 6).

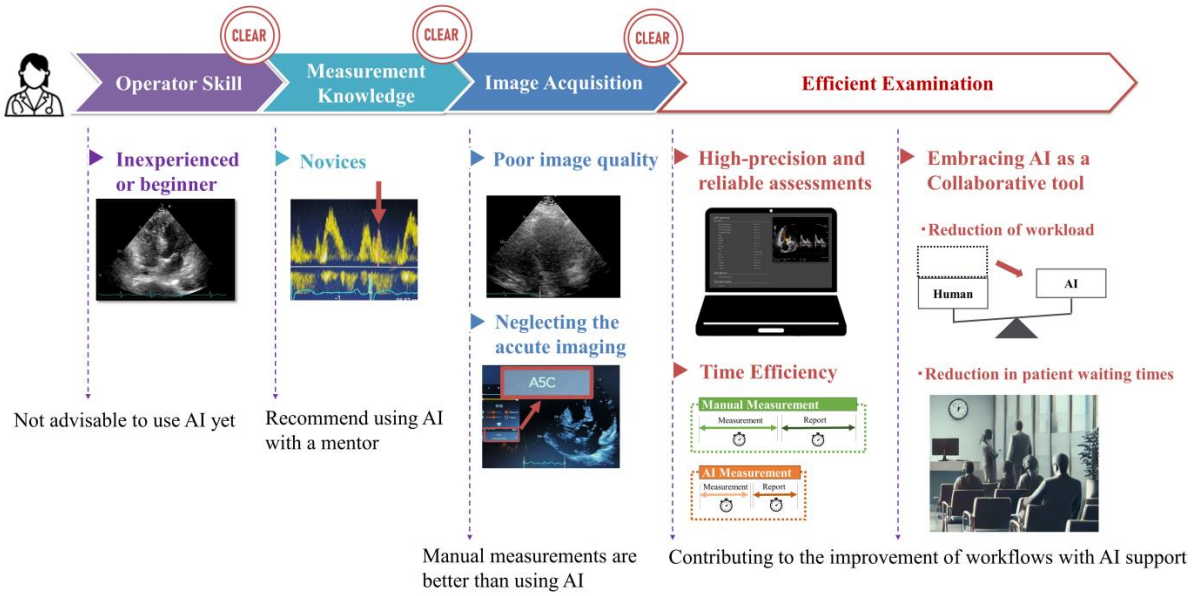
A particularly promising application is AI-assisted phenotyping of conditions that share overlapping echocardiographic appearances but carry different clinical implications. Cardiac amyloidosis, an infiltrative cardiomyopathy that can mimic other causes of increased wall thickness, is one example where improved phenotyping is clinically important, not least because of the recent emergence of effective disease-specific therapies. AI models trained on echocardiographic video clips have demonstrated high accuracy in distinguishing cardiac amyloidosis from phenotypic mimics, with external validation across 18 international sites achieving 85% sensitivity and 93% specificity [55]. More broadly, AI-based phenotyping of hypertrophic cardiac disease and its phenocopies represents a growing area of clinical relevance, enabling more precise differentiation between conditions that were previously difficult to distinguish on conventional criteria. Similarly, AI tools for detecting HF with preserved ejection fraction (HFpEF) have been developed and validated, addressing a condition that remains challenging to diagnose with conventional echocardiographic criteria [56].

Perhaps most significant for addressing access disparities is AI-enabled image acquisition guidance for non-expert operators. Prospective trials have demonstrated that nurses and other healthcare professionals without prior ultrasound experience can acquire diagnostic-quality echocardiographic

[51] Healthier together – EU non-communicable diseases initiative - Public Health

images when guided by AI-based software providing real-time feedback on probe positioning [57]. In one international study, novices using AI guidance achieved image quality non-inferior to expert sonographers for assessment of ventricular size and function [58]. This capability has significant implications for screening programmes and primary care settings where trained sonographers are scarce. AI-enhanced point-of-care echocardiography with handheld devices could enable HF screening by non-specialists, with studies showing that novices with only two weeks of training can detect reduced ejection fraction with high accuracy [59].

Figure 6: Strategies for the effective use of AI in echocardiography.



Source: Hirata, Y., and Kenya K., 2025 [52].

Challenges remain. Image quality significantly affects AI performance, and poorly acquired images can lead to erroneous measurements. Current guidance recommends that inexperienced operators should not rely solely on AI without mentorship, particularly during the learning phase. Algorithm performance may vary across vendors, patient populations, and imaging conditions, necessitating ongoing validation. Data privacy, clinician trust, and integration into clinical workflows remain barriers to widespread adoption.

In summary, AI-enhanced echocardiography represents one of the most promising avenues for equitable expansion of cardiovascular diagnostics. Unlike CT- or MRI-based tools, which require substantial infrastructure, potential radiation exposure, and specialist interpretation, targeted echocardiography can be deployed at the point of care with portable devices. AI reduces operator dependency, improves consistency, and may enable earlier detection of cardiac disease in settings where traditional expertise is limited. These characteristics make AI-enhanced echocardiography particularly relevant for narrowing disparities between well-resourced centres and underserved populations across Europe.

Expert Assessment

AI-enhanced echocardiography received a high readiness score, reflecting the availability of validated commercial products and integration into major vendor platforms. Impact was rated slightly lower: while the technology holds genuine promise for accelerating analysis and extending cardiac assessment to low-resource settings, real-world gains remain uncertain and experts expect its clinical value to grow as deployment matures.

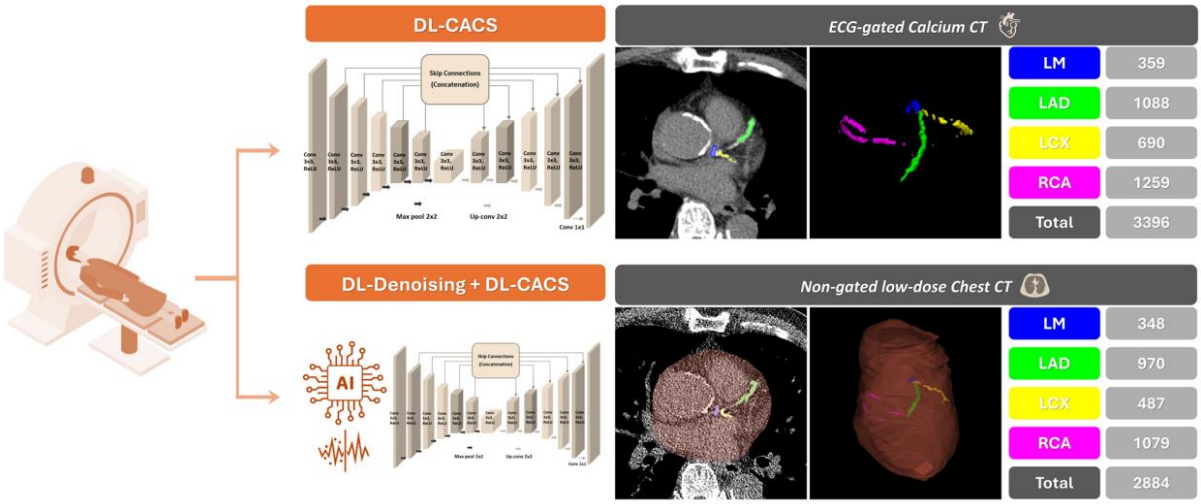
Coronary Artery Calcium Scoring

CAC scoring is one of the most clinically established methods for cardiovascular prevention and early diagnosis, and it remains the clearest example of an AI-driven imaging tool already transitioning into routine deployment. CAC quantification on CT, traditionally expressed as the Agatston score [60], has been validated as a robust and reproducible marker of subclinical atherosclerosis. Clinical guidelines endorse its use for refining preventive treatment decisions, particularly in asymptomatic individuals at intermediate risk, where it contributes one piece of a broader risk assessment picture alongside classical risk factors. Its clinical value lies in guiding decisions on preventive therapies such as statins rather than as a standalone diagnostic tool, with thresholds ranging from 0 (very low risk) to ≥1000 (very high-risk) embedded in clinical practice [49].

Historically, CAC scoring was performed manually or semi-automatically, which was time-consuming, operator-dependent, and therefore underutilised despite its prognostic value. AI has transformed this landscape by enabling rapid, accurate, and reproducible scoring. CNN and U-Net–based pipelines have demonstrated high agreement with manual Agatston scoring, while reducing processing time to seconds per scan [61][62]. A meta-analysis of 25 studies confirmed strong agreement between automated and manual CAC scoring (pooled $\kappa \approx 0.83$), reinforcing the robustness of AI-CAC across diverse datasets and protocols [48]. Such reproducibility underpins the growing consensus that AI-CAC is not just research-ready but clinically ready.

One of the most transformative opportunities lies in opportunistic CAC assessment on ECG-non-gated CT scans. Although the Agatston method was developed on gated cardiac CT, studies show high correlation between gated and non-gated CAC scores [63]. A recent multivendor validation study confirmed near-perfect performance of a fully automated DL system on ECG-gated CT and good to excellent performance on non-gated low-dose chest CT, with residual misclassification attributable largely to protocol differences rather than model failures [64] (Figure 7). This opens the door to dual-purpose screening strategies: for example, lung cancer screening programmes or oncologic surveillance often involve low-dose chest CT in older adults with a history of smoking, a population also at elevated risk for CVD. Integrating automated CAC scoring into these scans enables simultaneous assessment of cancer and cardiovascular risk, improving preventive care without additional imaging burden. Fully automated pipelines reduce processing time from minutes to seconds, making high-throughput evaluation feasible for screening programmes and large population studies. Commercial systems (e.g. Siemens AI-Rad Companion, Coreline AVIEW, Nanox AI HealthCCSng, Artrya DeepC) and standardised reporting frameworks such as CAC-DRS further support integration into daily practice.

Figure 7: CAC scoring on ECG-gated calcium CT and non-gated low-dose chest CT.



Source: Kim, S. et al. 2025 [64].

Challenges remain. Non-gated acquisition may underestimate Agatston scores, with some patients reclassified to lower categories compared with gated scans. Xie et al. reported that 9% of CAC-positive patients on gated CT were downgraded to CAC = 0 on non-gated scans [65]. To mitigate this, qualitative grading frameworks such as CAC-DRS [66] have been proposed, allowing visual classification of non-gated images into very low, mild, moderate, and severe categories, which mirror quantitative scoring and support clinical decision-making. Beyond technical considerations, access and equity pose important constraints. CT remains less available than ultrasound, particularly in primary care and resource-limited settings, and involves ionising radiation, limiting its suitability for repeated screening or younger populations. Prioritising CT-based AI applications without parallel investment in alternative modalities risks widening existing disparities. Ultrasound-based tools, which are cheaper, portable, radiation-free, and widely deployed, may offer greater potential for scalable, equitable early detection. AI-enhanced echocardiography, for example, can automate cardiac function assessment with accuracy comparable to expert cardiologists and is increasingly validated for use by non-specialist operators.

In summary, CAC scoring stands out as one of the most clinically mature AI applications in cardiovascular imaging. It combines decades of evidence with modern DL pipelines, reproducible validation, integration into guidelines, and growing commercial availability. The extension to non-gated CT imaging expands its role into opportunistic screening, particularly for lung cancer and oncology populations at elevated risk. AI-driven CAC scoring therefore exemplifies how AI can move from proof-of-concept to routine preventive cardiology.

Expert Assessment

CAC scoring was rated highly for both readiness and impact. The technology is already integrated into most dedicated cardiac CT scanners, and opportunistic scoring from routine thorax scans is increasingly common. The main limitation flagged by experts is inconsistent performance across centres. On impact, the ability to screen large populations for cardiovascular risk without additional

imaging burden was seen as the key driver, though efficient integration into clinical workflows remains a work in progress.

CT Plaque Analysis and CT-Derived Fractional Flow Reserve

While CAC scoring provides a robust estimate of overall calcified plaque burden, it does not capture the full complexity of coronary atherosclerosis. Cardiovascular risk is not only determined by the quantity of plaque but also by its composition, structure, and biological behaviour, referred to as plaque morphology and plaque dynamics. Vulnerable plaques, even when non-calcified or minimally stenotic, can lead to acute coronary events due to their propensity to rupture or erode. These factors are not reflected in calcium scoring and require more advanced imaging approaches.

AI methods have been developed to automatically segment coronary arteries, detect stenoses, and characterise plaque morphology. Reviews emphasise that AI enables automated CCTA analysis with reliable plaque quantification and reduced interobserver variability. These tools detect non-calcified low--attenuation plaque, positive remodelling, and other high-risk features linked to future acute coronary syndromes. Importantly, plaque morphology provides incremental prognostic information beyond calcium scoring alone: studies show that lesions with low-attenuation cores or positive remodelling carry elevated event risk even when CAC is low. In line with this, recent AI-driven plaque staging systems with improved long-term risk stratification have been proposed to adjust treatment intensity. [67] [68].

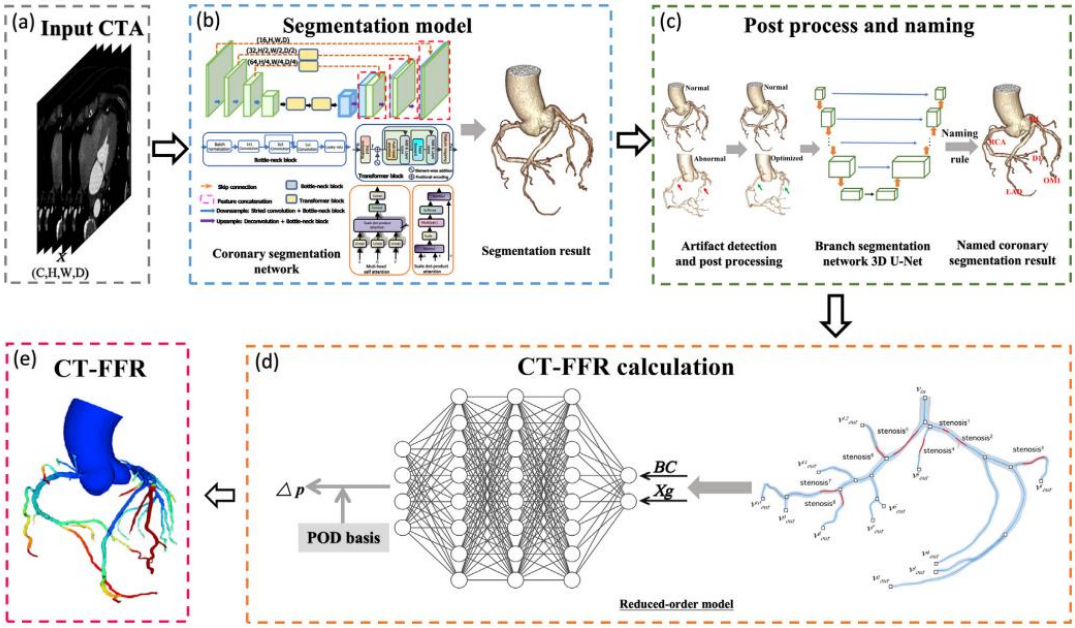
Beyond anatomical plaque characterisation, AI also supports functional assessment through non-invasive fractional flow reserve derived from CCTA (FFR-CT). Conventional FFR-CT relied on computational fluid dynamics (CFD), which is computationally expensive and limits scalability. Recent DL approaches have enabled rapid estimation directly from CT data, with diagnostic performance comparable to invasive FFR. Studies demonstrate that DL-based FFR-CT achieves strong correlation and agreement with invasive measurements while reducing computation times from hours to seconds [69]. Hybrid approaches combining physics-based modelling with neural networks further improve prediction robustness [70]. Systematic reviews confirm that DL-enabled FFR-CT enhances functional assessment beyond anatomical stenosis, improving diagnostic accuracy and guiding revascularisation decisions. Comparative analyses of commercial AI-based FFR-CT tools also indicate good reproducibility across platforms, although variability between vendors remains an important consideration [71]. This functional perspective is clinically important, since stenosis severity alone is an imperfect predictor of ischemia, and AI-based FFR-CT provides physiologic insights that support more precise treatment planning.

Recent evidence shows that DL–based CT-FFR achieves diagnostic accuracies greater than 0.8, with sensitivities and specificities often exceeding 90%. Computation time has been reduced from several hours with CFD-based approaches to under one minute with fully automated pipelines [72] [73] (Figure 8). Modern implementations integrate lumen and plaque segmentation with reduced-order flow modelling, yielding reproducible results across scanners and clinical sites. Automated CT-FFR has been successfully validated in multicentre studies, demonstrating strong correlation with invasive FFR ($r \approx 0.8$) and high success rates (>99%) even in routine and acute chest pain settings [72].

AI-based CT-FFR quantifies the haemodynamic significance of coronary lesions and, when combined with plaque characterisation from CCTA, enables a more comprehensive assessment of high-risk features such as thin fibrous caps, lipid-rich necrotic cores, and microcalcifications that are linked to plaque rupture and acute coronary syndromes [71]. Furthermore, the integration of AI-FFR with

traditional cardiovascular risk factors has been shown to improve prognostic accuracy for major adverse cardiovascular events (MACE), compared with anatomical assessment alone [72].

Figure 8: Pipeline of CT-FFR calculation.



Source: Guo, B. et al. 2024 [72].

Challenges remain. Accuracy decreases in heavily calcified lesions due to blooming and beam-hardening artifacts. Algorithm performance may vary with scanner type, reconstruction kernel, and patient characteristics such as heart rate or diabetes status. In that context external validation across populations and adherence to standardised acquisition and reconstruction protocols are essential for robust deployment. Challenges also extend beyond technical validation. The American Heart Association (AHA) scientific statement on AI in cardiovascular imaging underlines that adoption requires transparent model reporting, representativeness of training data, and adherence to FAIR and MIDaR principles for data quality and interoperability [74]. Lack of explainability, automation bias, and limited clinician training remain barriers to trust and integration into clinical workflow. Ethical and regulatory frameworks, including those under the MDR, emphasise traceability, accountability, and risk management in AI-driven diagnostic tools. As with CAC scoring, access and equity considerations apply. CT-based tools remain less available in primary care and resource-limited settings, involve ionising radiation, and require specialist infrastructure. Prioritising these applications without parallel investment in more accessible modalities risks widening disparities between healthcare systems and patient populations.

In summary, AI-driven plaque analysis and FFR-CT are more complex than CAC scoring but are rapidly moving toward clinical adoption. As underlined in recent evaluations, generalisability through external validation is essential, given heterogeneity in CT acquisition protocols, vendors, and populations. Commercial platforms such as HeartFlow, cFFR, and Siemens' AI-Rad Companion Cardiac CT are already being deployed in clinical practice in Europe, marking an important step toward broader adoption. AI-enhanced plaque analysis and CT-derived FFR represent the next frontier in coronary risk stratification after CAC. By integrating anatomical, morphological, and physiological information, these tools deliver more precise identification of at-risk patients and enable individualised preventive and interventional strategies. While CE- and FDA-cleared solutions demonstrate clinical

readiness, widespread and safe deployment depends on harmonised validation standards, cross-vendor benchmarking, and clinician training. Strategies for equitable access must be embedded early in the adoption process, ensuring that AI tools are tested across varied settings, supported by public infrastructure where needed, and integrated in a way that promotes transparency and clinical trust.

Expert Assessment

CT plaque analysis received a low readiness score, reflecting its largely research-based use and limited multi-centre clinical validation. Experts also raised questions about whether AI-based plaque characterisation will ultimately prove clinically relevant in routine practice, tempering expectations around its potential impact despite the theoretical value of identifying vulnerable plaques.

CT-derived FFR was rated more favourably on readiness, with commercial products already available, though access remains largely restricted to well-resourced or private settings. Impact was rated moderately, with experts noting that broader clinical benefit will depend significantly on cost reduction, and that current enthusiasm is partly driven by commercial marketing rather than established clinical evidence.

AI-Enhanced ECG and Wearable Sensing for Early Risk Detection

While AI-driven CT techniques provide detailed anatomical and physiological insight into coronary disease, electrocardiography remains the most widely available cardiovascular diagnostic test globally. Recent advances in DL have transformed the ECG from a reactive diagnostic tool into a predictive and continuous monitoring instrument. AI-enhanced ECG (AI-ECG) algorithms can detect subtle waveform abnormalities associated with ischemia, myocardial scarring, or early left ventricular dysfunction long before overt symptoms or imaging findings emerge [75].

Large-scale studies have demonstrated that deep neural networks trained on millions of standard resting ECGs can predict long-term cardiovascular mortality, incident myocardial infarction, and the future development of structural heart disease. Models such as the Stanford Estimator of ECG Risk (SEER) [76] have achieved discriminative performance comparable to traditional risk scores like SCORE2 [46] or ASCVD [77], while requiring no laboratory or imaging data. By leveraging routine, low-cost ECGs, AI enables scalable risk assessment in primary care and screening programs where advanced imaging may not be feasible [78].

In the context of IHD, AI-ECG methods have shown the ability to identify both acute and chronic ischemic signatures. DL models have demonstrated high diagnostic accuracy for detecting obstructive coronary artery disease and prior myocardial infarction from a single 10-second ECG, in some studies surpassing expert interpretation and enabling early referral for imaging confirmation [79]. Multimodal frameworks that combine ECG waveforms with traditional risk factors or clinical metadata have shown further improvement in risk stratification and prediction of MACE, outperforming

models based on demographics and comorbidities alone [78]. AI-based ECG analysis has also been extended to portable and wearable devices, supporting continuous, real-world monitoring of IHD. Single-lead or smartwatch-derived ECGs analysed by DL have demonstrated reliable detection of ischemic changes, arrhythmias, and repolarisation abnormalities in ambulatory conditions [80]. Beyond detection, longitudinal wearable data provide a foundation for dynamic risk monitoring, allowing continuous reassessment of cardiovascular status as physiology and lifestyle change. Such real-time surveillance could in principle enable adaptive prevention strategies and more timely therapeutic interventions, shifting the clinical paradigm from episodic testing to continuous cardiovascular health management.

Challenges remain. Data heterogeneity, motion artifacts, and varying device quality can affect signal reliability. Privacy and data governance remain major concerns, as ECG signals are inherently identifiable and may contain biometric signatures that require robust data protection frameworks. The lack of harmonised standards for training, validation, and reporting complicates regulatory approval and cross-vendor interoperability. Explainability and clinician trust are additional prerequisites for integration into clinical workflows, alongside transparent performance reporting and equitable validation across populations.

In summary, AI-enhanced ECG and wearable sensing complement imaging-based risk assessment by bridging the gap between population-level screening and individual diagnostics. While CAC scoring, plaque characterisation, and CT-FFR offer detailed anatomical and functional evaluation once structural disease is present, AI-ECG offers a scalable approach for early physiological risk profiling. It can detect subtle conduction abnormalities, silent ischemia, or repolarisation patterns linked to myocardial stress, which often arise downstream of hypertension, hyperlipidemia, or other risk exposures. These models do not detect atherosclerosis directly but may identify patterns statistically associated with future cardiovascular events, even in seemingly healthy individuals. As validation accumulates across populations and care settings, AI-ECG and wearable analytics are likely to play a growing role in preventive cardiology, particularly for the early detection of individuals at elevated risk for IHD.

Expert Assessment

Readiness and impact scores reflect a balance across the range of applications covered in this section, with impact rated higher than readiness overall. Automated ECG reading is a mature technology where AI offers incremental gains, while AI extraction of novel predictive signals remains under clinical evaluation. High-quality wearable sensors exist but remain expensive, limiting broad deployment. The high impact score reflects the potential of these tools for early diagnosis and continuous cardiovascular surveillance, particularly if device costs fall and screening pipelines become more efficient.

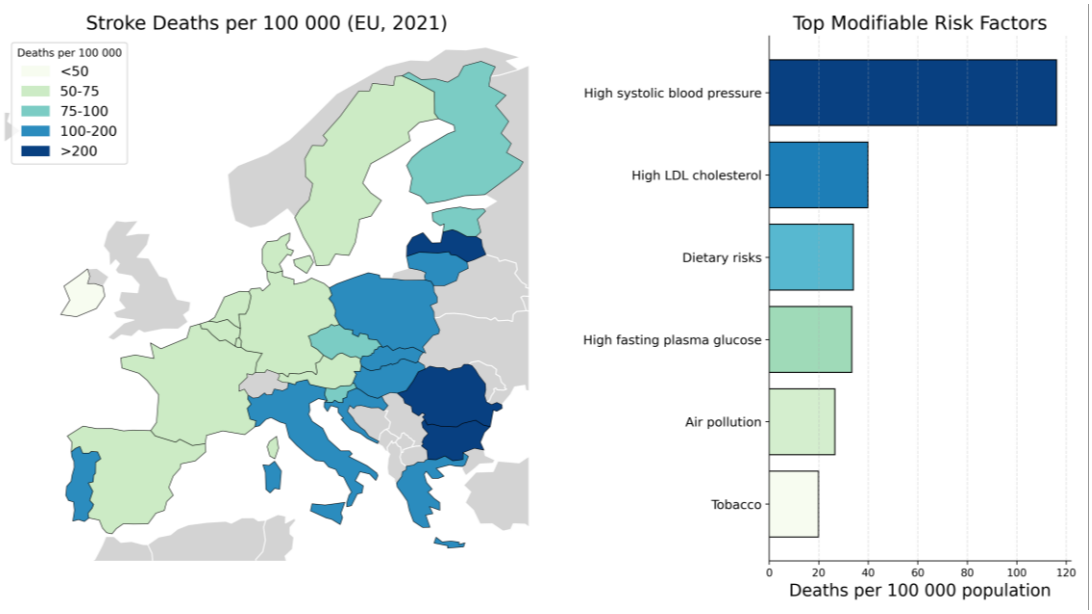
4.2 Cardioembolic Stroke and Atrial Fibrillation

4.2.1 Epidemiology and Risk Factors

Stroke is a leading cause of death and long-term disability worldwide. It is a heterogeneous condition, with three main subtypes: ischaemic stroke, caused by an obstruction of blood flow to the brain; intracerebral haemorrhage, resulting from bleeding within the brain tissue; and subarachnoid haemorrhage, characterised by bleeding into the space between the brain and the skull.

The burden of stroke varies substantially across Europe (Figure 9). Prevalence differs markedly between Member States, with Eastern European countries such as Bulgaria recording rates several times higher than those observed in Western and Southern Europe. Among subtypes, ischaemic stroke is by far the most common, followed by intracerebral haemorrhage and subarachnoid haemorrhage. Mortality patterns reflect similar regional disparities, with Bulgaria recording the highest death rates and Ireland among the lowest. The same east-to-west gradient is observed for stroke-related disability, measured both in years lived with disability and disability-adjusted life years. Since 1990, stroke prevalence has shown a significant downward trend in Europe, more pronounced for ischaemic stroke and intracerebral haemorrhage than for subarachnoid haemorrhage [81].

Figure 9: Stroke deaths per 100,000 in the EU (left) and the main modifiable risk factors (right).



Source: Global Burden of Disease (GBD).

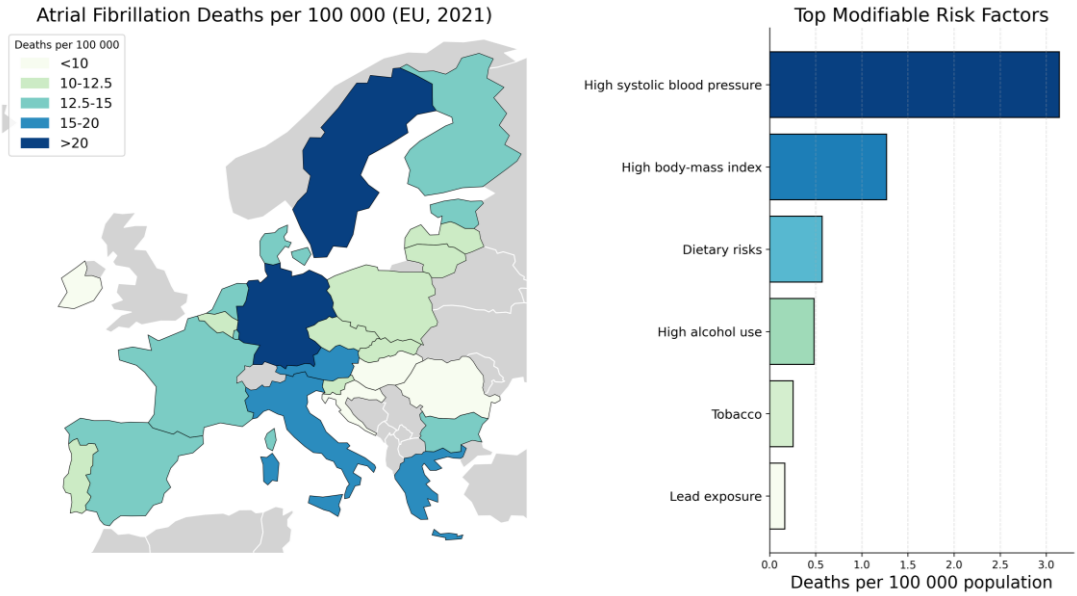
Stroke-induced disability represents one of its most significant long-term consequences. Many survivors experience hemiparesis, speech and language impairments, cognitive deficits, and visual or sensory disturbances, which limit their ability to perform daily activities independently. This loss of autonomy often requires long-term rehabilitation, caregiving, and social support, imposing psychological, social, and economic strain on patients, families, and society [82]. The marked variability in outcomes across countries suggests differences in access to rehabilitation services, quality of acute care, and secondary prevention, underscoring the need for coordinated efforts to reduce stroke-related disability and improve survivors' quality of life.

Among modifiable risk factors, high systolic blood pressure is by far the most important determinant of stroke burden across Europe (Figure 9, right panel), consistently the leading contributor to

stroke-related deaths, Years Lived with Disability (YLD), and Disability-Adjusted Life Year (DALY) across all age groups and sexes. High LDL cholesterol ranks second, followed by dietary risks, high fasting plasma glucose, ambient air pollution, and tobacco use.

Cardioembolic mechanisms account for 20 to 30% of ischaemic strokes, though this proportion is likely underestimated given the challenges in detecting paroxysmal AF and other occult cardiac sources [83]. These strokes are typically more severe than other subtypes: emboli originating from the heart tend to be large, occluding major cerebral arteries and causing extensive territorial infarctions. AF is the leading cardiac source, currently affecting over eleven million people in the European Union with projections exceeding 14 million by 2060 [84]. Compared with individuals in normal sinus rhythm, those with AF face approximately fivefold higher stroke risk and twice the risk of all-cause mortality [85]. AF prevalence remains below 1% in adults under 55 but rises sharply to 9 to 12% in those over 75 [86], underlying approximately one in six ischaemic strokes overall and one in four among patients over 80 [87]. The European Community Stroke Project, a multinational registry across seven countries, found that AF patients had substantially worse outcomes: at three months, 33% had died compared with 20% of non-AF patients, and AF independently increased the probability of disability by 50% [88].

Figure 10: Atrial fibrillation deaths per 100,000 in the EU (left) and the main modifiable risk factors (right).



Source: [Global Burden of Disease (GBD)](#).

Unlike IHD, AF is not primarily an atherosclerotic disorder but the result of progressive structural and electrical remodelling of the atrial myocardium. Chronic pressure overload, metabolic inflammation, and fibrotic changes alter conduction pathways and create the substrate for arrhythmia. Consequently, AF onset is driven largely by long-term exposure to modifiable cardiovascular risk factors. GDB 2021 data identify high systolic blood pressure as the leading contributor to AF-related mortality in Europe, followed by elevated body mass index, dietary risks, high alcohol consumption, and tobacco use (Figure 10, right panel). Hypertension increases left atrial pressure and wall stress, leading to enlargement and fibrosis; obesity amplifies these effects through systemic inflammation and sleep apnoea; and excess alcohol consumption increases AF risk through oxidative stress and altered calcium handling [89]. AF-related mortality follows a geographic pattern distinct from overall stroke: rates are highest in Northern and Central Europe (Sweden, Finland,

Germany) rather than the East, likely reflecting differences in diagnostic intensity, population age structure, and reporting practices (Figure 10).

A critical challenge is undetected AF. Up to one third of affected individuals are unaware of their condition until presenting with stroke, because AF is often paroxysmal and asymptomatic [90]. Traditional screening methods such as pulse palpation or short-term ECG monitoring detect only a fraction of cases. Studies using implantable cardiac monitors in cryptogenic stroke patients have detected previously undiagnosed AF in 12% at one year and up to 30% at three years, compared with only 2 to 3% detected with conventional 24-hour monitoring [91] [92]. Other cardiac sources of embolism include left ventricular thrombus following myocardial infarction, valvular heart disease, and patent foramen ovale [93].

Despite comprehensive evaluation, 20 to 30% of ischaemic strokes remain cryptogenic, without an identified cause [94]. Many are presumed cardioembolic, with occult AF or atrial cardiomyopathy as the underlying mechanism. This diagnostic gap, combined with the severity of cardioembolic stroke and the large population harbouring undiagnosed AF, has driven substantial interest in AI-based approaches to detect AF from ECG and wearable data, predict which patients harbour undiagnosed arrhythmia, and identify echocardiographic markers of embolic risk.

4.2.2 High-Potential AI Applications

AI-Enhanced ECG for Detection of Occult Atrial Fibrillation

AF is the most common cardiac cause of stroke, yet paroxysmal AF often escapes detection on routine monitoring [95]. Approximately 20% of patients who have a stroke associated with AF are first diagnosed at the time of stroke or shortly thereafter, and stroke is the initial manifestation of AF in nearly one-quarter of cases. AI-enhanced electrocardiography has demonstrated the ability to identify patients with underlying AF from ECGs recorded during sinus rhythm, detecting subtle abnormalities invisible to the human eye.

For instance, the landmark Mayo Clinic study [96] developed a convolutional neural network (CNN) trained on over 180,000 patients that achieved an Area Under the (Receiving Operating Characteristic) Curve (AUC) of 0.87 for identifying patients with AF from a standard 10-second, 12-lead ECG recorded during sinus rhythm. Subsequent external validation and replication studies have shown more variable performance. A systematic review of 14 studies encompassing 33 AI models reported a median AUC of 0.74 (95% CI 0.63–0.83), with substantial heterogeneity depending on study design, ECG format, population characteristics, and AF confirmation timeframe [97]. Nevertheless, across high-quality studies with external validation, AI models for predicting new-onset AF from sinus rhythm ECGs consistently achieve AUROCs in the range of 0.69–0.85, often matching or exceeding established clinical risk scores such as CHARGE-AF [98] [99].

When applied to stroke populations, these AI-ECG models show promise. In patients with embolic stroke of undetermined source (ESUS), a transformer-based AI model applied to sinus rhythm ECGs achieved an AUC of 0.81 for predicting AF detection on subsequent insertable cardiac monitor surveillance, improving to 0.88 when integrated with clinical parameters [100]. The AI algorithm exhibited greater accuracy in identifying longer AF episodes and showed a temporal trend indicating that AI-based AF risk scores increased as the ECG recording approached AF onset. This enables targeted deployment of extended cardiac monitoring resources to patients most likely to benefit, rather than applying resource-intensive monitoring uniformly. AI models can also be applied to continuous ECG monitoring data from stroke units, combining raw ECG signals with derived heart rate variability metrics to achieve improved AF prediction [101].

Beyond binary AF detection, AI can improve stroke risk stratification in patients with known AF. Traditional scores such as CHA_2DS_2-VASc have well-documented limitations, including poor precision for intermediate-risk patients. Up to 7,000 strokes still occur annually among approximately 1 million patients assessed as "low-risk" by CHA_2DS_2-VASc [31]. Explainable AI models incorporating broader clinical features and accounting for interactions between risk factors have shown improved discrimination compared with conventional scores, potentially enabling more personalised anticoagulation decisions.

Challenges remain. Performance of AI-ECG models varies substantially across populations and settings, with external validation studies consistently showing lower accuracy than development cohorts. The clinical significance of AI-detected AF risk is uncertain: whether patients flagged as high-risk but without documented AF should receive anticoagulation, or whether intensified monitoring improves outcomes, remains unproven.

In summary, AI-enhanced electrocardiography offers a promising approach to closing the AF detection gap that underlies a substantial proportion of cardioembolic strokes. AI-ECG models enable risk stratification from routine clinical recordings, guiding selective deployment of extended monitoring to patients most likely to benefit. As validation accumulates and clinical pathways are established, these tools may help reduce the burden of preventable cardioembolic stroke.

Expert Assessment

Readiness was rated moderately, reflecting the maturity of automated ECG reading as a foundation while AI extraction of novel predictive signals remains under clinical evaluation. Impact was rated higher, driven by the prevalence of ECG as a clinical tool and the potential to identify undiagnosed AF at scale. Experts noted that realising this potential will depend on resolving sensitivity and specificity trade-offs and establishing clear clinical pathways for high-risk patients.

Wearables and Continuous Rhythm Monitoring

Consumer wearable devices, particularly smartwatches equipped with photoplethysmography (PPG) and single-lead ECG capabilities, offer continuous, non-invasive monitoring that can detect paroxysmal AF episodes that would be missed by intermittent screening. The Apple Heart Study enrolled over 400,000 participants without known AF; among those receiving irregular pulse notifications who subsequently wore an ECG patch, the positive predictive value for AF was 84% [32]. Similar validation studies have demonstrated high sensitivity and specificity for AF detection across multiple smartwatch platforms [12] (Figure 11).

AI algorithms enhance the diagnostic performance of wearable-acquired data. Machine learning models can reduce the burden of inconclusive single-lead ECG tracings, improving the clinical utility of consumer devices [103]. AI-based analysis of handheld single-lead ECGs has demonstrated the ability to predict incident AF up to 2 years in advance, extending the utility of these devices beyond simple arrhythmia detection to true risk prediction [104]. A recent randomised controlled trial demonstrated that 6-month smartwatch-based screening significantly enhanced detection of new-onset AF compared with standard care in patients at elevated stroke risk [105].

For stroke prevention, wearables may be particularly valuable for secondary prevention monitoring after cryptogenic stroke. However, current evidence suggests that smartwatches cannot substitute

for established methods such as insertable cardiac monitors in high-risk patients, given the need for prolonged monitoring to detect infrequent paroxysmal episodes [106]. Nevertheless, wearables represent a scalable, cost-effective component of a stepped screening approach, with AI-enhanced algorithms progressively improving their diagnostic yield.

Figure 11: Sensitivity and specificity for 5 consumer wearable smart devices.

Manufacturer	Apple	Samsung	Withings	Fitbit	AliveCor
Version	Watch 6	Galaxy Watch3	ScanWatch	Sense	Kardia Mobile
Sensitivity (95% CI)	85% (72%-94%)	85% (72%-94%)	58% (42%-72%)	66% (51%-79%)	79% (64%-89%)
Specificity (95% CI)	75% (67%-83%)	75% (66%-82%)	75% (67%-83%)	79% (70%-86%)	69% (60%-77%)

Source: Mannhart, D. et al. 2023 [12].

Challenges remain. Consumer device notifications may generate anxiety and prompt unnecessary healthcare utilisation in low-risk individuals. AF patients using wearables can experience fear and anxiety in response to irregular rhythm notifications, with wearable users more likely to contact clinics and send messages to healthcare providers [107]. Signal quality varies with wear patterns, skin type, and motion, leading to false positives that burden both patients and clinicians [106]. Furthermore, evidence on the utility of consumer wearable technologies and the overall cost-effectiveness of population-based screening remains too sparse to provide clear guidance, limiting integration into clinical pathways [108].

In summary, wearables represent a scalable, cost-effective component of a stepped screening approach for AF detection. While they cannot replace prolonged monitoring with insertable cardiac monitors in high-risk patients such as those with cryptogenic stroke, they may serve as a first-line tool for population-level surveillance, identifying individuals who warrant further evaluation. As AI-enhanced algorithms continue to improve diagnostic yield, wearables are likely to play an expanding role in both primary and secondary stroke prevention.

Expert Assessment

Readiness was rated moderately, reflecting good performance on high-quality devices while noting that consumer-grade wearables still face challenges around signal noise, variable data quality, and the need for better patient selection. Impact was rated higher, with experts recognising the potential of continuous monitoring for population-level AF detection, while emphasising that this potential will only be realised if device costs fall and wearables are embedded in well-designed screening pipelines.

Echocardiographic Assessment of Cardiac Embolic Sources

Beyond rhythm detection, echocardiography plays a central role in identifying structural cardiac sources of embolism, including LAA thrombus, patent foramen ovale (PFO), valvular abnormalities, and intracardiac masses. AI applications in this domain are emerging rapidly, though most remain in early validation stages.

Left Atrial Appendage Thrombus Prediction

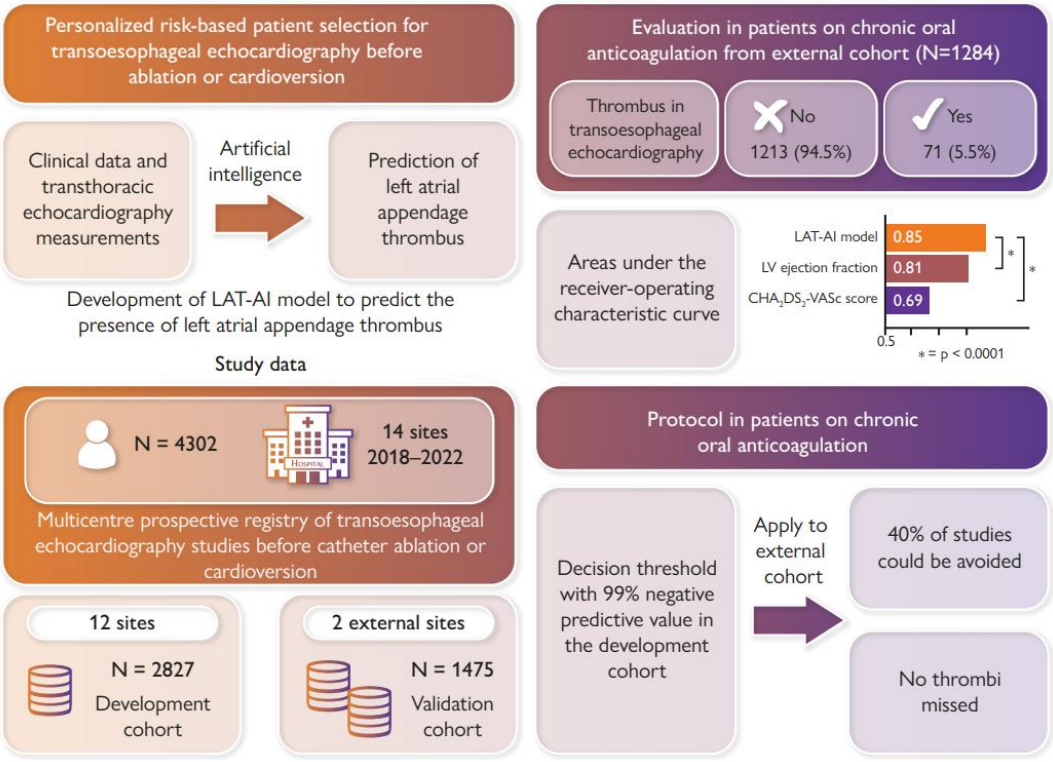
LAA is the source of more than 99% of intracardiac thrombi responsible for cardioembolic stroke in patients with AF [109]. Transesophageal echocardiography (TEE) remains the gold standard for LAA thrombus detection, with high sensitivity and specificity. However, TEE is semi-invasive, requires passage of a probe through the throat[52], causes patient discomfort, and demands specialised equipment and expertise, all of which limit its scalability. CT is increasingly used as an alternative, given limitations in transthoracic echocardiography's ability to visualise the LAA adequately. Against this background, AI-based tools are being developed to identify patients who genuinely require invasive or semi-invasive imaging, potentially reducing unnecessary procedures while maintaining diagnostic safety.

The LATTEE (Left Atrial Thrombus on Transoesophageal Echocardiography) registry represents the most robust evidence in this space [110]. This 13-site prospective study enrolled over 4,300 patients undergoing TEE before cardioversion or catheter ablation across Poland. The investigators developed a machine learning model (LAT-AI) trained on clinical and transthoracic echocardiography (TTE) features from 12 sites (n=2,827) and externally validated on patients from two independent sites (n=1,284). The model achieved an AUC of 0.85 for predicting LAA thrombus, significantly outperforming both left ventricular ejection fraction and CHA_2DS_2-VASc score alone. Feature importance analysis identified left atrial dimension, non-paroxysmal arrhythmia status, NYHA functional class, and INR values among the most predictive variables. Importantly, when applied with a threshold designed for 99% negative predictive value, the model could potentially avoid TEE in approximately 40% of patients, a substantial reduction in procedural burden without compromising diagnostic safety [110] (Figure 12).

Other groups have developed similar machine learning models incorporating transthoracic echocardiography parameters alongside clinical and laboratory data. A recent study trained four machine learning algorithms (Random Forest, Logistic Regression, Support Vector Machine, and XGBoost) on 698 patients with non-valvular AF, with prospective validation in 140 additional patients. Significant predictors of LAA thrombus included permanent AF type, HF, elevated BNP and D-dimer levels, mitral regurgitation severity, reduced left ventricular ejection fraction, left atrial diameter, CHA_2DS_2-VASc score, and LAA emptying velocity [111]. These models achieved high discriminative performance, though external validation in diverse populations remains limited.

[52] oropharyngeal intubation

Figure 12: Development and validation of an AI model (LAT-AI) to detect left atrial appendage thrombus by transoesophageal echocardiography.



Source: Pieszko, K. et al., 2024 [110].

Expert Assessment

Readiness was rated moderate, reflecting a promising but still largely research-based evidence base with limited validation across diverse populations. Impact was also rated moderate to good: while the potential to reduce unnecessary invasive procedures is meaningful given the prevalence of cardioembolic stroke, experts noted uncertainty about how AI-based thrombus prediction would translate into changes in clinical management.

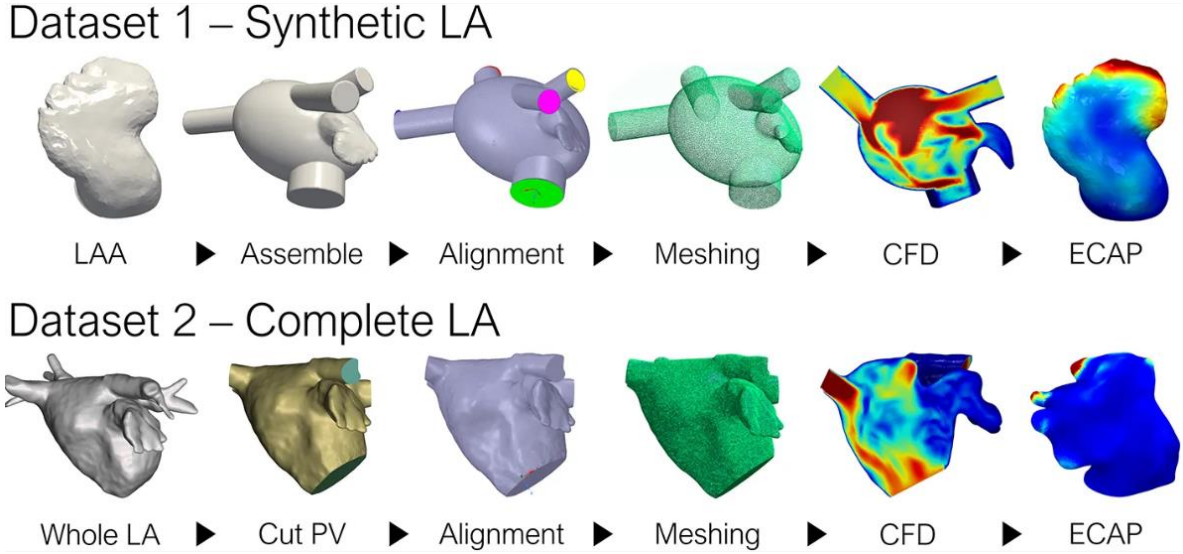
Computational Fluid Dynamics and Digital Twin Approaches

An emerging frontier involves computational fluid dynamics (CFD) simulations to model blood flow patterns within the left atrium and LAA, enabling patient-specific assessment of thrombotic risk based on haemodynamic parameters such as blood velocity, wall shear stress, and endothelial cell activation potential (ECAP). CFD studies have demonstrated that LAA morphology significantly influences haemodynamic behaviour, with certain morphologies associated with greater blood stasis and higher thrombotic risk [112]. Beyond thrombosis risk assessment, CFD has also been applied to procedural planning for LAA occlusion (LAAO), enabling prediction of device-related thrombus formation and optimisation of device sizing and positioning for a given patient geometry [113].

However, traditional CFD simulations are computationally intensive, requiring hours to days of processing time, which precludes their integration into routine clinical workflows. To address this

limitation, a group has developed a DL surrogate model capable of predicting CFD-derived thrombosis risk indices instantaneously from patient-specific LAA geometry alone. This model, trained on hundreds of synthetic and real LAA geometries, can predict ECAP distributions with average errors below 5%, dramatically reducing computational time while preserving predictive accuracy [114] [115] (Figure 13). More recently, researchers have proposed DT frameworks that integrate clinical data, morphological features from imaging, and CFD-derived haemodynamic parameters using unsupervised machine learning to identify distinct patient phenogroups with different stroke risk profiles [116].

Figure 13: Generation of ECAP maps from synthetic and real data.



Source: Moralez Ferez, X. et al., 2021 [114].

While these computational approaches remain largely investigational, they represent a promising direction for moving beyond simplistic clinical risk scores toward truly personalised thrombotic risk assessment. Validation in prospective cohorts and demonstration of improved clinical outcomes will be essential before widespread adoption.

Expert Assessment

Readiness was rated moderate to good, with CFD approaches still largely confined to research settings while DT frameworks are beginning to move toward clinical implementation, particularly data-driven variants that do not rely on computationally intensive simulations. Impact was similarly rated moderate to good: CFD faces inherent scalability constraints, but DTs were seen as having strong longer-term potential, with experts expecting their clinical value to grow as simulation capabilities become more robust and accessible.

Valvular Heart Disease and Other Embolic Sources

Several other cardiac conditions increase stroke risk through various mechanisms. Severe aortic stenosis is associated with increased thromboembolic risk, and AI-ECG models have been developed to detect moderate-to-severe aortic stenosis from standard 12-lead ECGs with AUCs exceeding 0.90,

potentially enabling population-level screening [117]. Infective endocarditis causes stroke through septic emboli from infected valvular vegetations; early detection and treatment reduces neurological complications. Mitral valve disease, particularly rheumatic mitral stenosis, remains a significant cause of cardioembolic stroke globally, especially in low- and middle-income countries.

Fully automated echocardiography interpretation systems using DL can now detect and grade multiple valvular lesions, including aortic stenosis, aortic regurgitation, mitral stenosis, and mitral regurgitation, with AUROCs of 0.88–0.99 in prospective validation across 1,374 consecutive echocardiograms [118]. While these systems are not specifically designed for stroke risk assessment, they may facilitate more comprehensive evaluation of potential embolic sources. The recent EchoNext model, validated across diverse health systems, demonstrated successful detection of multiple forms of structural heart disease from ECGs, supporting the potential for AI to expand access to heart disease screening at scale [119].

Expert Assessment

Readiness was rated moderate to good, reflecting solid performance of AI tools for automated measurement from imaging, though experts noted that non-AI tools are already performant in this area and that large multimodal datasets for further validation remain limited. Impact was also rated moderate to good, driven by the growing prevalence of valvular disease in an ageing population, with experts emphasising that clinical relevance will depend on integration with echocardiography rather than ECG-based approaches alone.

Patent Foramen Ovale Detection and Risk Assessment

Patent foramen ovale, a remnant of foetal circulation present in approximately 25% of the adult population, has been implicated as a major contributor to cryptogenic stroke through paradoxical embolism. The prevalence of PFO rises to 40–50% among patients with cryptogenic stroke, suggesting a causal relationship in appropriately selected individuals. Multiple randomised controlled trials, including RESPECT [120], CLOSE [121], REDUCE [122], and DEFENSE-PFO [123], have now demonstrated that transcatheter PFO closure significantly reduces recurrent stroke risk compared with medical therapy alone in patients younger than 60 years with cryptogenic stroke, with relative risk reductions ranging from 45% to 97% and numbers needed to treat of approximately 20–42 over five years [124][125]. These trials have led to regulatory approvals and guideline endorsements for PFO closure in appropriately selected patients.

AI applications for PFO detection remain in early development. Several single-centre studies have explored DL approaches for automating PFO detection and right-to-left shunt grading from contrast transthoracic echocardiography, reporting accuracies of 78–90% and diagnostic times of 1–2 seconds compared with several minutes for manual physician review [126]. Machine learning has also been applied to predict which PFO patients are at highest risk for cryptogenic stroke based on TEE morphologic and functional characteristics, with one study achieving an AUC of 0.82 [127]. However, these remain proof-of-concept studies with small sample sizes (150–200 patients), lack external validation, and have not been implemented clinically. No FDA-cleared or CE-marked AI tools currently exist specifically for PFO detection from echocardiography, in contrast to the more mature AI applications for other structural heart conditions such as aortic stenosis or HF with preserved ejection fraction.

Expert Assessment

Readiness was rated low to moderate, reflecting the early stage of AI development in this area, limited research activity, and the absence of validated clinical tools. Impact was rated moderate, with experts noting that PFO closure remains a relatively niche indication and that the added value of AI in this context is unclear.

4.3 Hypertensive Heart Disease

4.3.1 Epidemiology and Risk Factors

HHD represents a spectrum of cardiac structural and functional changes arising from chronically elevated blood pressure. These include left ventricular hypertrophy, myocardial fibrosis, impaired diastolic function, and eventually HF. While hypertension is a major risk factor for multiple cardiovascular conditions, HHD constitutes a distinct clinical and epidemiological entity. It reflects the cumulative myocardial impact of sustained pressure overload and remains a major contributor to premature cardiovascular death, particularly in Central and Eastern Europe [128].

According to GDB 2021 estimates[53], HHD accounted for approximately 1.33 million deaths globally in 2021, with wide variation in age-standardised mortality between regions [128][129]. As shown in Figure 14, countries such as Bulgaria, Romania, Slovakia, and the Baltic States report mortality rates exceeding 70 deaths per 100,000 population, whereas rates in Western Europe, including France, Spain, and the Netherlands, remain below 10 per 100,000. Bulgaria recorded the highest age-standardised mortality rate globally at 103.4 per 100,000. This east–west gradient is among the steepest observed for any cardiovascular cause and reflects persistent disparities in hypertension detection, treatment, and control, as well as broader differences in diet, health behaviours, and health system capacity [130][131].

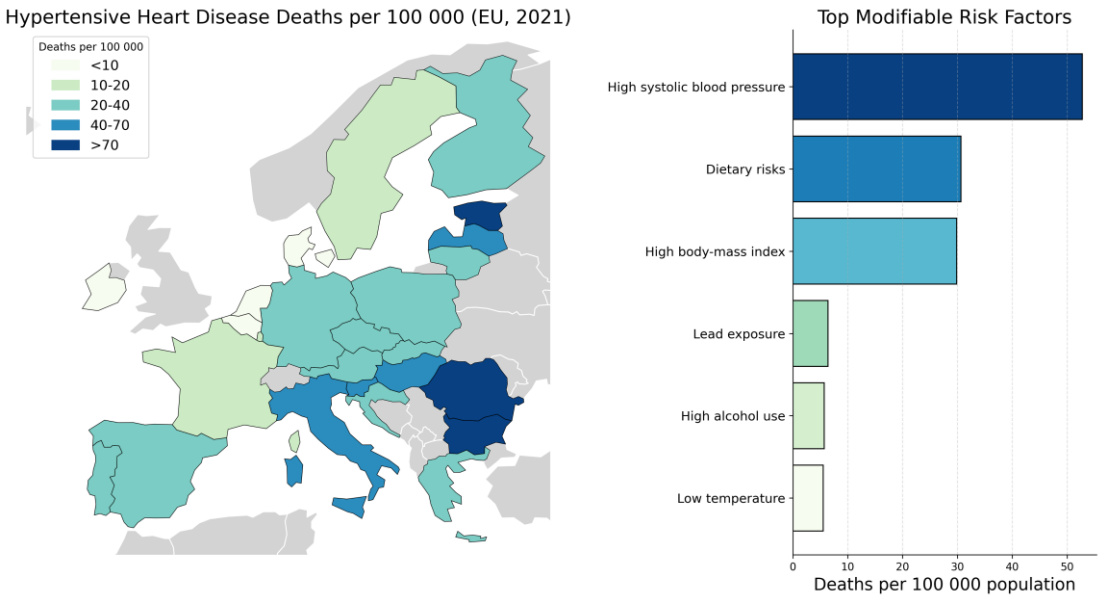
High systolic blood pressure is the unequivocal driver of HHD, accounting for nearly all attributable deaths in Europe. The condition develops insidiously over years of poorly controlled hypertension, with early left ventricular hypertrophy often going undetected until symptoms of HF or arrhythmia emerge. Among persons with hypertension, the prevalence of left ventricular hypertrophy detected by echocardiography ranges from 36 to 41%, though figures as high as 58 to 77% have been reported in high-risk hypertensive populations [132][133]. The right panel of Figure 14 highlights the dominant modifiable contributors to HHD mortality in the EU. High systolic blood pressure alone explains over 50 deaths per 100,000 population, followed by dietary risks and elevated body mass index. These risk factors are highly interrelated: excess sodium intake, low potassium consumption, and diets high in processed foods contribute directly to hypertension, while obesity promotes sympathetic activation, insulin resistance, and renal sodium retention, all of which amplify blood pressure and accelerate myocardial damage.

[53] *Global Burden of Disease (GBD)*

Environmental and behavioural exposures further compound risk. Lead exposure remains a non-negligible contributor, particularly in regions with legacy industrial pollution or inadequate water infrastructure. Excess alcohol consumption is associated with increased blood pressure and direct cardiotoxicity. In some regions, particularly Eastern Europe and the Baltics, low winter temperatures exacerbate seasonal blood pressure fluctuations and increase the incidence of hypertensive crises, contributing to higher seasonal mortality rates [134].

HHD is often underdiagnosed due to its gradual progression and nonspecific symptoms. Unlike coronary artery disease, which can present acutely, HHD tends to evolve silently until the onset of HF, AF, or sudden cardiac death. Echocardiographic detection of left ventricular hypertrophy and impaired diastolic function is useful for identifying subclinical disease, but access remains uneven across Europe, particularly in rural and lower-income regions. Moreover, many individuals with HHD are unaware they have hypertension, or remain undertreated due to therapeutic inertia, poor adherence, or fragmented primary care services. In countries with high HHD mortality, rates of blood pressure awareness, treatment, and control remain below 50%, far from the levels required to prevent long-term cardiac damage [130][131].

Figure 14: Hypertensive heart disease deaths per 100,000 in the EU (left) and the main modifiable risk factors (right).



Source: [Global Burden of Disease (GBD)]

The epidemiology of HHD is closely tied to demographic and socioeconomic trends. The condition disproportionately affects older adults, but the rising prevalence of obesity, sedentary lifestyles, and early-onset hypertension has led to an increasing number of middle-aged adults presenting with cardiac hypertrophy and impaired diastolic filling. In most Member States, men exhibit higher rates of HHD mortality, reflecting earlier onset of hypertension and lower treatment adherence. However, women with HHD may be more likely to develop HF with preserved ejection fraction, a form that remains poorly understood and frequently underdiagnosed [135].

From a policy perspective, the continued burden of HHD across Europe reflects a failure to manage the most modifiable cardiovascular risk factor. Despite the availability of effective, low-cost antihypertensive medications, blood pressure control rates remain suboptimal in many EU countries. In Central and Eastern Europe, health system constraints, out-of-pocket medication costs, and limited

integration of preventive care undermine the effectiveness of hypertension management. Population-wide interventions such as salt reduction policies, front-of-pack labelling, and fiscal measures to limit processed food consumption remain underused despite clear evidence of benefit.

The geographic pattern of HHD mortality in Europe offers a stark reminder of the unfinished agenda in cardiovascular prevention. Unlike some forms of heart disease that require advanced imaging or genetic screening to detect, HHD develops from a risk factor that is easily measurable and almost always modifiable. Its persistence as a leading cause of death in several EU countries reflects ongoing gaps in the implementation and accessibility of effective prevention and control strategies.

4.3.2 High-Potential AI Applications

Deep Learning on ECG for Detection of Left Ventricular Hypertrophy

Electrocardiography reflects the electrical and structural consequences of elevated blood pressure, including autonomic imbalance, conduction changes, and cardiac remodelling. Traditional ECG criteria for left ventricular hypertrophy have notoriously poor sensitivity, detecting fewer than half of cases confirmed by echocardiography. DL offers a substantial improvement by extracting subtle patterns across the entire 12-lead signal that are invisible to conventional interpretation.

The most promising approaches anchor DL outputs to imaging-verified phenotypes rather than relying on noisy hypertension labels from office blood pressure readings. An AI model developed using ECG recordings from over 28,000 patients aged 20 to 60 years achieved an AUC of 0.89 for detecting echocardiography-verified Left Ventricular Hypertrophy (LVH), with consistent performance (AUC 0.86) in an independent validation cohort and external validation in a Japanese population (AUC 0.83) [136]. Importantly, this study demonstrated that AI-predicted LVH independently predicted cardiovascular and all-cause mortality over six-year follow-up, with hazard ratios of 1.91 and 1.54 respectively, even after adjustment for age, sex, and comorbidities. This linkage to hard clinical endpoints addresses a critical gap in the field, where most models report only discrimination metrics without demonstrating downstream clinical relevance.

Other groups have developed CNN- LSTM (Long Short-Term Memory) architectures achieving similarly strong performance, with sensitivity substantially exceeding traditional voltage criteria [137]. DL has also shown ability to distinguish hypertrophic cardiomyopathy from pressure-induced hypertrophy on ECG, a clinically important differentiation with implications for family screening and sudden death prevention [138]. A recent systematic review identified growing evidence for ECG-based AI in LVH detection, though highlighted persistent challenges in generalisability across devices, demographic groups, and clinical settings [139].

The principal advantage of ECG-based AI is scalability. ECGs are ubiquitous, inexpensive, and already embedded in clinical workflows worldwide. An AI-enabled ECG could function as a first-line screening tool to identify patients who warrant confirmatory echocardiography, potentially improving early detection of HHD in primary care and community settings where access to imaging is limited.

Challenges remain. Generalisation across devices, demographic groups, and clinical settings is a persistent limitation, and most models have been validated on technical metrics rather than clinical outcomes. ECG alone may be insufficient given the heterogeneity of HHD presentations.

In summary, the principal advantage of ECG-based AI for LVH detection is scalability: ECGs are ubiquitous, inexpensive, and already embedded in clinical workflows worldwide. Combined with

strong diagnostic performance and a demonstrated link to cardiovascular mortality, an AI-enabled ECG could function as a first-line screening tool to identify patients who warrant confirmatory echocardiography, potentially improving early detection of HHD in primary care and community settings where access to imaging is limited. Realising this potential will require integration into structured preventive pathways and broader validation across diverse populations.

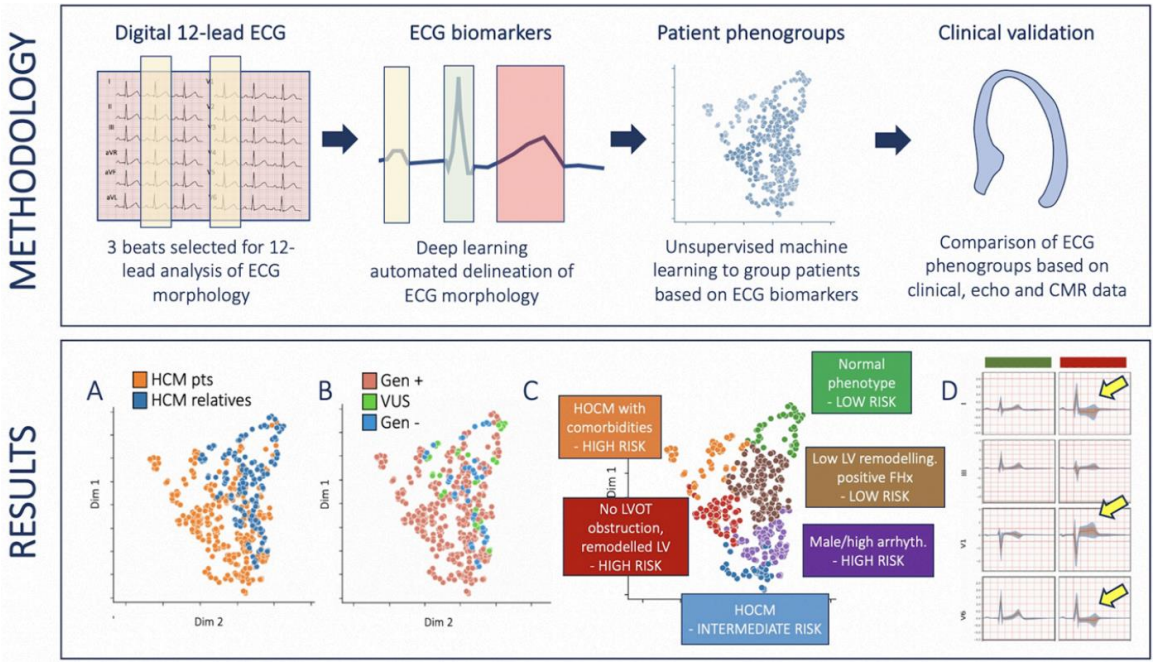
Expert Assessment

Readiness was rated moderate to good, reflecting availability in research settings and on high-end systems, with experts noting that ECG alone may be insufficient given the heterogeneity of HHD presentations. Impact was rated high, driven by the large prevalence of the condition and the scalability of ECG as a first-line screening tool, though experts noted that realising this potential will require integration into structured preventive and clinical pathways.

Multimodal Unsupervised Phenotyping

Beyond simple classification, unsupervised machine learning offers the potential to identify clinically meaningful disease phenotypes by integrating complex, high-dimensional data that clinicians cannot easily synthesise. Recent work has demonstrated the value of applying this approach to whole-cardiac-cycle echocardiographic data in hypertension and hypertrophic cardiomyopathy [140] [141] (Figure 15).

Figure 15: Unsupervised machine learning identifies clinically distinct phenogroups in hypertrophic cardiomyopathy from 12-lead ECG morphology.



Source: Jimenez-Perez, G. et al., 2022 [141].

Rather than relying on single summary measurements such as ejection fraction or peak strain, these methods use entire deformation and velocity curves from the cardiac cycle as input to

clustering algorithms. In patients with hypertension, this approach identified distinct phenogroups corresponding to normal cardiac function and others to advanced pressure-overload remodelling, capturing patterns that would be difficult to discern from conventional measurements alone. The methodology has been extended to hypertrophic cardiomyopathy, where multicentre studies integrating echocardiographic, clinical, and genetic data identified phenogroups with markedly different risk profiles, from high-risk clusters with pathogenic genotypes and family history of sudden death to lower-risk groups with milder phenotypes [141][142].

Multimodal DL approaches combining ECG and echocardiography have achieved strong performance for distinguishing hypertrophic cardiomyopathy from HHD, with an AUC of 0.91 reported for the joint model compared with lower accuracy for either modality alone [143]. These approaches represent a shift from AI as a diagnostic replacement toward AI as a tool for disease characterisation and risk stratification, augmenting rather than supplanting clinical reasoning.

Challenges remain. These approaches are at an early research stage and face significant technical challenges in integrating large multimodal datasets across heterogeneous clinical settings. Validation in prospective cohorts and demonstration of impact on clinical decision-making will be required before they can move toward routine use.

In summary, multimodal unsupervised phenotyping represents a shift from AI as a diagnostic replacement toward AI as a tool for disease characterisation and risk stratification. Its broad applicability across cardiovascular conditions and its potential contribution to precision medicine give it high long-term impact, even if clinical deployment remains a longer-term prospect.

Expert Assessment

Readiness was rated low, reflecting the early research stage of these approaches and the technical challenges of integrating large multimodal datasets. Impact was rated high by the experts, who saw multimodal phenotyping as having broad potential across cardiovascular conditions and as a key step toward precision medicine, even if clinical deployment remains a longer-term prospect.

Electronic Health Record-Based Risk Stratification

EHRs and routinely collected clinical data represent the most mature foundation for AI applications in hypertension management. These data include demographics, longitudinal blood pressure measurements, medication histories, laboratory results, and comorbidity profiles, features already embedded in clinical workflows that lend themselves naturally to predictive modelling. Compared with imaging or wearable modalities, EHR-based AI is closest to real-world implementation because it relies on existing data infrastructure and imposes minimal additional cost.

Machine learning approaches applied to EHR data have shown encouraging results for identifying patients at risk of incident hypertension, treatment-resistant hypertension, and secondary complications such as left ventricular hypertrophy, chronic kidney disease, or HF. A meta-analysis of 52 hypertension prediction studies compared machine learning algorithms with traditional logistic regression and Cox models, finding pooled C-statistics of 0.76 and 0.75 respectively [144]. This modest difference suggests that algorithmic complexity alone does not guarantee better prediction; careful feature selection and data quality may matter more than the choice of model architecture.

More sophisticated approaches that exploit the temporal structure of EHR data have shown greater promise. In a study of over 230,000 patients, long short-term memory networks trained on sequences of vital signs, laboratory values, and diagnoses, achieved an AUC of 0.94 for predicting hypertension onset within one year [145]. This suggests that capturing how clinical variables evolve over time, rather than simply aggregating them, may offer meaningful improvements in risk stratification.

Despite these advances, translational maturity remains constrained by methodological and infrastructural limitations. Ground truth labels derived from single office blood pressure readings are noisy compared with ambulatory or home monitoring. Data heterogeneity across institutions and inconsistent coding practices undermine model portability [146]. Many studies report only discrimination metrics without addressing calibration, subgroup performance, or clinical utility [147]. Few models have been prospectively tested within clinical workflows, and almost none have demonstrated improvements in patient outcomes.

The most defensible role for EHR-based AI is as a risk stratification and decision support tool, enabling early identification of high-risk individuals and guiding targeted follow-up or preventive interventions rather than serving as a diagnostic replacement. Successful implementation will require sustained investment in data standardisation, transparency regarding model performance across subgroups, and prospective validation demonstrating impact on clinical outcomes.

Challenges remain. Ground truth labels, data heterogeneity, and inconsistent coding practices continue to undermine model portability and generalisation. Federated multi-national studies will be needed to demonstrate broader validity across heterogeneous health systems, and few models have yet demonstrated improvements in patient outcomes in prospective clinical settings.

In summary, EHR-based AI holds high impact potential by enabling detection of often-missed conditions at scale using routinely collected data. Its most defensible role is as a risk stratification and decision support tool, and realising this potential will depend on sustained investment in data standardisation, interoperability, and prospective validation.

Expert Assessment

Readiness was rated moderate, reflecting a solid research foundation using existing clinical infrastructure, but with experts noting the need for federated multi-national studies to demonstrate broader validity and portability across heterogeneous systems. Impact was rated high by the experts, driven by the potential to detect often-missed conditions at scale using routinely collected data, though they acknowledged that realising this potential will require significant investment in data standardisation and interoperability.

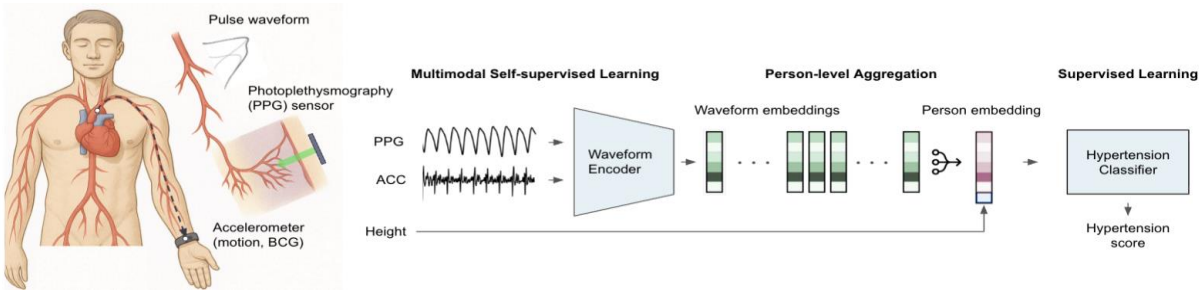
Wearables and Cuffless Blood Pressure Monitoring

Cuffless blood pressure estimation using photoplethysmography (PPG), alone or combined with electrocardiography, has attracted substantial commercial and research interest. In September 2025, Apple introduced a Hypertension Notification Feature in its smartwatch, cleared by the FDA, which uses a machine learning algorithm trained on data from over 100,000 individuals to identify

signs of hypertension from PPG signals collected opportunistically over 30 days[54]. The feature achieves a specificity of 92% but a sensitivity of only 41%, meaning that more than half of hypertensive individuals will not be identified, though those who receive a notification most probably have elevated blood pressure [148].

Recent prospective validation studies have shown more promising results. In a multisite study of 196 participants not taking antihypertensive medication, Google developed a multimodal AI system combining PPG and accelerometry from a consumer smartwatch that detected hypertension with accuracy comparable to office and home blood pressure measurements when benchmarked against 24-hour ambulatory monitoring [149] (Figure 16). However, this study excluded treated hypertensives, and broader challenges remain: calibration drift over time, device-to-device variability, and limited validation across diverse populations continue to constrain clinical utility. Neither the Apple nor the Google system has been endorsed by scientific societies for diagnosis or management of hypertension, and confirmation by validated cuff-based measurement remains essential.

Figure 16: Overview of a Google smartwatch-based AI system for hypertension detection.



Source: Di Achille, P. et al. 2025 [149].

These limitations notwithstanding, wearable-based hypertension detection may improve substantially in coming years. Advances in sensor technology, larger and more diverse training datasets, and hybrid approaches combining multiple sensing modalities are likely to enhance accuracy [150]. The integration of continuous PPG monitoring with contextual data such as activity, sleep, and heart rate variability may enable more robust detection algorithms. For now, the most appropriate role for these technologies is opportunistic population-level screening in untreated individuals, potentially identifying those who should undergo formal evaluation, rather than diagnosis or monitoring of treated hypertensives. As the technology matures, wearables may eventually enable the continuous, unobtrusive blood pressure surveillance that has long been a goal of hypertension management.

Challenges remain. Sensitivity is still limited, calibration drift over time and device-to-device variability pose ongoing technical hurdles, and validation across diverse and treated populations is still insufficient for clinical endorsement. The gap between consumer availability and clinical readiness remains wide.

In summary, wearable-based blood pressure monitoring holds high long-term potential for population-level detection of undiagnosed hypertension, but its current role is appropriately limited to opportunistic screening in untreated individuals. Clinical value will depend on improving sensitivity,

[54] https://www.accessdata.fda.gov/cdrh_docs/pdf25/K250507.pdf

broadening validation, and embedding these tools within structured preventive pathways rather than relying on standalone consumer use.

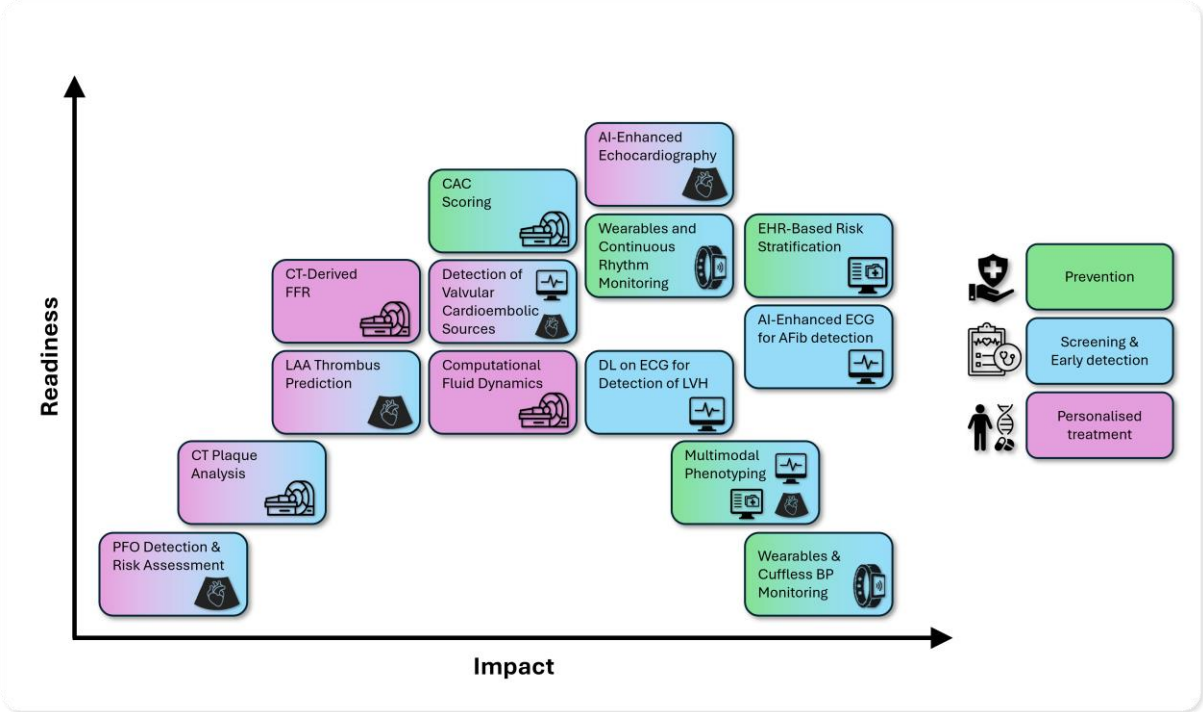
Expert Assessment

Readiness was rated low to moderate, reflecting promising early results on high-end devices but the need for broader validation across diverse populations and real-world conditions. Impact was rated high, with experts highlighting the potential of continuous blood pressure monitoring at population scale, while noting that clinical value will depend on integration into structured preventive pathways rather than standalone consumer use.

4.4 Summary of Expert Assessments

Across the 14 applications assessed, a consistent pattern emerges: readiness and impact do not always align. Some of the most clinically mature tools, such as AI-enhanced echocardiography and CAC scoring, score well on both dimensions. Others, particularly multimodal phenotyping, EHR-based risk stratification, and wearable blood pressure monitoring, were rated lower on readiness despite high anticipated impact, reflecting the gap between research promise and clinical deployment.

Figure 17: Expert assessment of 14 high-potential AI applications in cardiovascular care, mapped against their readiness for clinical use and their potential population health impact. Applications are colour-coded by domain: prevention (green), screening and early detection (blue), and personalised treatment (pink).



Source: own elaboration.

Applications in screening and early detection generally show stronger readiness, with AI-enhanced ECG for AF detection, continuous rhythm monitoring, and detection of valvular cardioembolic

sources already demonstrating validated performance in clinical or near-clinical settings. Personalised treatment applications, including CT plaque analysis, CFD and DT approaches, and LAA thrombus prediction, tend to score lower on readiness, as most remain confined to research or specialised centres.

Experts consistently highlighted that impact scores reflect potential rather than current reality. Realising that potential will in most cases require broader validation, cost reductions, and integration into structured clinical pathways. Figure 17 maps all 14 applications on a readiness-impact matrix, providing an at-a-glance view of where the field stands across the three CVD subtypes examined in this report.

5 Conclusions

CVD claims over 1.7 million lives in Europe each year. AI has attracted substantial investment as a potential tool for improving diagnosis, risk stratification, and care delivery. This report has examined the evidence across the cardiovascular care continuum.

The evidence is mixed. Some AI applications are already embedded in routine clinical practice across European hospitals. Others have accumulated strong validation data and could deliver meaningful benefit with targeted investment in implementation. Many more remain unproven in the settings where they would actually be used. Distinguishing between these categories is essential for setting policy priorities and directing resources where they can make a difference.

5.1 AI Across the Cardiovascular Care Continuum

AI tools are present at every stage of cardiovascular care, though their maturity varies considerably. Some are already CE-marked and deployed in hundreds of hospitals. Others show consistent performance across validation studies but await the implementation support and outcome evidence needed for widespread adoption. The sections that follow trace AI applications from prevention through to treatment, noting where the technology stands and what would be required to move forward.

Identifying individuals at risk before symptoms develop is a natural application for AI. CAC scoring is among the most established: AI can quantify calcium deposits, a strong predictor of future heart attacks, with accuracy matching manual expert assessment, and the same analysis can be applied opportunistically to scans performed for other indications such as lung cancer screening. AI can also detect left ventricular hypertrophy from routine ECGs with far greater sensitivity than traditional criteria, and AI-detected hypertrophy predicts cardiovascular death even after accounting for other risk factors. Given that ECGs are inexpensive and ubiquitous, this could serve as a first-line screening tool in primary care, though implementation remains limited and outcome evidence is still needed. Wearable technology is evolving rapidly: smartwatches can now identify signs of elevated blood pressure from pulse signals, though the technology remains more specific than sensitive, and confirmation with standard measurement is essential. Medical societies have not endorsed these tools for diagnosis or management, but they may have a role in identifying untreated individuals who should undergo formal evaluation.

Cardiac function assessment is well established. AI can measure heart chamber size and pumping function as accurately as expert cardiologists, while reducing interpretation time by 50 to 70%. AI-assisted echocardiographic assessment has matched or exceeded standard sonographer readings in blinded comparisons. Perhaps more significant for access to care, AI can guide non-expert operators to acquire diagnostic-quality images with minimal training, opening the possibility of cardiac assessment in settings that lack specialist services. Several CE-marked platforms are deployed across European hospitals. Arrhythmia detection spans clinical and consumer settings. AI can identify rhythm abnormalities from standard 12-lead ECG recordings with reliability comparable to cardiologists, and several platforms are CE-marked for automated interpretation. Smartwatches extend this capability outside the clinic, detecting irregular heart rhythms suggestive of AF, though confirmation with standard methods remains necessary. Detection of undiagnosed AF represents a significant opportunity not yet fully realised. Roughly one-third of patients who suffer an AF-related stroke have never been diagnosed, because the arrhythmia is often intermittent and silent. AI can identify high-risk patients from a routine ECG, even when recorded during normal rhythm, detecting subtle

abnormalities invisible to human readers. Trial evidence that AI-guided screening reduces stroke rates, rather than just improving detection, is still needed.

Guiding intervention decisions has a clear application in coronary artery disease. AI-enabled analysis of CT angiography can estimate non-invasively whether a narrowed coronary artery is restricting blood flow, helping clinicians decide who needs intervention and who can be managed with medication alone. This approach is now recommended in ESC guidelines, and several CE-marked platforms are available across Europe. Emergency stroke care represents perhaps the clearest example of AI adding value. Every minute of delay costs years of healthy life. AI systems that detect major vessel blockages from CT scans are deployed in over a thousand hospitals globally, automatically alerting specialist teams and compressing time to treatment. Meta-analyses confirm significant reductions in door-to-treatment times. Reducing unnecessary invasive testing is an emerging application. AI models trained on clinical and echocardiographic data show promise in identifying patients at low risk of left atrial appendage thrombus who may not require semi-invasive imaging before certain procedures, though external validation in diverse populations remains limited. Disease characterisation represents another growing area. Multimodal approaches integrating ECG, echocardiography, and clinical data are being applied to distinguish between conditions that present similarly but carry different implications. In hypertrophic cardiomyopathy, AI-assisted phenotyping has identified patient subgroups with markedly different risk profiles, with consequences for family screening and sudden death prevention. These applications represent a shift from AI as a diagnostic replacement toward AI as a tool for augmenting clinical reasoning.

These tools share common limitations regardless of where they are applied along the care pathway, though none are insurmountable. Most have been validated on technical performance rather than on whether their use improves patient outcomes, patient experience, clinician workload, or system efficiency. This is not unusual for emerging medical technologies, and it reflects the natural sequence of development: technical validation precedes clinical implementation. But it does mean that for many tools, the case for adoption rests more on plausible benefit than demonstrated impact. Closing this evidence gap should be a priority.

Adoption remains uneven. Well-resourced academic centres have led implementation, while smaller hospitals, primary care networks, and health systems in less affluent Member States often lack the infrastructure, IT systems, or expertise to deploy these tools. Many institutions operate with legacy systems, fragmented EHRs, and insufficient computing capacity that create technical barriers to AI integration. This pattern is common with new health technologies and can be addressed through targeted investment and knowledge sharing. Without such efforts, however, AI risks widening rather than narrowing existing disparities in cardiovascular outcomes across Europe.

Regulatory clearance provides important safeguards but offers limited assurance of real-world value. Emerging evidence, largely based on non-EU experience, suggests that AI-enabled medical devices may be recalled at higher rates than conventional devices, with one recent analysis finding that over 40% of recalls occurred within the first year of market authorisation, at roughly double the rate observed for conventional devices, and with diagnostic or measurement errors among the most common causes. Post-market surveillance could be strengthened, and the pathway from CE marking to demonstrated benefit in routine practice deserves more attention from both regulators and health systems. Closing that gap requires not only stronger post-market surveillance, but also greater investment in the intermediate step that often receives least attention: local trials and implementation studies within healthcare settings, which allow institutions to assess whether a tool performs reliably in their specific patient populations, workflows, and technical environments before

committing to full deployment. This stage is sometimes facilitated through EU grant funding, and deserves wider recognition as a critical part of the adoption pathway.

The workforce dimension warrants consideration. AI tools are sometimes presented as solutions to staff shortages, but their implementation creates its own demands: training, workflow integration, quality assurance, and ongoing maintenance. When thoughtfully implemented, these tools can reduce burden and free clinicians for tasks that require human judgement. When poorly implemented, they can add complexity without commensurate benefit. The difference often lies in how much attention is paid to the needs of healthcare professionals during deployment.

The patient perspective also deserves attention. Most AI development has focused on clinical accuracy, with less consideration of how patients experience AI-assisted care and whether they trust algorithmic recommendations. Consumer-facing AI is already shaping how millions of Europeans understand their cardiovascular health, largely outside any clinical governance framework. Patients arrive at consultations having received alerts, risk scores, and preliminary assessments from apps and wearables that clinicians may have no visibility of. This is a present challenge that requires urgent attention to communication standards, integration pathways, and realistic public expectations.

The measure of success for cardiovascular AI should not be technical performance alone. The healthcare Quadruple Aim provides a useful framework: AI should be assessed on whether it improves outcomes for patients, enhances the experience of care, supports healthcare professionals in their work, and helps health systems operate more sustainably.

5.2 Policy Priorities

Realising the potential of AI in cardiovascular care will require coordinated action across multiple fronts. The following priorities emerge from the challenges identified in this report.

Prioritise Validation Over Novelty. The field does not lack AI models, but it often lacks rigorous evidence that these models improve patient outcomes. Funding bodies should place greater emphasis on clinical utility, independent validation, and comparative evaluation alongside technical performance, and should actively incentivise head-to-head comparisons between competing tools. The EU4Health Cardiovascular Flagship Action and Testing and Experimentation Facilities offer mechanisms to advance this agenda.

Accelerate Data Readiness. The European Health Data Space provides a long-term framework, but institutions need support now to prepare for its implementation. At the hospital level, clinicians still lack simple, secure, and efficient ways to exchange data across departments and institutions, a basic prerequisite for care coordination. This means investment in data standardisation, interoperability solutions, and the workforce of clinical informaticians needed to enable routine data sharing and to curate datasets for AI development and validation. Health Data Access Bodies will play a central role, but their effectiveness depends on Member State implementation and adequate resourcing.

Modernise infrastructure and Ensure Equitable Access. AI deployment depends on infrastructure that many healthcare institutions currently lack. Investment is needed to upgrade legacy IT systems, improve interoperability between clinical applications, and ensure adequate computing capacity and network bandwidth at the hospital level. At the European level, AI Factories and federated data infrastructures provide shared resources for training and validating AI models, but their value depends on institutions being equipped to connect to and benefit from them. These challenges are most acute in smaller hospitals, primary care networks, and less-resourced Member States. EU

funding mechanisms should support infrastructure modernisation and AI adoption in under-resourced settings. Without such efforts, AI risks widening rather than narrowing existing disparities in cardiovascular care across Europe.

Build Workforce Capacity. AI literacy must be integrated into medical education at all levels. Clinicians need not understand the computational details of machine learning, but they must be able to evaluate AI outputs critically and maintain appropriate oversight. The DIGITAL and EU4Health programmes fund training initiatives, and the Apply AI Strategy identifies healthcare as a priority domain, but sustained investment will be required to close existing skills gaps.

Streamline Regulatory Pathways. The regulatory burden for AI medical devices, while necessary to protect patients, falls disproportionately on start-ups and small companies, precisely the profile of many cardiovascular AI innovators. Recent initiatives, including the proposed Digital Omnibus Package and the ongoing revision of the medical devices framework, aim to simplify aspects of the regulatory landscape, but continued attention is needed to reduce duplication between overlapping frameworks, accelerate notified body capacity, and lower the cost of compliance without compromising safety standards. Regulatory sandboxes can help innovators navigate requirements more efficiently, and harmonised guidance from bodies such as the MDCG should continue to clarify expectations for AI-specific challenges.

Clarify the Role of Consumer AI. Guidance is needed on how data from wearables and health apps should be integrated into clinical workflows, and how to manage the demand generated by alerts and self-diagnoses. The regulatory status of consumer AI tools varies considerably, creating confusion for both patients and clinicians. Recent MDCG guidance has clarified that app stores and developers may be considered economic operators under the MDR, and the EHDS explicitly includes data from wearables and wellness applications within its scope for both primary and secondary use. However, practical questions remain about how patient-generated health data should be incorporated into clinical decision-making, what validation standards should apply, and how to ensure interoperability with EHRs. Public communication should help citizens understand what consumer AI tools can and cannot reliably do, and clinical pathways should be developed to manage the interface between consumer-generated alerts and professional care.

5.3 Looking Ahead

What distinguishes the applications that have succeeded from those that have stalled is rarely the sophistication of the underlying technology. It is the quality of the evidence, the fit with clinical workflows, and the availability of the infrastructure needed to deploy and sustain them. These are the dimensions that deserve the most policy attention going forward.

Converting validated tools into population-level benefit requires sustained investment in implementation science, clinical trial infrastructure, and data governance alongside continued technical development. AI alone will not resolve the fundamental challenges facing European health systems: workforce shortages, funding constraints, and uneven access to care. But thoughtfully deployed and rigorously evaluated, it can make a meaningful contribution. The measure of success should not be the number of tools developed or approved, but whether they improve what matters: better outcomes for patients, better experience of care, sustainable costs for health systems, and better working conditions for healthcare professionals.

References

[1] OECD (2025), *The State of Cardiovascular Health in the European Union*, OECD Publishing, Paris, https://doi.org/10.1787/ea7a15f4-en.

[2] COMTE, V., BERTOLINI, L., HULSMAN, R., CONSOLI, S., LEONI, G. et al., *AI-driven Innovation in Medical Imaging - Focus on Lung Cancer and Cardiovascular Diseases*, Publications Office of the European Union, Luxembourg, 2025, https://data.europa.eu/doi/10.2760/6281523, JRC142224.

[3] BERTOLINI, L., COMTE, V., RUIZ SERRA, V., GIERSCHMANN, L., ORFEI, L. et al., *Explainable AI in Cardiovascular Health - Methods, Applications, and Innovations*, Publications Office of the European Union, Luxembourg, 2025, https://data.europa.eu/doi/10.2760/4891725, JRC143595.

[4] ABENDROTH DIAS, K., ARIAS CABARCOS, P., BACCO, F.M., BASSANI, E., BERTOLETTI, A. et al., *Generative AI Outlook Report - Exploring the Intersection of Technology, Society and Policy*, NAVAJAS CAWOOD, E., VESPE, M., KOTSEV, A. and VAN BAVEL, R. (editors), Publications Office of the European Union, Luxembourg, 2025, https://data.europa.eu/doi/10.2760/1109679, JRC142598.

[5] GRIESINGER, C.B., REINA, V., PANIDIS, D. and CHASSAIGNE, H., *AI evidence pathway for operationalising trustworthy AI in health: An ontology unfolding ethical principles into translational and fundamental concepts*, Publications Office of the European Union, Luxembourg, 2025, https://data.europa.eu/doi/10.2760/8107037, JRC140726.

[6] MOCHAN, A., FARINHA, J., BAILEY, G., RODRIGUEZ, L., ZANCA, F. and POLVORA, A., *Imaging the Future - Horizon scanning for emerging technologies and breakthrough innovations in the field of medical imaging and AI*, Publications Office of the European Union, Luxembourg, 2024, https://data.europa.eu/doi/10.2760/1426669, JRC140099.

[7] Timmis, A., Aboyans, V., Vardas, P., Townsend, N., Torbica, A., Kavousi, M., Boriani, G., Huculeci, R., Kazakiewicz, D., Scherr, D. and Karagiannidis, E., 2024. *European society of cardiology: the 2023 atlas of cardiovascular disease statistics*. European Heart Journal, *45*(38), pp.4019-4062.

[8] Chong, B., Jayabaskaran, J., Jauhari, S.M., Chan, S.P., Goh, R., Kueh, M.T.W., Li, H., Chin, Y.H., Kong, G., Anand, V.V. and Wang, J.W., 2025. *Global burden of cardiovascular diseases: projections from 2025 to 2050*. European journal of preventive cardiology, *32*(11), pp.1001-1015.

[9] Mahajan, A., Heydari, K. and Powell, D., 2025. *Wearable AI to enhance patient safety and clinical decision-making.* npj Digital Medicine, *8*(1), p.176.

[10] Hughes, A., Shandhi, M.M.H., Master, H., Dunn, J. and Brittain, E., 2023. *Wearable devices in cardiovascular medicine*. Circulation research, *132*(5), pp.652-670.

[11] Bayoumy, K., Gaber, M., Elshafeey, A., Mhaimeed, O., Dineen, E.H., Marvel, F.A., Martin, S.S., Muse, E.D., Turakhia, M.P., Tarakji, K.G. and Elshazly, M.B., 2021. *Smart wearable devices in cardiovascular care: where we are and how to move forward*. Nature Reviews Cardiology, *18*(8), pp.581-599.

[12] Mannhart, D., Lischer, M., Knecht, S., du Fay de Lavallaz, J., Strebel, I., Serban, T., Vögeli, D., Schaer, B., Osswald, S., Mueller, C. and Kühne, M., 2023. *Clinical validation of 5 direct-to-consumer wearable smart devices to detect atrial fibrillation: BASEL wearable study*. Clinical Electrophysiology, *9*(2), pp.232-242.

[13] Liu, T., Krentz, A., Lu, L. and Curcin, V., 2025. *Machine learning based prediction models for cardiovascular disease risk using electronic health records data: systematic review and meta-analysis*. European Heart Journal-Digital Health, *6*(1), pp.7-22.

[14] Datta, S., Morassi Sasso, A., Kiwit, N., Bose, S., Nadkarni, G., Miotto, R. and Böttinger, E.P., 2022. *Predicting hypertension onset from longitudinal electronic health records with deep learning*. JAMIA open, 5(4), p.ooac097.

[15] Corral-Acero, J., Margara, F., Marciniak, M., Rodero, C., Loncaric, F., Feng, Y., Gilbert, A., Fernandes, J.F., Bukhari, H.A., Wajdan, A. and Martinez, M.V., 2020. *The 'Digital Twin'to enable the vision of precision cardiology*. European heart journal, *41*(48), pp.4556-4564.

[16] Costa, F., Gomez Doblas, J.J., Díaz Expósito, A., Adamo, M., D'Ascenzo, F., Kołtowski, L., Saba, L., Mendieta, G., Gragnano, F., Calabrò, P. and Badimon, L., 2025. *Artificial intelligence in cardiovascular pharmacotherapy: applications and perspectives*. European Heart Journal, *46*(37), pp.3616-3627.

[17] "Hu, Y., Huerta, J., Cordella, N., Mishuris, R.G. and Paschalidis, I.C., 2023. *Personalized hypertension treatment recommendations by a data-driven model*. BMC Medical Informatics and Decision Making, 23(1), p.44.

[18] Bracken, A., Reilly, C., Feeley, A., Sheehan, E., Merghani, K. and Feeley, I., 2025. *Artificial intelligence (AI)–powered documentation systems in healthcare: a systematic review*. Journal of medical systems, 49(1), p.28.

[19] Albrecht, M., Shanks, D., Shah, T., Hudson, T., Thompson, J., Filardi, T., Wright, K., Ator, G.A. and Smith, T.R., 2025. *Enhancing clinical documentation with ambient artificial intelligence: a quality improvement survey assessing clinician perspectives on work burden, burnout, and job satisfaction*. JAMIA open, *8*(1), p.ooaf013.

[20] Zhao, J., Liu, H., Chen, Y. and Song, F., 2025. *Application of artificial intelligence tools and clinical documentation burden: a systematic review and meta-analysis*. BMC Medical Informatics and Decision Making.

[21] Bozyel, S., Şimşek, E., Koçyiğit, D., Güler, A., Korkmaz, Y., Şeker, M., Ertürk, M. and Keser, N., 2024. *Artificial intelligence-based clinical decision support systems in cardiovascular diseases*. Anatolian journal of cardiology, 28(2), p.74.

[22] Barzilai, D.H., Sudri, K., Goshen, G., Klang, E., Zimlichman, E., Barbash, I. and Shelly, M.C., 2025. *Randomized controlled trials evaluating artificial intelligence in cardiovascular care: a systematic review*. JACC: Advances, 4(11), p.102152.

[23] Cai, Y., Cai, Y.Q., Tang, L.Y., Wang, Y.H., Gong, M., Jing, T.C., Li, H.J., Li-Ling, J., Hu, W., Yin, Z. and Gong, D.X., 2024. Artificial intelligence in the risk prediction models of cardiovascular disease and development of an independent validation screening tool: a systematic review. BMC medicine, *22*(1), p.56.

[24] Bodenheimer, T. and Sinsky, C., 2014. *From triple to quadruple aim: care of the patient requires care of the provider*. The Annals of Family Medicine, 12(6), pp.573-576.

[25] Gregory, L., Lock, F., Harvey, H. and Zanca, F., 2026. *Economic evaluations of AI applications in radiology: a systematic review*. European Radiology, pp.1-11.

[26] Molwitz, I., Ristow, I., Erley, J., Akinci D'Antonoli, T., Tejani, A.S., Klontzas, M.E., Huisman, M., Adam, G., Nüesch, S. and Adams, L., 2025. *Economic value of AI in radiology: a systematic review*. Radiology: Artificial Intelligence, 8(1), p.e250090.

[27] Brin, D. and Tau, N., 2025. *Cost-effectiveness of artificial intelligence tools in radiology: a systematic review*. European Radiology, pp.1-11.

[28] Fraser, A.G., Biasin, E., Bijnens, B., Bruining, N., Caiani, E.G., Cobbaert, K., Davies, R.H., Gilbert, S.H., Hovestadt, L., Kamenjasevic, E. and Kwade, Z., 2023. *Artificial intelligence in medical device software and high-risk medical devices–a review of definitions, expert recommendations and regulatory initiatives*. Expert review of medical devices, *20*(6), pp.467-491.

[29] Lee, B., Kramer, P., Sandri, S., Chanda, R., Favorito, C., Nasef, O., Ross, J.S., Sharfstein, J. and Dai, T., 2025, August. *Early recalls and clinical validation gaps in artificial intelligence–enabled medical devices*. In JAMA health forum (Vol. 6, No. 8, pp. e253172-e253172). American Medical Association.

[30] Haug, C.J. and Harrison, E.M., 2026. *Which Human-in-the-Loop? Why Context, Culture, and Health Systems Matter*. NEJM AI, 3(3), p.AIe2600084.

[31] Van Gelder, I.C., Rienstra, M., Bunting, K.V., Casado-Arroyo, R., Caso, V., Crijns, H.J., De Potter, T.J., Dwight, J., Guasti, L., Hanke, T. and Jaarsma, T., 2024. *2024 ESC Guidelines for the management of atrial fibrillation developed in collaboration with the European Association for Cardio-Thoracic Surgery (EACTS) Developed by the task force for the management of atrial fibrillation of the European Society of Cardiology (ESC), with the special contribution of the European Heart Rhythm Association (EHRA) of the ESC. Endorsed by the European Stroke Organisation (ESO)*. European heart journal, *45*(36), pp.3314-3414.

[32] Perez, M.V., Mahaffey, K.W., Hedlin, H., Rumsfeld, J.S., Garcia, A., Ferris, T., Balasubramanian, V., Russo, A.M., Rajmane, A., Cheung, L. and Hung, G., 2019. *Large-scale assessment of a smartwatch to identify atrial fibrillation*. New England Journal of Medicine, *381*(20), pp.1909-1917.

[33] Buda, K.G. and Sengupta, J., 2024. *Smartwatches and atrial fibrillation: what works and what needs improvement*. American College of Cardiology.

[34] Costa, R.T., Adib, K., Salama, N., Davia, S., Millana, A.M., Traver, V. and Davtyan, K., 2025. *Electronic health records and data exchange in the WHO European region: A subregional analysis of achievements, challenges, and prospects*. International Journal of Medical Informatics, *194*, p.105687.

[35] European Commission: Directorate-General for Health and Food Safety, EEIG, Open Evidence and PwC, *Study on the deployment of AI in healthcare – Final report*, Publications Office of the European Union, 2025, https://data.europa.eu/doi/10.2875/2169577.

[36] Nawabi, J., Eminovic, S., Weissflog, J.S., Guelen, M.S., Desser, D., Meddeb, A., Bressem, K., Payabvash, S., Maier, C.M., Albers, G.W. and Wattjes, M.P., 2025. *Artificial intelligence in radiology: A comparative analysis of reimbursement and regulatory developments in the US and EU*. European Journal of Radiology Artificial Intelligence, p.100056.

[37] Day, S., Shah, V., Kaganoff, S., Powelson, S. and Mathews, S.C., 2022. *Assessing the clinical robustness of digital health startups: cross-sectional observational analysis*. Journal of medical Internet research, 24(6), p.e37677.

[38] Marešová, P., Klimova, B., Honegr, J., Kuča, K., Ibrahim, W.N.H. and Selamat, A., 2020. *Medical device development process, and associated risks and legislative aspects-systematic review*. Frontiers in public health, 8, p.308.

[39] Van Norman, G.A., 2016. *Drugs, devices, and the FDA: part 2: an overview of approval processes: FDA approval of medical devices*. JACC: Basic to Translational Science, 1(4), pp.277-287.

[40] Williams, G.A., Falkenbach, M., Schaaijk, A.V., Batenburg, R.S. and Wismar, M., 2025. *Closing the digital skills gap in healthcare: Identifying core digital skills and competencies and education and training opportunities for health professionals in the European Union*.

[41] Timmis, A., Vardas, P., Townsend, N., Torbica, A., Katus, H., De Smedt, D., Gale, C.P., Maggioni, A.P., Petersen, S.E., Huculeci, R. and Kazakiewicz, D., 2022. *European Society of Cardiology: cardiovascular disease statistics 2021: executive summary.* European Heart Journal-Quality of Care and Clinical Outcomes, *8*(4), pp.377-382.

[42] Timmis, A., Vardas, P., Townsend, N., Torbica, A., Katus, H., De Smedt, D., Gale, C.P., Maggioni, A.P., Petersen, S.E., Huculeci, R. and Kazakiewicz, D., 2022. *European Society of Cardiology: cardiovascular disease statistics 2021: executive summary*. European Heart Journal-Quality of Care and Clinical Outcomes, *8*(4), pp.377-382.

[43] Institute for Health Metrics and Evaluation (IHME), 2024. *Global burden of disease 2021: findings from the GBD 2021 study*. Institute for health metrics and evaluation.

[44] Visseren, F.L., Mach, F., Smulders, Y.M., Carballo, D., Koskinas, K.C., Bäck, M., Benetos, A., Biffi, A., Boavida, J.M., Capodanno, D. and Cosyns, B., 2021. *2021 ESC Guidelines on cardiovascular disease prevention in clinical practice: Developed by the Task Force for cardiovascular disease prevention in clinical practice with representatives of the European Society of Cardiology and 12 medical societies With the special contribution of the European Association of Preventive Cardiology (EAPC)*. European heart journal, *42*(34), pp.3227-3337.

[45] Deo, R. and Albert, C.M., 2012. *Epidemiology and genetics of sudden cardiac death*. Circulation, *125*(4), pp.620-637.

[46] SCORE2 working group and ESC Cardiovascular risk collaboration, *SCORE2 risk prediction algorithms: new models to estimate 10-year risk of cardiovascular disease in Europe*, European Heart Journal, Volume 42, Issue 25, 1 July 2021, Pages 2439–2454, https://doi.org/10.1093/eurheartj/ehab309.

[47] Eng, D., Chute, C., Khandwala, N., Rajpurkar, P., Long, J., Shleifer, S., Khalaf, M.H., Sandhu, A.T., Rodriguez, F., Maron, D.J. and Seyyedi, S., 2021. *Automated coronary calcium scoring using deep learning with multicenter external validation*. NPJ digital medicine, *4*(1), p.88.

[48] Aromiwura, A.A. and Kalra, D.K., 2024. *Artificial intelligence in coronary artery calcium scoring*. Journal of Clinical Medicine, 13(12), p.3453.

[49] Gennari, A.G., Rossi, A., De Cecco, C.N., van Assen, M., Sartoretti, T., Giannopoulos, A.A., Schwyzer, M., Huellner, M.W. and Messerli, M., 2024. *Artificial intelligence in coronary artery calcium score: rationale, different approaches, and outcomes*. The international journal of cardiovascular imaging, *40*(5), pp.951-966.

[50] Huang, J.D., Wang, J., Ramsey, E., Leavey, G., Chico, T.J. and Condell, J., 2022. *Applying artificial intelligence to wearable sensor data to diagnose and predict cardiovascular disease: a review*. Sensors, 22(20), p.8002.

[51] Moshawrab, M., Adda, M., Bouzouane, A., Ibrahim, H. and Raad, A., 2023. *Smart wearables for the detection of cardiovascular diseases: a systematic literature review*. Sensors, 23(2), p.828.

[52] Hirata, Y. and Kusunose, K., 2025. *AI in echocardiography: state-of-the-art automated measurement techniques and clinical applications*. JMA journal, 8(1), pp.141-150.

[53] Olaisen, S., Smistad, E., Espeland, T., Hu, J., Pasdeloup, D., Østvik, A., Aakhus, S., Roesner, A., Malm, S., Stylidis, M. and Holte, E., 2024. *Automatic measurements of left ventricular volumes and ejection fraction by artificial intelligence: clinical validation in real time and large databases*. European Heart Journal-Cardiovascular Imaging, *25*(3), pp.383-395.

[54] Tromp, J., Bauer, D., Claggett, B.L., Frost, M., Iversen, M.B., Prasad, N., Petrie, M.C., Larson, M.G., Ezekowitz, J.A. and Solomon, S.D., 2022. *A formal validation of a deep learning-based automated workflow for the interpretation of the echocardiogram*. Nature Communications, *13*(1), p.6776.

[55] Slivnick, J.A., Hawkes, W., Oliveira, J., Woodward, G., Akerman, A., Gomez, A., Hamza, I., Desai, V.K., Barrett-O'Keefe, Z., Grogan, M. and Dispenzieri, A., 2025. *Cardiac amyloidosis detection from a single echocardiographic video clip: a novel artificial intelligence-based screening tool*. European heart journal, *46*(40), pp.4090-4101.

[56] Akerman, A.P., Porumb, M., Scott, C.G., Beqiri, A., Chartsias, A., Ryu, A.J., Hawkes, W., Huntley, G.D., Arystan, A.Z., Kane, G.C. and Pislaru, S.V., 2023. *Automated echocardiographic detection of heart failure with preserved ejection fraction using artificial intelligence*. JACC: Advances, *2*(6), p.100452.

[57] Mor-Avi, V., Khandheria, B., Klempfner, R., Cotella, J.I., Moreno, M., Ignatowski, D., Guile, B., Hayes, H.J., Hipke, K., Kaminski, A. and Spiegelstein, D., 2023. *Real-time artificial intelligence–based guidance of echocardiographic imaging by novices: image quality and suitability for diagnostic interpretation and quantitative analysis*. Circulation: Cardiovascular Imaging, *16*(11), p.e015569.

[58] Trost, B., Rodrigues, L., Ong, C., Dezellus, A., Goldberg, Y.H., Bouchat, M., Roger, E., Moal, O., Singh, V., Moal, B. and Lafitte, S., 2025. *Artificial intelligence empowers novice users to acquire diagnostic-quality echocardiography*. JACC: Advances, *4*(8), p.102005.

[59] Huang, W., Koh, T., Tromp, J., Chandramouli, C., Ewe, S.H., Ng, C.T., Lee, A.S.Y., Teo, L.L.Y., Hummel, Y., Huang, F. and Lam, C.S.P., 2024. *Point-of-care AI-enhanced novice echocardiography for screening heart failure (PANES-HF)*. Scientific Reports, *14*(1), p.13503.

[60] Agatston, A.S., Janowitz, W.R., Hildner, F.J., Zusmer, N.R., Viamonte Jr, M. and Detrano, R., 1990. *Quantification of coronary artery calcium using ultrafast computed tomography*. Journal of the American college of cardiology, 15(4), pp.827-832.

[61] Abdelrahman, K., Shiyovich, A., Huck, D.M., Berman, A.N., Weber, B., Gupta, S., Cardoso, R. and Blankstein, R., 2024. *Artificial intelligence in coronary artery calcium scoring detection and quantification*. Diagnostics, 14(2), p.125.

[62] Ihdayhid, A.R., Lan, N.S., Williams, M., Newby, D., Flack, J., Kwok, S., Joyner, J., Gera, S., Dembo, L., Adler, B. and Ko, B., 2023. *Evaluation of an artificial intelligence coronary artery calcium scoring model from computed tomography*. European radiology, *33*(1), pp.321-329.

[63] Xie, X., Zhao, Y., de Bock, G.H., de Jong, P.A., Mali, W.P., Oudkerk, M. and Vliegenthart, R., 2013. *Validation and prognosis of coronary artery calcium scoring in nontriggered thoracic computed tomography: systematic review and meta-analysis*. Circulation: Cardiovascular Imaging, *6*(4), pp.514-521.

[64] Kim, S., Park, E.A., Ahn, C., Jeong, B., Lee, Y.S., Lee, W. and Kim, J.H., 2025. *Performance of fully automated deep-learning-based coronary artery calcium scoring in ECG-gated calcium CT and non-gated low-dose chest CT*. European Radiology, 35(11), pp.708.

[65] Xie, X., Zhao, Y., de Bock, G.H., de Jong, P.A., Mali, W.P., Oudkerk, M. and Vliegenthart, R., 2013. *Validation and prognosis of coronary artery calcium scoring in nontriggered thoracic computed tomography: systematic review and meta-analysis*. Circulation: Cardiovascular Imaging, *6*(4), pp.514-521.

[66] Hecht, H.S., Blaha, M.J., Kazerooni, E.A., Cury, R.C., Budoff, M., Leipsic, J. and Shaw, L., 2018. *CAC-DRS: coronary artery calcium data and reporting system. An expert consensus document of the society of cardiovascular computed tomography (SCCT)*. Journal of cardiovascular computed tomography, *12*(3), pp.185-191.

[67] Mastrodicasa, D., Van Assen, M., Huisman, M., Leiner, T., Williamson, E.E., Nicol, E.D., Allen, B.D., Saba, L., Vliegenthart, R. and Hanneman, K., 2025. *Use of AI in cardiac CT and MRI: a scientific statement from the ESCR, EuSoMII, NASCI, SCCT, SCMR, SIIM, and RSNA*. Radiology, *314*(1), p.e240516.

[68] Kwiecinski, J., 2024. *Artificial Intelligence-Based Quantitative Coronary Plaque Analysis*. Cardiovascular Imaging, 17(3), pp.281-283.

[69] Giannopoulos, A.A., Keller, L., Sepulcri, D., Boehm, R., Garefa, C., Venugopal, P., Mitra, J., Ghose, S., Deak, P., Pack, J.D. and Davis, C.L., 2023. *High-speed on-site deep learning–based FFR-CT algorithm: evaluation using invasive angiography as the reference standard*. American Journal of Roentgenology, *221*(4), pp.460-470.

[70] Liu, J., Li, B., Yang, Y., Huang, S., Sun, H., Liu, J. and Liu, Y., 2024. *A comprehensive approach to prediction of fractional flow reserve from deep-learning-augmented model*. Computers in Biology and Medicine, 169, p.107967.

[71] Li, J., Yang, Z., Sun, Z., Zhao, L., Liu, A., Wang, X., Jin, Q. and Zhang, G., 2024. *CT coronary fractional flow reserve based on artificial intelligence using different software: a repeatability study*. BMC medical imaging, 24(1), p.288.

[72] Guo, B., Jiang, M., Guo, X., Tang, C., Zhong, J., Lu, M., Liu, C., Zhang, X., Qiao, H., Zhou, F. and Xu, P., 2024. *Diagnostic and prognostic performance of artificial intelligence-based fully-automated on-site CT-FFR in patients with CAD*. Science Bulletin, *69*(10), pp.1472-1485.

[73] An, Z., Tian, J., Zhao, X., Zhang, M., Zhang, L., Yang, X., Liu, L. and Song, X., 2023. *Machine Learning–Based CT Angiography–Derived Fractional Flow Reserve for Diagnosis of Functionally Significant Coronary Artery Disease*. Cardiovascular Imaging, *16*(3), pp.401-404.

[74] Armoundas, A.A., Narayan, S.M., Arnett, D.K., Spector-Bagdady, K., Bennett, D.A., Celi, L.A., Friedman, P.A., Gollob, M.H., Hall, J.L., Kwitek, A.E. and Lett, E., 2024. *Use of artificial intelligence in improving outcomes in heart disease: a scientific statement from the American Heart Association*. Circulation, *149*(14), pp.e1028-e1050.

[75] Moreno-Sánchez, P.A., García-Isla, G., Corino, V.D., Vehkaoja, A., Brukamp, K., Van Gils, M. and Mainardi, L., 2024. *ECG-based data-driven solutions for diagnosis and prognosis of cardiovascular diseases: A systematic review*. Computers in Biology and Medicine, *172*, p.108235.

[76] Hughes, J.W., Tooley, J., Torres Soto, J., Ostropolets, A., Poterucha, T., Christensen, M.K., Yuan, N., Ehlert, B., Kaur, D., Kang, G. and Rogers, A., 2023. *A deep learning-based electrocardiogram risk score for long term cardiovascular death and disease*. NPJ digital medicine, *6*(1), p.169.

[77] Goff Jr, D.C., Lloyd-Jones, D.M., Bennett, G., Coady, S., D'Agostino Sr, R.B., Gibbons, R., Greenland, P., Lackland, D.T., Levy, D., O'donnell, C.J. and Robinson, J.G., 2014. *2013 ACC/AHA guideline on the assessment of cardiovascular risk: a report of the American College of Cardiology/American Heart Association Task Force on Practice Guidelines*. Journal of the American college of cardiology, *63*(25), pp.2935-2959.

[78] Muzammil, M.A., Javid, S., Afridi, A.K., Siddineni, R., Shahabi, M., Haseeb, M., Fariha, F.N.U., Kumar, S., Zaveri, S. and Nashwan, A.J., 2024. *Artificial intelligence-enhanced electrocardiography for accurate diagnosis and management of cardiovascular diseases*. Journal of electrocardiology, *83*, pp.30-40.

[79] Akbilgic, O., Butler, L., Karabayir, I., Chang, P.P., Kitzman, D.W., Alonso, A., Chen, L.Y. and Soliman, E.Z., 2021. *ECG-AI: electrocardiographic artificial intelligence model for prediction of heart failure*. European Heart Journal-Digital Health, *2*(4), pp.626-634.

[80] Song, W.H., Tse, G., Chen, K.Y. and Liu, T., 2025. *Artificial intelligence-enabled single-lead electrocardiogram in early detection of ischemic heart disease*. World Journal of Cardiology, 17(7), p.108510.

[81] Zhang, L., Lu, H. and Yang, C., 2024. *Global, regional, and national burden of stroke from 1990 to 2019: A temporal trend analysis based on the Global Burden of Disease Study 2019*. International Journal of Stroke, 19(6), pp.686-694.

[82] Strilciuc, S., Grad, D.A., Radu, C., Chira, D., Stan, A., Ungureanu, M., Gheorghe, A. and Muresanu, F.D., 2021. *The economic burden of stroke: a systematic review of cost of illness studies*. Journal of medicine and life, 14(5), p.606.

[83] Arboix, A. and Alioc, J., 2010. *Cardioembolic stroke: clinical features, specific cardiac disorders and prognosis*. Current cardiology reviews, 6(3), pp.150-161.

[84] Krijthe, B.P., Kunst, A., Benjamin, E.J., Lip, G.Y., Franco, O.H., Hofman, A., Witteman, J.C., Stricker, B.H. and Heeringa, J., 2013. *Projections on the number of individuals with atrial fibrillation in the European Union, from 2000 to 2060*. European heart journal, *34*(35), pp.2746-2751.

[85] Chugh, S.S., Havmoeller, R., Narayanan, K., Singh, D., Rienstra, M., Benjamin, E.J., Gillum, R.F., Kim, Y.H., McAnulty Jr, J.H., Zheng, Z.J. and Forouzanfar, M.H., 2014. *Worldwide epidemiology of atrial fibrillation: a Global Burden of Disease 2010 Study*. Circulation, *129*(8), pp.837-847.

[86] Go, A.S., Hylek, E.M., Phillips, K.A., Chang, Y., Henault, L.E., Selby, J.V. and Singer, D.E., 2001. *Prevalence of diagnosed atrial fibrillation in adults: national implications for rhythm management and stroke prevention: the AnTicoagulation and Risk Factors in Atrial Fibrillation (ATRIA) Study*. Jama, *285*(18), pp.2370-2375.

[87] Ali, A., Bailey, C. and Abdelhafiz, A.H., 2012. *Stroke prevention with oral anticoagulation in older people with atrial fibrillation-a pragmatic approach*. Aging and disease, 3(4), p.339.

[88] Lamassa, M., Di Carlo, A., Pracucci, G., Basile, A.M., Trefoloni, G., Vanni, P., Spolveri, S., Baruffi, M.C., Landini, G., Ghetti, A. and Wolfe, C.D., 2001. *Characteristics, outcome, and care of stroke associated with atrial fibrillation in Europe: data from a multicenter multinational hospital–based registry (The European Community Stroke Project)*. Stroke, *32*(2), pp.392-398.

[89] Voskoboinik, A., Prabhu, S., Ling, L.H., Kalman, J.M. and Kistler, P.M., 2016. *Alcohol and atrial fibrillation: a sobering review*. Journal of the American College of Cardiology, 68(23), pp.2567-2576.

[90] Freedman, B., Camm, J., Calkins, H., Healey, J.S., Rosenqvist, M., Wang, J., Albert, C.M., Anderson, C.S., Antoniou, S., Benjamin, E.J. and Boriani, G., 2017. *Screening for atrial fibrillation: a report of the AF-SCREEN international collaboration*. circulation, *135*(19), pp.1851-1867.

[91] Sanna, T., Diener, H.C., Passman, R.S., Di Lazzaro, V., Bernstein, R.A., Morillo, C.A., Rymer, M.M., Thijs, V., Rogers, T., Beckers, F. and Lindborg, K., 2014. *Cryptogenic stroke and underlying atrial fibrillation*. New England Journal of Medicine, 370(26).

[92] Gladstone, D.J., Spring, M., Dorian, P., Panzov, V., Thorpe, K.E., Hall, J., Vaid, H., O'Donnell, M., Laupacis, A., Côté, R. and Sharma, M., 2014. *Atrial fibrillation in patients with cryptogenic stroke*. New England Journal of Medicine, 370(26), pp.2467-2.

[93] Kamel, H. and Healey, J.S., 2017. *Cardioembolic stroke*. Circulation research, 120(3), pp.514-526.

[94] Hart, R.G., Diener, H.C., Coutts, S.B., Easton, J.D., Granger, C.B., O'Donnell, M.J., Sacco, R.L. and Connolly, S.J., 2014. *Embolic strokes of undetermined source: the case for a new clinical construct*. The Lancet Neurology, 13(4), pp.429-438.

[95] Gladstone, D.J., Spring, M., Dorian, P., Panzov, V., Thorpe, K.E., Hall, J., Vaid, H., O'Donnell, M., Laupacis, A., Côté, R. and Sharma, M., 2014. *Atrial fibrillation in patients with cryptogenic stroke*. New England Journal of Medicine, 370(26), pp.2467-2.

[96] Attia, Z.I., Noseworthy, P.A., Lopez-Jimenez, F., Asirvatham, S.J., Deshmukh, A.J., Gersh, B.J., Carter, R.E., Yao, X., Rabinstein, A.A., Erickson, B.J. and Kapa, S., 2019. *An artificial intelligence-enabled ECG algorithm for the identification of patients with atrial fibrillation during sinus rhythm: a retrospective analysis of outcome prediction*. The Lancet, *394*(10201), pp.861-867.

[97] Tsiartas, E., Nayak, D. and Meade, A., 2025. *Artificial intelligence capabilities in identifying atrial fibrillation using baseline sinus rhythm ECG: a systematic review*. Open Heart, 12(2).

[98] Mrak, Z., Naji, F.H. and Dinevski, D., 2026. *Artificial Intelligence Applied to Electrocardiograms Recorded in Sinus Rhythm for Detection and Prediction of Atrial Fibrillation: A Scoping Review*. Medicina, 62(1), p.199.

[99] Raghunath, S., Pfeifer, J.M., Ulloa-Cerna, A.E., Nemani, A., Carbonati, T., Jing, L., vanMaanen, D.P., Hartzel, D.N., Ruhl, J.A., Lagerman, B.F. and Rocha, D.B., 2021. *Deep neural networks can predict new-onset atrial fibrillation from the 12-lead ECG and help identify those at risk of atrial fibrillation–related stroke*. Circulation, *143*(13), pp.1287-1298.

[100] Choi, J., Kim, J.Y., Cho, M.S., Kim, M., Kim, J., Oh, I.Y., Cho, Y. and Lee, J.H., 2024. *Artificial intelligence predicts undiagnosed atrial fibrillation in patients with embolic stroke of*

undetermined source using sinus rhythm electrocardiograms. Heart Rhythm, *21*(9), pp.1647-1655.

[101] Schoels, M., Krumm, L., Nelde, A., Olma, M.C., Nolte, C.H., Scheitz, J.F., Klammer, M.G., Leithner, C., Meisel, A., Scheibe, F. and Krämer, M., 2025. *Artificial intelligence for prediction of atrial fibrillation in the stroke unit: a retrospective derivation validation cohort study*. EBioMedicine, *118*.

[102] Zimmerman, R.M., Hernandez, E.J., Tristani-Firouzi, M., Yandell, M. and Steinberg, B.A., 2025. *Explainable artificial intelligence for stroke risk stratification in atrial fibrillation*. European Heart Journal-Digital Health, 6(3), pp.317-325.

[103] Weidlich, S., Mannhart, D., Kennedy, A., Doggart, P., Serban, T., Knecht, S., Du Fay De Lavallaz, J., Kuehne, M., Sticherling, C. and Badertscher, P., 2023. *Reducing the burden of inconclusive smart-device single-lead ECG tracings via a novel atificial intelligence algorithm*. European Heart Journal, *44*(Supplement_2), pp.ehad655-2922.

[104] Khurshid, S., Friedman, S.F., Al-Alusi, M.A., Kany, S., Sommers, T., Anderson, C.D., Ho, J.E., McManus, D.D., Borowsky, L.H., Ashburner, J.M. and Lubitz, S.A., 2025. *Artificial intelligence-enabled analysis of handheld single-lead electrocardiograms to predict incident atrial fibrillation: an analysis of the VITAL-AF randomized trial.* npj Digital Medicine.

[105] Khurshid, S., Friedman, S.F., Al-Alusi, M.A., Kany, S., Sommers, T., Anderson, C.D., Ho, J.E., McManus, D.D., Borowsky, L.H., Ashburner, J.M. and Lubitz, S.A., 2025. *Artificial intelligence-enabled analysis of handheld single-lead electrocardiograms to predict incident atrial fibrillation: an analysis of the VITAL-AF randomized trial.* npj Digital Medicine.

[106] Papalamprakopoulou, Z., Stavropoulos, D., Moustakidis, S., Avgerinos, D., Efremidis, M. and Kampaktsis, P.N., 2024. *Artificial intelligence-enabled atrial fibrillation detection using smartwatches: current status and future perspectives*. Frontiers in Cardiovascular Medicine, *11*, p.1432876.

[107] Rosman, L., Lampert, R., Zhuo, S., Li, Q., Varma, N., Burg, M., Gaffey, A.E., Armbruster, T. and Gehi, A., 2024. *Wearable devices, health care use, and psychological well-being in patients with atrial fibrillation*. Journal of the American Heart Association, *13*(15), p.e033750.

[108] Rienstra, M., Tzeis, S., Bunting, K.V., Caso, V., Crijns, H.J., De Potter, T.J., Sanders, P., Svennberg, E., Casado-Arroyo, R., Dwight, J. and Guasti, L., 2024. *Spotlight on the 2024 ESC/EACTS management of atrial fibrillation guidelines: 10 novel key aspects*. Europace, *26*(12), p.euae298.

[109] Cresti, A. and Camara, O., 2023. *Left atrial thrombus—are all atria and appendages equal?*. Cardiac Electrophysiology Clinics, 15(2), pp.119-132.

[110] Pieszko, K., Hiczkiewicz, J., Łojewska, K., Uziębło-Życzkowska, B., Krzesiński, P., Gawałko, M., Budnik, M., Starzyk, K., Wożakowska-Kapłon, B., Daniłowicz-Szymanowicz, L. and Kaufmann, D., 2024. *Artificial intelligence in detecting left atrial appendage thrombus by transthoracic echocardiography and clinical features: the Left Atrial Thrombus on Transoesophageal Echocardiography (LATTEE) registry*. European Heart Journal, *45*(1), pp.32-41.

[111] Mai, P., Huo, H., Li, X., Zhou, D., He, F., Li, Y. and Wang, H., 2025. *A new integrated machine learning model: application to improve the accuracy of predicting left atrial appendage thrombus in patients with non-valvular atrial fibrillation*. Frontiers in Medicine, *12*, p.1661696.

[112] Bosi, G.M., Cook, A., Rai, R., Menezes, L.J., Schievano, S., Torii, R. and Burriesci, G., 2018. *Computational fluid dynamic analysis of the left atrial appendage to predict thrombosis risk*. Frontiers in cardiovascular medicine, 5, p.34.

[113] Albors, C., Mill, J., Olivares, A.L., Iriart, X., Cochet, H. and Camara, O., 2024. *Impact of occluder device configurations in in-silico left atrial hemodynamics for the analysis of device-related thrombus*. PLOS Computational Biology, 20(9), p.e1011546.

[114] Morales Ferez, X., Mill, J., Juhl, K.A., Acebes, C., Iriart, X., Legghe, B., Cochet, H., De Backer, O., Paulsen, R.R. and Camara, O., 2021. *Deep learning framework for real-time estimation of in-silico thrombotic risk indices in the left atrial appendage*. Frontiers in Physiology, *12*, p.694945.

[115] Morales, X., Mill, J., Simeon, G., Juhl, K.A., De Backer, O., Paulsen, R.R. and Camara, O., 2021, June. *Geometric deep learning for the assessment of thrombosis risk in the left atrial appendage*. In *International Conference on Functional Imaging and Modeling of the Heart* (pp. 639-649). Cham: Springer International Publishing.

[116] Saiz-Vivó, M., Mill, J., Iriart, X., Cochet, H., Piella, G., Sermesant, M. and Camara, O., 2025. *Digital twin integrating clinical, morphological and hemodynamic data to identify stroke risk factors*. npj Digital Medicine, 8(1), p.369.

[117] Cohen-Shelly, M., Attia, Z.I., Friedman, P.A., Ito, S., Essayagh, B.A., Ko, W.Y., Murphree, D.H., Michelena, H.I., Enriquez-Sarano, M., Carter, R.E. and Johnson, P.W., 2021. *Electrocardiogram screening for aortic valve stenosis using artificial intelligence*. European heart journal, *42*(30), pp.2885-2896.

[118] Yang, F., Chen, X., Lin, X., Chen, X., Wang, W., Liu, B., Li, Y., Pu, H., Zhang, L., Huang, D. and Zhang, M., 2022. *Automated analysis of Doppler echocardiographic videos as a screening tool for valvular heart diseases*. Cardiovascular Imaging, 15(4), pp.5.

[119] Poterucha, T.J., Jing, L., Ricart, R.P., Adjei-Mosi, M., Finer, J., Hartzel, D., Kelsey, C., Long, A., Rocha, D., Ruhl, J.A. and vanMaanen, D., 2025. *Detecting structural heart disease from electrocardiograms using AI*. Nature, 644(8075), pp.221-230.

[120] Saver, J.L., Carroll, J.D., Thaler, D.E., Smalling, R.W., MacDonald, L.A., Marks, D.S. and Tirschwell, D.L., 2017. *Long-term outcomes of patent foramen ovale closure or medical therapy after stroke*. New England Journal of Medicine, 377(11), pp.1022-1032.

[121] Mas, J.L., Derumeaux, G., Guillon, B., Massardier, E., Hosseini, H., Mechtouff, L., Arquizan, C., Béjot, Y., Vuillier, F., Detante, O. and Guidoux, C., 2017. *Patent foramen ovale closure or anticoagulation vs. antiplatelets after stroke*. New England Journal of Medicine, *377*(11), pp.1011-1021.

[122] Søndergaard, L., Kasner, S.E., Rhodes, J.F., Andersen, G., Iversen, H.K., Nielsen-Kudsk, J.E., Settergren, M., Sjöstrand, C., Roine, R.O., Hildick-Smith, D. and Spence, J.D., 2017. *Patent foramen ovale closure or antiplatelet therapy for cryptogenic stroke*. New England Journal of Medicine, *377*(11), pp.1033-1042.

[123] Lee, P.H., Song, J.K., Kim, J.S., Heo, R., Lee, S., Kim, D.H., Song, J.M., Kang, D.H., Kwon, S.U., Kang, D.W. and Lee, D., 2018. *Cryptogenic stroke and high-risk patent foramen ovale: the DEFENSE-PFO trial*. Journal of the American College of Cardiology, *71*(20), pp.2335-2342.

[124] Mojadidi, M.K., Zaman, M.O., Elgendy, I.Y., Mahmoud, A.N., Patel, N.K., Agarwal, N., Tobis, J.M. and Meier, B., 2018. *Cryptogenic stroke and patent foramen ovale*. Journal of the American College of Cardiology, 71(9), pp.1035-1043.

[125] Turc, G., Calvet, D., Guerin, P., Sroussi, M., Chatellier, G., Mas, J.L. and CLOSE Investigators, 2018. *Closure, anticoagulation, or antiplatelet therapy for cryptogenic stroke with patent foramen ovale: systematic review of randomized trials, sequential meta-analysis, and new insights from the CLOSE study*. Journal of the American Heart Association, *7*(12), p.e008356.

[126] Yang, J., Zhang, S., Zhou, Y., Yu, H., Zhang, H., Lan, T., Zhang, M., Huang, W., Zhang, W., Cheng, L. and Li, Y., 2023. *The efficiency of a Machine learning approach based on Spatio-Temporal information in the detection of patent foramen ovale from contrast transthoracic echocardiography Images: A primary study*. Biomedical Signal Processing and Control, *84*, p.104813.

[127] Bai, J., Yang, J., Song, W., Liu, Y., Xu, H. and Liu, Y., 2022. *Intelligent prediction of cryptogenic stroke using patent foramen ovale from TEE imaging data and machine learning methods*. International Journal of Computational Intelligence Systems, *15*(1), p.13.

[128] Wu, X., Sha, J., Yin, Q., Gu, Y. and He, X., 2025. *Global burden of hypertensive heart disease and attributable risk factors, 1990–2021: Insights from the global burden of disease study 2021*. Scientific Reports, 15(1), p.14594.

[129] *Safiri, S., Karamzad, N., Singh, K., Carson-Chahhoud, K., Adams, C., Nejadghaderi, S.A., Almasi-Hashiani, A., Sullman, M.J., Mansournia, M.A., Bragazzi, N.L. and Kaufman, J.S., 2022. Burden of ischemic heart disease and its attributable risk factors in 204 countries and territories, 1990–2019.* European journal of preventive cardiology*, 29(2), pp.420-431.*

[130] Zhou, B., Carrillo-Larco, R.M., Danaei, G., Riley, L.M., Paciorek, C.J., Stevens, G.A., Gregg, E.W., Bennett, J.E., Solomon, B., Singleton, R.K. and Sophiea, M.K., 2021. *Worldwide trends in hypertension prevalence and progress in treatment and control from 1990 to 2019: a pooled analysis of 1201 population-representative studies with 104 million participants*. The lancet, *398*(10304), pp.957-980.

[131] Wolf-Maier, K., Cooper, R.S., Kramer, H., Banegas, J.R., Giampaoli, S., Joffres, M.R., Poulter, N., Primatesta, P., Stegmayr, B. and Thamm, M., 2004. *Hypertension treatment and control in five European countries, Canada, and the United States*. Hypertension, *43*(1), pp.10-17.

[132] Cuspidi, C., Sala, C., Negri, F., Mancia, G. and Morganti, A., 2012. *Prevalence of left-ventricular hypertrophy in hypertension: an updated review of echocardiographic studies*. Journal of human hypertension, 26(6), pp.343-349.

[133] Heimark, S., Mehlum, M.H., Mancia, G., Søraas, C.L., Liestøl, K., Wachtell, K., Larstorp, A.C., Rostrup, M., Mariampillai, J.E., Kjeldsen, S.E. and Julius, S., 2023. *Middle-aged and older patients with left ventricular hypertrophy: higher mortality with drug treated systolic blood pressure below 130 mm Hg*. Hypertension, *80*(8), pp.1739-1748.

[134] Woodhouse, P.R., Khaw, K.T. and Plummer, M., 1993. *Seasonal variation of blood pressure and its relationship to ambient temperature in an elderly population*. Journal of hypertension, 11(11), pp.1267-1274.

[135] Sotomi, Y., Hikoso, S., Nakatani, D., Mizuno, H., Okada, K., Dohi, T., Kitamura, T., Sunaga, A., Kida, H., Oeun, B. and Sato, T., 2021. *Sex differences in heart failure with preserved ejection fraction*. Journal of the American Heart Association, *10*(5), p.e018574.

[136] Liu, C.M., Hsieh, M.E., Hu, Y.F., Wei, T.Y., Wu, I.C., Chen, P.F., Lin, Y.J., Higa, S., Yagi, N., Chen, S.A. and Tseng, V.S., 2022. *Artificial intelligence–enabled model for early detection of left ventricular hypertrophy and mortality prediction in young to middle-aged adults*. Circulation: Cardiovascular Quality and Outcomes, *15*(8), p.e008360.

[137] Zhao, X., Huang, G., Wu, L., Wang, M., He, X., Wang, J.R., Zhou, B., Liu, Y., Lin, Y., Liu, D. and Yu, X., 2022. *Deep learning assessment of left ventricular hypertrophy based on electrocardiogram*. Frontiers in Cardiovascular Medicine, 9, p.952089.

[138] Ko, W.Y., Siontis, K.C., Attia, Z.I., Carter, R.E., Kapa, S., Ommen, S.R., Demuth, S.J., Ackerman, M.J., Gersh, B.J., Arruda-Olson, A.M. and Geske, J.B., 2020. *Detection of hypertrophic*

cardiomyopathy using a convolutional neural network-enabled electrocardiogram. Journal of the American College of Cardiology, *75*(7), pp.722-733.

[139] Cirillo, C., Matarrese, M.A., Monda, E., Pagnano, M.E., Vitale, J., Verrillo, F., Palmiero, G., Bassolino, S., Buono, P., Caiazza, M. and Loffredo, F., 2025. *Artificial intelligence for left ventricular hypertrophy detection and differentiation on echocardiography, cardiac magnetic resonance and cardiac computed tomography: A systematic review*. International Journal of Cardiology, *422*, p.132979.

[140] Loncaric, F., Castellote, P.M.M., Sanchez-Martinez, S., Fabijanovic, D., Nunno, L., Mimbrero, M., Sanchis, L., Doltra, A., Montserrat, S., Cikes, M. and Crispi, F., 2021. *Automated pattern recognition in whole-cardiac cycle echocardiographic data: capturing functional phenotypes with machine learning*. Journal of the american society of echocardiography, *34*(11), pp.1170-1183.

[141] Jimenez-Perez, G., Loncaric, F., Marti Castellote, P.M., Ramos Jovani, M., Gonzales Lopez, E., Gonzales Mirelis, J., Piella, G., Camara, O., Garcia-Alvarez, A., Garcia-Pavia, P. and Sitges, M., 2022. *Machine learning-based phenotyping and risk assessment of hypertrophic cardiomyopathy-linking ECGs, morphology and genotypes*. European Heart Journal-Cardiovascular Imaging, *23*(Supplement_1), pp.jeab289-431.

[142] Loncaric, F., Marti Castellote, P.M., Gonzalez Lopez, E., Sanchis, L., Romero, T., Prat, S., Gonzalez Mirelis, J.F., Doltra, A., Ramos Jovani, M., Aguado, A. and Piella, G., 2021. *Exploring phenotypes in hypertrophic cardiomyopathy with machine learning data integration. A multicentric, multimodality pilot study*. European Heart Journal, *42*(Supplement_1), pp.ehab724-3072.

[143] Soto, J.T., Weston Hughes, J., Sanchez, P.A., Perez, M., Ouyang, D. and Ashley, E.A., 2022. *Multimodal deep learning enhances diagnostic precision in left ventricular hypertrophy*. European Heart Journal-Digital Health, 3(3), pp.380-389.

[144] Chowdhury, M.Z.I., Naeem, I., Quan, H., Leung, A.A., Sikdar, K.C., O'Beirne, M. and Turin, T.C., 2022. *Prediction of hypertension using traditional regression and machine learning models: A systematic review and meta-analysis*. PloS one, 17(4), p.e0266334.

[145] Datta, S., Morassi Sasso, A., Kiwit, N., Bose, S., Nadkarni, G., Miotto, R. and Böttinger, E.P., 2022. *Predicting hypertension onset from longitudinal electronic health records with deep learning*. JAMIA open, 5(4), p.ooac097.

[146] Mathur, P., Srivastava, S., Xu, X. and Mehta, J.L., 2020. *Artificial intelligence, machine learning, and cardiovascular disease*. Clinical Medicine Insights: Cardiology, 14, p.1179546820927404."

[147] Cho, J.S. and Park, J.H., 2024. *Application of artificial intelligence in hypertension*. Clinical Hypertension, 30(1), p.11.

[148] Stergiou, G.S., Menti, A., Mariglis, D. and Kollias, A., 2026. *The quest for accurate wearable blood pressure monitors*. Hypertension Research, 49(3), pp.1025-1029.

[149] Di Achille, P., Cai, L., Wu, J., Gao, M., Daryani, B., Wang, J., Khanna, U., Ko, H., Pathak, A., Malhotra, M. and Patel, S., 2025. *Opportunistically Detecting Signs of Hypertension on a Consumer Smartwatch*. medRxiv, pp.2025-12.

[150] Mukkamala, R., Hahn, J.O., Inan, O.T., Mestha, L.K., Kim, C.S., Töreyin, H. and Kyal, S., 2015. *Toward ubiquitous blood pressure monitoring via pulse transit time: theory and practice*. IEEE transactions on biomedical engineering, 62(8), pp.1879-1901.

List of abbreviations and definitions

Abbreviations	Full term	Definition
AF	Atrial Fibrillation	An irregular and often rapid heart rhythm that increases the risk of stroke and other cardiovascular complications.
AI	Artificial Intelligence	The theory and development of computer systems able to perform tasks that normally require human intelligence, such as learning, reasoning, and decision-making.
AUC / AUROC	Area Under the (Receiver Operating Characteristic) Curve	A standard metric for evaluating the discriminative performance of classification models; values closer to 1 indicate better performance.
CAC	Coronary Artery Calcium	Calcium deposits in the coronary arteries, quantified by computed tomography (CT) scanning as a marker of subclinical atherosclerosis.
CCTA	Coronary Computed Tomography Angiography	An imaging technique used to visualise the coronary arteries and detect stenoses or plaque.
CFD	Computational Fluid Dynamics	Numerical simulation of fluid flow, used to model blood flow patterns and assess thrombotic risk in the heart.
CNN	Convolutional Neural Network	A type of deep learning (DL) architecture particularly suited to image analysis tasks.
CT	Computed Tomography	A medical imaging technique using X-rays to produce detailed cross-sectional images of the body.
CVD	Cardiovascular Disease	A broad category of conditions affecting the heart and blood vessels, including coronary artery disease, stroke, heart failure, and others.
DALY	Disability-Adjusted Life Year	A measure of overall disease burden combining years of life lost to premature death and years lived with disability.
DL	Deep Learning	A subset of machine learning using multi-layered neural networks to learn complex patterns from data.

Abbreviations	Full term	Definition
DT	Digital Twin	A virtual replica of a physical system or patient, continuously updated with real-world data, used to simulate, predict, and optimise the behaviour of its physical counterpart.
ECG	Electrocardiogram	A recording of the electrical activity of the heart, used to detect arrhythmias, ischaemia, and structural abnormalities.
EHR	Electronic Health Record	A digital record of a patient's medical history, diagnoses, treatments, and clinical data, used to support healthcare delivery and continuity of care, and increasingly leveraged as a data source for AI-driven research and clinical decision support.
ESUS	Embolic Stroke of Undetermined Source	A subtype of ischaemic stroke in which no clear cause is identified despite thorough investigation.
FFR-CT	Fractional Flow Reserve derived from Computed Tomography	A non-invasive physiologic simulation technique that models coronary blood flow from CCTA data using computational fluid dynamics, to assess the haemodynamic significance of coronary artery stenoses without invasive catheterisation.
HF	Heart Failure	A clinical syndrome with symptoms and/or signs caused by a structural and/or functional cardiac abnormality, corroborated by elevated natriuretic peptide levels and/or objective evidence of pulmonary or systemic congestion.
IHD	Ischaemic Heart Disease	A group of conditions resulting from a mismatch between myocardial oxygen supply and demand, most commonly due to atherosclerosis of the coronary arteries and/or functional alterations of the coronary microcirculation, encompassing clinical presentations from stable angina to myocardial infarction.
LAA	Left Atrial Appendage	A blind-ended outpouching of the left atrium and the predominant site of thrombus formation in atrial fibrillation, responsible for the majority of AF-related cardioembolic strokes.
LAAO	Left Atrial Appendage Occlusion	A procedure to seal off the LAA to prevent thrombus formation in patients with atrial fibrillation who cannot take anticoagulants.

Abbreviations	Full term	Definition
LLM	Large Language Model	A type of AI model trained on large volumes of text, capable of generating and interpreting natural language.
LSTM	Long Short-Term Memory	A type of recurrent neural network suited to learning from sequential or time-series data.
LVEF	Left Ventricular Ejection Fraction	The fraction of blood pumped out of the left ventricle with each heartbeat; a key measure of cardiac function.
LVH	Left Ventricular Hypertrophy	Thickening of the heart muscle wall, typically caused by sustained high blood pressure.
MACE	Major Adverse Cardiovascular Events	A composite clinical endpoint commonly including heart attack, stroke, and cardiovascular death.
ML	Machine Learning	A subset of artificial intelligence in which algorithms learn patterns from data to make predictions or decisions, improving their performance with experience without being explicitly programmed.
MRI	Magnetic Resonance Imaging	A non-invasive medical imaging technique that uses strong magnetic fields and radiofrequency pulses to induce resonance of hydrogen atoms in body tissues, producing detailed images of internal organs and structures without the use of ionising radiation.
PFO	Patent Foramen Ovale	A small opening between the upper chambers of the heart that fails to close after birth, associated with cryptogenic stroke.
U-Net	U-shaped Network	An encoder-decoder convolutional neural network architecture with skip connections between corresponding encoder and decoder layers, widely used for biomedical image segmentation tasks, enabling precise localisation from very few training images.
YLD	Years Lived with Disability	A measure of the burden of non-fatal health outcomes, representing the number of years lived in less than full health due to disease or injury.

List of Figures

List of Tables

Getting in touch with the EU

In person

All over the European Union there are hundreds of Europe Direct centres. You can find the address of the centre nearest you online (european-union.europa.eu/contact-eu/meet-us_en).

On the phone or in writing

Europe Direct is a service that answers your questions about the European Union. You can contact this service:

1. by freephone: 00 800 6 7 8 9 10 11 (certain operators may charge for these calls),
2. at the following standard number: +32 22999696,
3. via the following form: european-union.europa.eu/contact-eu/write-us_en.

Finding information about the EU

Online

Information about the European Union in all the official languages of the EU is available on the Europa website (europa.eu).

EU publications

You can view or order EU publications at op.europa.eu/en/publications. Multiple copies of free publications can be obtained by contacting Europe Direct or your local documentation centre (european-union.europa.eu/contact-eu/write-us_en).

EU law and related documents

For access to legal information from the EU, including all EU law since 1951 in all the official language versions, go to EUR-Lex (eur-lex.europa.eu).

Open data from the EU

The portal data.europa.eu provides access to open datasets from the EU institutions, bodies and agencies. These can be downloaded and reused for free, for both commercial and non-commercial purposes. The portal also provides access to a wealth of datasets from European countries.

Science for policy

The Joint Research Centre (JRC) provides independent, evidence-based knowledge and science, supporting EU policies to positively impact society

Scan the QR code to visit:

Joint Research Centre

https://joint-research-centre.ec.europa.eu

Publications Office
of the European Union