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FROM DATA TO CLINICAL DECISIONS: A REVIEW OF ARTIFICIAL INTELLIGENCE AND MODERN TECHNOLOGIES IN CARDIOVASCULAR CARE

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ABSTRACT

Background: Cardiovascular diseases remain the leading cause of death worldwide and represent a major clinical, social, and economic burden. The traditional model of care is based mainly on medical visits and office-based measurements, whereas many risk factors and symptoms develop in the patient's everyday environment.
Methods: This article is a narrative and systematizing review. The literature was searched using terms related to cardiovascular diseases, digital health, artificial intelligence, machine learning, wearable devices, telemonitoring, heart failure, cardiac imaging, prevention, risk assessment, and electronic health records.
Results: Digital technologies can support many areas of cardiovascular care. Artificial intelligence may assist in ECG interpretation, arrhythmia detection, identification of left ventricular dysfunction, and analysis of imaging studies. Wearable devices, mobile applications, and telemonitoring enable long-term monitoring of heart rhythm, physical activity, and selected risk factors; however, their results require clinical interpretation.
Conclusions: Modern technologies have great potential in the prevention, diagnosis, and monitoring of cardiovascular diseases, but they should support rather than replace physicians' clinical judgment. They provide the greatest value when they are validated and integrated into a well-organized care pathway.

KEYWORDS
Cardiovascular Diseases, Artificial Intelligence, Telemedicine, Wearable Devices, Prevention, Remote Monitoring

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1. Introduction

Cardiovascular diseases comprise a broad group of disorders of the heart and blood vessels, including ischemic heart disease, stroke, heart failure, arterial hypertension, cardiomyopathies, cardiac arrhythmias, and peripheral vascular disease. Their significance is particularly high because they are responsible for the largest number of deaths worldwide and contribute substantially to the loss of healthy life years. According to the World Health Organization, in 2022 approximately 19.8 million people died from cardiovascular diseases, accounting for more than 2 in 5 deaths, 42.5% of all deaths; most of these deaths, 82%, were related to myocardial infarction and stroke (World Health Organization [WHO], 2025). In the European region, the burden is also very high, and arterial hypertension, unhealthy diet, tobacco smoking, diabetes, obesity, low physical activity, and air pollution are among the most important modifiable risk factors (WHO Regional Office for Europe, 2024).

Classical cardiovascular prevention is based primarily on identifying risk factors, estimating the probability of a cardiovascular event, treating hypertension and dyslipidemia, controlling glycemia, supporting smoking cessation, and promoting physical activity and healthy nutrition. European guidelines on cardiovascular prevention emphasize that therapeutic decisions should not be the same for all patients. A stepwise and individualized approach is recommended, taking into account factors such as age, sex, risk level, comorbidities, and the patient's expectations and preferences (Visseren et al., 2021). In practice, however, many high-risk individuals remain undiagnosed, and some patients with established disease do not achieve recommended therapeutic targets. Another problem is that patient care is often divided into single visits and brief measurements performed in the physician's office. Meanwhile, many decisions and behaviors that affect health take place every day, at home, at work, and in the patient's immediate environment, outside the direct control of the healthcare system.

Modern technologies create an opportunity to change the way patients are cared for. Instead of reacting only when a disease appears or worsens, it becomes possible to assess risk earlier, prevent complications, and better tailor interventions to the individual patient. Artificial intelligence can support the analysis of large amounts of medical data, such as laboratory results, diagnostic images, and recordings of cardiac activity. Wearable devices, such as smartwatches, allow daily monitoring of heart rate, physical activity, sleep, and cardiac rhythm. Telemedicine facilitates contact between the patient and the physician or therapeutic team without the need for frequent in-person visits. Mobile applications can support patients in changing their lifestyle, while electronic health records help assess health risk on an ongoing basis and respond more quickly to concerning changes. From a social perspective, these technologies are important not only medically, but also organizationally and ethically, because they influence access to healthcare services, the physician–patient relationship, responsibility for decisions, data privacy, and health inequalities.

The aim of this article is to show how modern technologies can support the prevention, diagnosis, and monitoring of cardiovascular diseases. The paper discusses solutions described in scientific studies that may help in earlier detection of health risks, more accurate disease diagnosis, and continuous observation of the patient's condition. Particular attention is given to artificial intelligence, telemedicine, wearable devices, mobile applications, and electronic health records. The article emphasizes that technologies do not replace contact with a physician, but they can improve care, support clinical decisions, and help patients take a more informed role in managing their health.

2. Methodology

To ensure the transparency of the review, a hierarchy of scientific evidence reliability was applied. Randomized clinical trials, meta-analyses, and systematic reviews were rated the highest, as they provide the most reliable data on the effectiveness and safety of the analyzed solutions. Prospective and validation studies were considered next, as they make it possible to assess the performance of technologies in specific patient groups and to determine whether the obtained results can be translated into clinical practice. Retrospective, single-center, and conceptual studies were assigned a lower rank, as their findings are usually more limited and more difficult to generalize.

The article is a narrative and systematizing review. This means that its aim was not to conduct a formal meta-analysis or a statistical comparison of the results of individual studies, but rather to present, in an organized manner, the most important applications of modern technologies in the prevention, diagnosis, and monitoring of cardiovascular diseases. The literature search was conducted using keywords corresponding to the main thematic areas of the paper, such as: *cardiovascular disease*, *digital health*, *artificial intelligence*, *machine learning*, *wearable devices*, *atrial fibrillation*, *ECG*, *telemonitoring*, *heart failure*, *cardiovascular imaging*, *prevention*, *risk prediction*, *electronic health records*, and their combinations.

The paper primarily used publications available in Google Scholar and PubMed, articles from peer-reviewed scientific journals, and documents prepared by scientific societies. The greatest importance was assigned to meta-analyses, systematic reviews, prospective studies, large population-based studies, clinical guidelines, and review articles. These sources best enable an assessment of whether a given technology is effective and safe, and whether it may have real applicability in clinical practice.

3. Results

3.1. Modern technologies in the prevention of cardiovascular diseases

The prevention of cardiovascular diseases is not limited solely to the treatment of individuals in whom the disease has already developed. It includes both actions carried out at the population level and individual care for patients at risk of developing the disease. In the traditional model, the physician assesses risk factors mainly during a medical visit, discusses the principles of a healthy lifestyle with the patient, and, when necessary, introduces appropriate pharmacological treatment.

Digital solutions make prevention more continuous and better adapted to the patient’s everyday functioning. They enable more frequent monitoring of selected health parameters and the analysis of data generated outside the doctor’s office during the patient’s daily life. This applies, for example, to measurements of blood pressure, physical activity, body weight, and other lifestyle-related information.

Such technologies may help assess risk more accurately, support patients in changing their habits, and identify more quickly those individuals who require greater medical attention or more intensive preventive measures. As a result, prevention becomes less episodic and more systematic, as well as better tailored to the patient’s actual needs.

3.1.1. Digital risk assessment and electronic medical records

The concept of “digital phenotyping” of risk is becoming increasingly important in the prevention of cardiovascular diseases. It involves combining traditional medical data, such as the patient’s age, blood pressure values, or lipid profile results, with information collected in a more continuous and dynamic way. This may include data on the frequency of medical visits, changes in body weight, levels of physical activity, heart rate recordings, medication use, comorbidities, and imaging results. Such an approach differs from classical risk assessment, which is often based on a single measurement and medical history taken during a visit. In the digital phenotyping model, not only the current value of a given parameter is important, but also the direction and pace of its changes. As a result, the patient can be assessed dynamically, taking into account how their health status changes over time.

This is particularly important in the case of hypertension, diabetes, obesity, chronic kidney disease, and heart failure, where risk usually increases gradually and results from the accumulation of multiple factors. Predictive models based on electronic medical records can help physicians identify relationships that are not always visible during a single visit. However, they should be approached with caution, as their performance depends on data quality. Information recorded in medical records or administrative systems may be incomplete, outdated, or contain errors. Therefore, the results of such models should support physicians in decision-making, but should not replace their knowledge, experience, and assessment of the patient’s condition (Rajkomar et al., 2019; Weng et al., 2017).

Cardiovascular risk assessment is the foundation of primary prevention. Tools such as SCORE2, QRISK, and the American College of Cardiology/American Heart Association calculators use classical variables: age, sex, blood pressure, cholesterol levels, smoking, and diabetes. Their advantage is that they are easy to use, understandable for both physicians and patients, and based on current clinical guidelines. However, their limitation is that they rely mainly on single measurements taken at a specific point in time. As a result, they do not always accurately reflect how a patient's condition changes over time, nor do they fully account for complex relationships between different risk factors. Electronic medical records make it possible to update risk automatically on the basis of laboratory data, diagnoses, medications, hospitalizations, home measurements, and textual information.

A systematic review and meta-analysis indicate that machine learning models based on electronic medical records may help predict the risk of cardiovascular diseases. In some studies, their effectiveness was comparable to, and sometimes even higher than, that of traditional risk scores. This may be because these algorithms are able to analyze a larger amount of clinical data and account for changes occurring in the patient over time (Liu et al., 2024). Such models may help identify patients who are classified as having moderate risk according to classical risk scores but who may in fact require earlier intervention. This may be suggested, for example, by a gradual increase in blood pressure, weight gain, more frequent use of healthcare services, the presence of comorbidities, or concerning changes in laboratory test results.

However, this does not mean that every predictive model automatically improves patient care. Before such a tool is used in practice, it should be tested in independent populations, properly calibrated, and evaluated for possible errors or inequalities in performance. It is also important to assess not only its statistical accuracy, for example the area under the ROC curve, but also whether it actually influences clinical decisions and improves patients' health outcomes.

The mere fact that an algorithm can predict an increased risk of disease does not yet mean that it will improve patient care. What happens next with such a result is crucial. If the physician cannot use it in practice, the patient does not understand the recommendations, or the healthcare system does not provide further diagnosis and treatment, even a well-performing algorithm will not bring real benefit. For this reason, digital risk assessment should be part of a broader care process, rather than merely a separate tool generating a result. Once increased risk has been identified, specific steps are needed, such as reminders about follow-up tests, referral for preventive counselling, patient education, implementation of guideline-based treatment, and assessment of the effects of the actions taken. Only then can technology genuinely support prevention, rather than simply increasing the amount of data available to physicians and patients.

3.1.2. Mobile applications and mHealth in changing health behaviours

The effectiveness of mobile applications in the prevention of cardiovascular diseases can be explained by their influence on patients' everyday behaviours. Applications can help users observe their own habits, receive feedback, set goals, and receive regular reminders about important health-related actions. They also often use elements of gamification, social support, and personalized messages aimed at increasing motivation and facilitating the maintenance of behavioural changes.

In cardiovascular prevention, such functions may support greater physical activity by increasing the number of steps taken, facilitate body weight control, help patients follow a diet with reduced salt and saturated fat intake, maintain adequate fluid intake, and remind them about regular blood pressure measurements and medication use. However, their effect is usually greater when the application is part of a broader care programme, rather than a standalone product used without contact with medical personnel. Reviews of mHealth indicate that the mere availability of an application does not guarantee lasting behavioural change; reliable content, ease of use, integration with care, and the possibility of contact with healthcare professionals are necessary (Santo et al., 2016; Widmer et al., 2015).

Mobile applications are among the most widely used digital tools in prevention. They can record physical activity, diet, body weight, sleep, blood pressure measurements, and medication intake. Their operation is based on mechanisms of self-monitoring, feedback, reminders, gamification, and goal personalization. In the context of cardiovascular diseases, long-term maintenance of behaviours is particularly important, as one-time education is rarely sufficient to achieve lasting lifestyle change.

Reviews on mHealth indicate that mobile solutions may improve access to care, support self-management, and increase patient engagement. However, their effectiveness depends on how they are designed, whether they are linked to clinical care, and whether they respond to the user's real needs (Jat & Grønli, 2023). An application that merely collects information may quickly be abandoned by the user because it does not provide the patient with clear guidance or a sense of purpose in using it. Solutions that provide understandable feedback, take into account the patient's level of knowledge, enable contact with healthcare professionals, and do not overload the user with excessive notifications are of greater importance. In this way, the application becomes genuine support in everyday prevention, rather than just another tool for collecting data.

In cardiovascular prevention, mobile applications should be evaluated primarily according to medical rather than purely technological criteria. Important aspects include consistency of recommendations with clinical guidelines, data protection, transparency of information sources, the possibility of exporting data for the physician, minimization of the risk of misinterpretation, and accessibility for older adults and people with lower digital literacy. Digital inequality is a particular problem. People with lower socioeconomic status, older adults, those living outside large urban centres, or those with limited Internet access often have both a higher cardiovascular risk and lower access to modern tools. Digital prevention may therefore either reduce or deepen inequalities, depending on how it is implemented.

3.1.3. Wearable devices as tools for prevention and early detection

Smartwatches, fitness bands, and skin sensors enable long-term monitoring of selected physiological parameters in the patient's everyday life. In the prevention of cardiovascular diseases, the most commonly analyzed data include step count, resting heart rate, heart rate variability, estimated energy expenditure, sleep quality and duration, and episodes of irregular heart rhythm. Although such devices do not always achieve the accuracy of certified medical equipment, their important advantage is the possibility of observation over a longer period of time and in the patient's natural environment (Bayoumy et al., 2021). As a result, they may indicate general trends, such as a decrease in physical activity, an increase in resting heart rate, or deterioration in sleep quality, and may also help patients better understand the relationship between lifestyle and physiological parameters.

In the scientific evaluation of wearable devices, however, three levels of their performance should be distinguished: the accuracy of signal measurement, the correctness of medical classification, and the clinical usefulness of the result. This means that a device may correctly record heart rate or a photoplethysmographic signal, but an alert about an irregular heart rhythm is not yet a diagnosis of arrhythmia. Such a result should be treated as a warning signal that may initiate further diagnostics, most often using electrocardiography.

The best-documented example of the use of wearable devices in cardiology is the detection of atrial fibrillation. The Apple Heart Study, which included a very large population of smartwatch users, showed that these devices can identify irregular heart rhythms in everyday conditions, outside the hospital and the doctor's office. At the same time, the study demonstrated the limitations of this type of population screening: notifications were relatively rare, and their significance depended, among other factors, on the user's age, the prevalence of atrial fibrillation in a given group, and the pre-test probability of an actual arrhythmia (Perez et al., 2019). The Fitbit Heart Study confirmed the possibility of prospective and remote detection of undiagnosed atrial fibrillation using photoplethysmography in users of wrist-worn devices (Lubitz et al., 2022).

Similar conclusions arise from studies on passive detection of atrial fibrillation using PPG sensors. Although algorithms analyzing such signals may achieve high accuracy, their results should be interpreted in the patient's clinical context, taking into account age, comorbidities, signal quality, and the risk of false-positive and false-negative results (Tison et al., 2018). False alarms may lead to unnecessary anxiety, additional tests, and a greater burden on the healthcare system, whereas ignoring repeated signals in a person with risk factors may mean a missed opportunity for earlier detection of arrhythmia and stroke prevention.

In clinical practice, the optimal solution is therefore a care pathway in which a consumer device serves a screening function, while the medical system ensures confirmation of the result and its interpretation. Decisions regarding anticoagulant treatment, heart rhythm control, or further testing should be made by a physician on the basis of an ECG recording, the patient's symptoms, age, stroke risk, bleeding risk, and comorbidities.

3.1.4. Teleprevention and personalization of interventions

Teleprevention involves the use of remote contact to provide counselling, control risk factors, and support the patient without the need for an in-person visit each time. It may include teleconsultations, online dietary consultations, smoking cessation support programmes, remote blood pressure monitoring, medication reminders, and health education. Its importance increased particularly after the COVID-19 pandemic; however, telemedicine is valuable also outside crisis situations. It is especially important for people living far from specialists, working shifts, or having limited mobility, as remote contact may reduce barriers to accessing care.

Reviews on telemedicine in cardiovascular diseases indicate that the effectiveness of such solutions depends not only on the availability of devices and digital platforms. Good organization of the entire care process is also important. It should be clearly defined who analyzes the patient's data, how often the data are checked, which values should trigger an intervention, how decisions are documented, and how staff overload caused by excessive information is prevented. Telemonitoring may support the treatment of chronic diseases such as hypertension, heart failure, and atrial fibrillation. These solutions may improve the control of disease-related parameters, strengthen patient self-management, support adherence to recommendations, and, in some studies, have a positive effect on quality of life and the number of hospitalizations (Russo et al., 2024). In prevention, feedback is also important. The patient should understand why a given parameter matters, what action they can take, and when they need help. Simply providing data without interpretation may be insufficient.

One important advantage of digital prevention is the possibility of better tailoring support to an individual patient. Algorithms can analyze user behaviour and, on this basis, adjust the frequency of reminders, physical activity goals, or educational content. As a result, the patient may receive information that is more closely related to their everyday needs, rather than general recommendations that are the same for everyone. In digital medicine, transparency is particularly important: the patient should know what data are collected, for what purpose, who has access to them, and whether the algorithm influences medical decision-making.

3.2. Modern technologies in the diagnosis of cardiovascular diseases

The diagnosis of cardiovascular diseases is based on a comprehensive assessment of the patient. The physician takes into account the reported symptoms, the findings of the physical examination, the ECG recording, laboratory tests, imaging studies, and tests assessing the functional capacity of the cardiovascular system. Modern technologies do not replace these elements, but they can complement and improve them.

Artificial intelligence may assist in ECG analysis and in detecting patterns that are difficult to notice during a standard assessment by a physician. Algorithms used in imaging may improve the performance of measurements and the assessment of myocardial function. Solutions based on multiple types of data simultaneously may, in turn, support the physician in differential diagnosis, especially when the patient's clinical presentation is unclear.

However, it should be remembered that high algorithm performance in a test study is not sufficient to consider it a safe clinical tool. What matters is whether the model also performs reliably in everyday practice, in patients of different ages, with different comorbidities, and with data of varying quality.

3.2.1. Artificial intelligence in electrocardiogram analysis

Electrocardiography is one of the most important areas of artificial intelligence application in cardiology, because ECG examination is inexpensive, widely available, routinely performed, and increasingly recorded in digital form. In clinical practice, it is used mainly to assess heart rhythm, detect ischemia, conduction disorders, myocardial hypertrophy, and certain electrolyte abnormalities.

Studies on deep neural networks have shown that algorithms can automatically recognize different types of arrhythmias with accuracy comparable to specialist assessment. Some models are also able to detect subtle patterns in ECG recordings that may be difficult to notice during visual interpretation of the test (Hannun et al., 2019; Ribeiro et al., 2020). One example is the identification of reduced left ventricular ejection fraction based on a 12-lead ECG, suggesting that the electrical signal may serve as an inexpensive screening tool to refer patients for echocardiography (Attia et al., 2019a). Other studies indicate the possibility of detecting susceptibility to atrial fibrillation even when the analyzed recording shows sinus rhythm (Attia et al., 2019b).

A good example of such an application is the study by Attia and colleagues, in which the authors examined whether a standard 12-lead ECG could be used to detect significant left ventricular dysfunction with the use of artificial intelligence. The authors applied a neural network analyzing the recording of the heart's electrical activity and compared its results with the assessment of left ventricular ejection fraction. An ejection fraction of 35% or less was considered significantly reduced. The study showed that the algorithm was able to identify patients who might have left ventricular systolic dysfunction, even if the ECG recording itself did not provide clear grounds for such a diagnosis in classical assessment (Attia et al., 2019a).

The importance of this approach results from the fact that impaired left ventricular function may remain asymptomatic for a long time, while at the same time preceding the development of heart failure. Early detection of this abnormality is important because appropriately selected treatment may slow disease progression and improve the patient's prognosis. Therefore, if ECG helps identify individuals requiring echocardiography, it may accelerate diagnosis and the initiation of treatment. Similar applications of artificial intelligence include predicting hyperkalemia, identifying features of hypertrophic cardiomyopathy, and detecting other disorders that are not always visible in standard ECG interpretation.

In clinical practice, it should be remembered that a result generated by an ECG algorithm is not yet a diagnosis. It may indicate an increased risk of a specific abnormality, such as left ventricular dysfunction, hyperkalemia, cardiac arrhythmias, or previously undiagnosed atrial fibrillation. The introduction of artificial intelligence into ECG interpretation requires appropriate determination of who analyzes alerts, how quickly they should be responded to, which tests should confirm the suspicion, and who is responsible for the final clinical decision. Without such organization, even an algorithm with high sensitivity may increase the number of unnecessary consultations, tests, and patient concerns.

AI models analyzing ECG have their limitations, and their effectiveness depends on the quality of the recording, the type of device used, the characteristics of the studied population, and how precisely the detected abnormality has been defined. Artificial intelligence should be treated as support for the physician, not as an independent diagnosis. Its performance should be monitored and errors analyzed, especially in different subgroups, for example according to sex, age, ethnicity, comorbidities, and device type. The operation and result of the algorithm are not always easy for the physician and patient to understand; therefore, AI systems used in ECG analysis should provide not only the final result, but also information that helps the physician evaluate it and relate it to the patient's clinical presentation.

3.2.2. AI-supported cardiac imaging

In cardiac imaging, artificial intelligence can assist physicians in performing repetitive measurements, improve image readability, support the detection of abnormalities, and combine imaging results with other patient-related information. In echocardiography, algorithms can support the assessment of cardiac structures, for example by automatically delineating the borders of the heart chambers, calculating left ventricular ejection fraction, assessing ventricular volumes, wall thickness, diastolic function, and myocardial strain.

In response to the problem of variability in echocardiographic assessment between different observers, the authors developed a deep learning algorithm called EchoNet-Dynamic, which analyzed echocardiographic videos. The model was used for three main tasks: delineating the borders of the left ventricle, estimating ejection fraction, and identifying heart failure with reduced ejection fraction. The study results showed high algorithm performance. EchoNet-Dynamic accurately segmented the left ventricle, achieving a Dice coefficient of 0.92, predicted ejection fraction with a mean absolute error of 4.1%, and classified heart failure with reduced ejection fraction with very good accuracy, reaching an AUC of 0.97. This means that the model may support a more reproducible and objective assessment of cardiac function in echocardiographic examination (Ouyang et al., 2020).

Artificial intelligence is also increasingly being used in coronary computed tomography angiography, or CCTA. This examination allows non-invasive assessment of vessel stenosis as well as the presence and characteristics of atherosclerotic plaque. In CCTA, AI algorithms can support the assessment of the coronary artery tree, cardiac structures, stenoses, and atherosclerotic lesions. As a result, they may shorten reporting time, increase measurement reproducibility, and assist in the analysis of a larger number of images. This is important because manual CCTA assessment is difficult, time-consuming, and may vary between specialists (van Herten et al., 2024).

Particularly important is the possibility of using AI to assess high-risk atherosclerotic plaques. The degree of arterial stenosis alone is not always sufficient for a complete assessment of the risk of acute coronary syndrome. Plaque characteristics, such as its structure, composition, and vulnerability to rupture, are also important. Algorithms may help detect such lesions more accurately, although the analysis of coronary images remains challenging due to cardiac and respiratory motion, the small size of the vessels, and the complexity of imaging data (Föllmer et al., 2024).

AI may also support other areas of cardiac imaging. Some models are based mainly on data analysis, while others also incorporate knowledge of cardiac anatomy and physiology. This may increase the diagnostic value of examinations, especially in patients with a more complex clinical presentation (Sermesant et al., 2021).

The results of the study by Wang and colleagues indicate that artificial intelligence may significantly support the interpretation of cardiac magnetic resonance imaging. CMR is a highly accurate examination for assessing cardiac function and diagnosing cardiovascular diseases, but its analysis requires time, experience, and access to specialists. The use of AI may partly reduce these barriers, as algorithms are able to automatically analyze images and support the detection of various cardiovascular diseases.

The two-stage assessment model proposed by the authors is of particular importance. First, the algorithm may be used for screening abnormalities based on cine images, and then it may support more detailed diagnostics using cine images and late gadolinium enhancement. Such an approach may accelerate the analysis of CMR examinations, increase the reproducibility of interpretation, and help direct patients to further diagnostics or treatment. The study also shows that AI may detect subtle imaging features that are not always obvious to humans (Wang et al., 2024).

Despite its considerable potential, AI should not replace physicians in the interpretation of imaging studies. Algorithm-generated results must be assessed in the context of the patient's symptoms, medical history, and other test results. Before such tools are widely implemented, their effectiveness must be confirmed in different populations and centers. Issues such as model explainability, data security, and the risk of errors or bias also remain important. Therefore, the safest direction for development is the use of AI as support for specialists, rather than as an independent tool making clinical decisions.

3.2.3. Diagnostics supported by consumer devices

The boundary between medical and consumer devices is becoming increasingly blurred. Smartwatches with a single-lead ECG function, wristbands using photoplethysmography, blood pressure monitors connected to an application, and smart scales are increasingly providing data that patients present to physicians during medical visits. Many cardiovascular symptoms occur in episodes and are not always present during examination; therefore, information collected by the patient during everyday functioning is particularly important. For example, an ECG recording taken at the moment of palpitations may help diagnose arrhythmia more quickly, especially when symptoms resolve before the medical visit.

All data collected by devices using artificial intelligence require careful interpretation, as devices differ in accuracy, operating principles, and algorithms. The information collected is not always fully transparent to the physician. Measurement quality may be affected by factors such as patient movement, improper placement of the device, poor skin contact, or irregular heart rhythm. Therefore, information from wearable devices should support diagnostics, but should not replace standard clinical assessment or confirmation of the diagnosis with an appropriate medical examination (Petek et al., 2023; Zarak et al., 2024).

It is also important to document basic information, such as the type of device, measurement conditions, recording duration, and the possibility of reviewing the original signal. This allows data from wearable devices to be assessed more safely together with the patient's symptoms, medical history, and test results.

3.3. Modern technologies in the monitoring of cardiovascular diseases

Monitoring patients with cardiovascular diseases is particularly important when the disease is chronic and requires long-term control. This applies, among others, to heart failure, hypertension, coronary artery disease after revascularization, atrial fibrillation, and cardiac rehabilitation. In such cases, the patient's condition may change between visits, which is why a single check-up every few months is not always sufficient to detect deterioration early.

Such activities may include monitoring blood pressure, heart rate, body weight, physical activity, dyspnea, edema, heart rhythm, and medication adherence. As a result, the physician may notice concerning changes earlier, while the patient gains a greater sense of safety and better control over the disease.

Wearable devices, mobile applications, telemonitoring, and home measurement devices make it possible to collect data outside the doctor's office as well. This allows the patient's condition to be observed continuously, rather than only during individual visits; disease exacerbation can be detected more quickly, the number of hospitalizations may be reduced, and treatment can be better adjusted to the patient's current condition (Lu et al., 2023).

3.3.1. Telemonitoring of heart failure

Heart failure is one of the most important areas of telemonitoring application, as the patient's condition may gradually deteriorate before hospitalization becomes necessary. Disease exacerbation may be preceded by weight gain, changes in blood pressure, an increased heart rate, worsening dyspnea, reduced physical activity, or deterioration of hemodynamic parameters. For this reason, remote monitoring may include daily measurements of body weight, blood pressure, heart rate, oxygen saturation, symptoms, ECG recordings, activity, and data from implantable devices (Scholte et al., 2023). In more advanced systems, these data are analyzed automatically, and concerning results generate an alert for a nurse or physician (Koehler et al., 2018).

However, the results of studies on heart failure telemonitoring are not unequivocal. Differences between studies result from the fact that telemonitoring programs include different patient groups, different sets of measurements, different follow-up periods, varying intensity of supervision, and different ways of responding to alerts (Cleland et al., 2005; Scholte et al., 2023). The TIM-HF2 study showed that, in appropriately selected patients with heart failure, an organized system of remote patient management may reduce the proportion of days lost due to unplanned cardiovascular hospitalizations or death. In this study, patients receiving remote management lost an average of 17.8 days per year, whereas patients receiving standard care lost 24.2 days per year; lower all-cause mortality was also observed in the telemonitoring group (Koehler et al., 2018).

However, not all programs produced similar benefits. In the BEAT-HF study, the use of remote monitoring after hospitalization for heart failure did not significantly reduce the number of rehospitalizations compared with usual care (Ong et al., 2016). This shows that merely collecting data from the patient is not sufficient if it is not accompanied by active treatment management and a clearly defined clinical response pathway.

The most important conclusion is that the effectiveness of telemonitoring does not result from the measurement device itself. The entire process is important: performing the measurement, interpreting the data, prioritizing alerts, making clinical decisions, and ensuring a rapid response from the therapeutic team. Meta-analyses indicate that well-designed telemonitoring may reduce the risk of hospitalization due to heart failure and, in some analyses, also mortality, but the effects depend on how the program is organized (Scholte et al., 2023).

Telemonitoring also has a practical and social dimension. For the patient, it may increase the sense of safety, as their parameters are monitored also between visits. At the same time, it may cause stress related to continuous measurement and fear of abnormal results. For medical staff, telemonitoring provides the opportunity for earlier intervention, but it may also lead to overload due to a large number of alerts. Therefore, clear alarm thresholds, prioritization algorithms, division of responsibilities, and patient education are needed. Good remote care should not replace contact with the patient, but rather complement it. Symptoms, well-being, and the context of the patient's life still require conversation and clinical assessment, as not everything can be reduced to numerical parameters (Koehler et al., 2018; Scholte et al., 2023).

3.3.2. Implantable devices and hemodynamic sensors

Implantable devices are an important source of data in the monitoring of patients with cardiovascular diseases, especially those with heart failure and rhythm disorders. Pacemakers, cardioverter-defibrillators, and cardiac resynchronization therapy devices can transmit information on heart rhythm, arrhythmia burden, battery status, lead function, percentage of pacing, patient activity, and delivered defibrillator therapies. This makes it possible to detect arrhythmias, technical device problems, or deterioration in the patient's clinical condition at an earlier stage (Hindricks et al., 2014).

Implantable hemodynamic sensors, which enable measurement of pulmonary artery pressure, are of particular importance in heart failure. An increase in filling pressures may occur before symptoms such as dyspnea, edema, or rapid weight gain become more pronounced. Therefore, regular analysis of these data may allow earlier modification of treatment, for example intensification of diuretic therapy, before a full symptomatic exacerbation of the disease develops and hospitalization becomes necessary. The CHAMPION trial showed that a treatment strategy based on remote measurements of pulmonary artery pressure reduced the number of hospitalizations due to heart failure in appropriately selected patients (Abraham et al., 2011).

The advantage of implantable devices is the greater continuity and reliability of measurement compared with many external devices. Data are collected automatically and may reflect changes occurring even before clear clinical symptoms appear. This approach fits well with the model of predictive care, in which the goal is not only to respond to disease exacerbation, but also to predict and prevent it earlier.

However, it should be remembered that implantable devices are not a solution for all patients. Their use is associated with costs, the invasiveness of the procedure, the need for appropriate patient qualification, the risk of complications, and the need for efficient infrastructure for receiving and interpreting data. For this reason, these tools are intended mainly for selected high-risk groups. From the perspective of the healthcare system, their value depends on whether they actually reduce the number of hospitalizations, improve patients' quality of life, and justify the costs of implementation and ongoing supervision.

3.3.3. Monitoring hypertension and risk factor control

Arterial hypertension remains one of the most important modifiable risk factors for cardiovascular diseases, and its control in the population is still insufficient. Home blood pressure measurements are an important element of diagnosis and treatment monitoring, as they make it possible to assess blood pressure values outside the doctor's office and better capture the actual control of the disease. Traditionally, they were based on paper diaries or patient declarations, which was associated with the risk of errors, incomplete records, and difficulties in assessing trends (Stergiou et al., 2021).

Digital blood pressure monitors connected to an application can improve this process. Automatic transmission of results reduces transcription errors, enables the analysis of blood pressure changes over time, and allows persistent abnormalities to be noticed more quickly. The HyperLink study showed that combining home blood pressure telemonitoring with pharmacist care improved blood pressure control compared with standard care. This means that the greatest value lies not in the measurements themselves, but in measurements combined with an active response from the medical team and the possibility of treatment modification (Margolis et al., 2013). Similarly, self-monitoring with telemonitoring used in primary care improved blood pressure control compared with standard care in the TASMINH4 study (McManus et al., 2018).

Similar solutions can be used to monitor other risk factors, such as lipid levels, diabetes, body weight, and physical activity (Kitsiou et al., 2017). Electronic systems may remind patients about laboratory tests, indicate lack of LDL-C control in a patient at high cardiovascular risk, signal persistently high blood pressure despite treatment, or identify gaps in prescription refills. The study by Persell and colleagues showed that the use of electronic medical records to identify patients with elevated cardiovascular risk and provide individualized patient contact increased the frequency of prescribing lipid-lowering medications, although the effect on LDL-C reduction became clearer only with longer follow-up (Persell et al., 2013). In turn, eHealth reviews indicate that digital interventions may improve treatment adherence in patients with cardiovascular diseases, especially when they include reminders, education, and feedback (Miao et al., 2024).

Such solutions may seem less advanced than algorithms analyzing medical images, but their practical importance is considerable. They help detect common problems in everyday care, such as delayed treatment intensification, lack of blood pressure or lipid control, and irregular medication use. As a result, they may improve the quality of prevention in large groups of patients.

At the same time, risk factor monitoring should be well designed. Not every single increase in blood pressure, heart rate, or poorer sleep result requires a physician's response. The system should distinguish normal physiological variability from changes that are truly clinically significant. Otherwise, it may unnecessarily increase patient anxiety and burden medical staff with excessive alerts.

Therefore, in cardiology technologies, what matters is not only the ability to detect abnormalities, but also the reduction of false alarms, ease of use, clear response thresholds, and consideration of the impact of continuous monitoring on the patient's behaviour and well-being.

3.4. Remote cardiac rehabilitation

Cardiac rehabilitation after myocardial infarction, revascularization, cardiac surgery, or exacerbation of heart failure is an important element of further patient care. Its aim is to improve physical capacity, quality of life, control of risk factors, and reduce the risk of subsequent cardiovascular events. Despite its documented benefits, patient participation in traditional rehabilitation programmes is often limited by distance from the centre, work responsibilities, transport problems, reduced mobility, or an insufficient number of available places. For this reason, home-based and remote models, including cardiac telerehabilitation, are gaining increasing importance (Taylor et al., 2010; Buckingham et al., 2016).

Telerehabilitation uses mobile applications, video consultations, activity sensors, heart rate monitors, and educational platforms to conduct exercise training and health education outside the rehabilitation centre. Studies comparing home-based rehabilitation with centre-based rehabilitation indicate that, in appropriately selected patients, both forms may produce similar clinical effects and improvements in quality of life. A Cochrane review showed that home-based and centre-based rehabilitation were comparable in terms of mortality, cardiac events, exercise capacity, risk factors, and quality of life; therefore, home-based rehabilitation may be a valuable alternative for patients who have difficulty participating in centre-based programmes (Taylor et al., 2010).

In coronary artery disease, telerehabilitation may be an alternative to traditional phase II rehabilitation, especially when the patient has difficulty regularly commuting to the centre. The meta-analysis by Ramachandran and colleagues indicates that home-based telerehabilitation in patients with coronary artery disease may improve physical capacity, activity, and selected quality-of-life parameters, with effectiveness similar to centre-based rehabilitation (Ramachandran et al., 2022). In patients with heart failure, a meta-analysis of randomized trials showed that home-based telerehabilitation may improve peak VO_2, distance in the 6-minute walk test, quality of life, and reduce the frequency of rehospitalizations (Gao et al., 2023).

Safe telerehabilitation requires appropriate patient qualification, determination of exercise intensity, and clear rules of conduct in the event of alarm symptoms such as chest pain, dyspnea, dizziness, or palpitations. Wearable devices may help monitor heart rate and activity, but they do not replace assessment by a physician or physiotherapist.

The greatest advantage of telerehabilitation is that it increases access to rehabilitation and allows the programme to be better adapted to the patient's life. Limitations include less control over exercise technique, the risk of excluding people with low digital skills, and the need to ensure contact with medical personnel. Therefore, telerehabilitation should be treated as an organized form of home-based or hybrid care, rather than independent use of an application.

4. Future technologies: digital twins, multimodal models and predictive care

Health digital twins are among the most advanced solutions being developed in digital medicine. In the simplest terms, they are computer models of a patient, an organ, or a specific disease process, created on the basis of medical data and updated as the patient's health status changes. In cardiology, such a model may reflect the structure of the heart, the conduction of electrical impulses, myocardial function, blood flow, and the body's possible response to treatment. As a result, in the future, a digital twin may help in more individualized treatment planning, risk assessment, and preparation for cardiac procedures (Rudnicka et al., 2024).

However, the use of digital twins in clinical practice is still limited. For such a model to be useful, it must be based on reliable data, accurate imaging, and properly validated assumptions. The problem is that even a very advanced computer simulation does not provide full clinical certainty. Its result depends on the quality of the input data, the way the model is constructed, and the simplifications that are necessary when representing complex biological processes. Therefore, a digital twin should be treated as a tool supporting the physician's decision, rather than as an automatic replacement for it.

Another important direction of development is multimodal models, that is, systems that analyze different types of data simultaneously. In cardiology, these may include ECG recordings, imaging results, laboratory test results, medical records, information from wearable devices, and genetic data. Such integration may facilitate a comprehensive assessment of the patient, as cardiovascular diseases rarely result from a single factor. Multimodal models could support physicians in summarizing medical records, detecting inconsistencies, preparing reports, and assessing risk based on multiple sources of information.

At the same time, large language models and other advanced AI systems require particular caution in medicine. They may generate responses that sound convincing but are factually incorrect, omit local guidelines, or reproduce errors present in training data. It is also important to clearly define responsibility for clinical decisions. The physician should know what data the system used, what the limitations of the result are, and whether the recommendation has been verified. Therefore, such technologies should function as assistive tools, subject to quality control, auditing, and clinical supervision, rather than as independent systems making medical decisions.

5. Limitations, ethical and social challenges

The implementation of modern technologies in cardiology is associated with important clinical, organizational, and ethical challenges. Many algorithms achieve high performance in retrospective studies, but their impact on real clinical outcomes, such as mortality, myocardial infarction, stroke, hospitalizations, and quality of life, remains insufficiently understood (Kelly et al., 2019). Therefore, prospective studies, external validation, randomized clinical trials, and analyses of costs and consequences of algorithm-based decisions are needed.

Model generalizability is another important issue. An algorithm developed in one center may perform worse in other populations, especially among older adults, women, patients with multimorbidity, ethnic minorities, and people with lower socioeconomic status. Models trained on data reflecting previous inequalities may reproduce them; therefore, subgroup performance analysis, fairness audits, and post-implementation monitoring are necessary (Char et al., 2018; Obermeyer et al., 2019).

Further challenges concern transparency and clinical responsibility. AI results may influence decisions about anticoagulant therapy, coronary angiography, or intensification of heart failure treatment; therefore, the system should clearly indicate the algorithm version, validation population, limitations, and uncertainty of the result. CONSORT-AI, SPIRIT-AI, TRIPOD-AI, and DECIDE-AI standards support transparent reporting of AI studies (Collins et al., 2024; Liu et al., 2020; Rivera et al., 2020; Vasey et al., 2022).

Data security and equity of access are also crucial. Cardiology data may reveal diseases, activity, lifestyle, location, and daily habits, so data collection should be minimized and protected through encryption, informed consent, and control over commercial use. Digitalization may improve access to care, but it may also deepen inequalities among people without Internet access, smartphones, digital skills, or financial resources for devices.

Technology should also protect the physician–patient relationship. Digital tools may support education, self-monitoring, and patient participation in treatment, but they should not replace conversation, empathy, and shared decision-making. Digital cardiology should support care rather than reduce the patient to data alone.

6. Implications for practice and health policy

The implementation of digital technologies in cardiology should be based on their real clinical value rather than on their novelty alone. Funding is justified when these solutions improve important health outcomes, such as reducing hospitalizations, shortening diagnostic time, improving risk factor control, or increasing participation in rehabilitation. Before implementation, effectiveness, safety, costs, the number of false alarms, impact on staff workload, and patients' quality of life should be assessed.

These technologies have the greatest value in patients with clearly defined clinical or organizational problems, including those after hospitalization for heart failure, with paroxysmal symptoms of arrhythmia, difficult-to-control hypertension, a need for cardiac rehabilitation, or in centers with a high volume of imaging studies. In such cases, they may support earlier detection of deterioration, faster confirmation of arrhythmia, better blood pressure control, and more efficient diagnostics.

Medical facilities should have procedures specifying when an alert from a patient's device requires consultation, who analyzes the data, when ECG confirmation is necessary, and how decisions are documented. Interoperability is also essential, meaning the integration of data from medical records, devices, applications, ECG recordings, and imaging studies in a clinically useful form, while maintaining patient consent and data protection.

Digital competencies of both staff and patients are also necessary. Physicians should understand the limitations of algorithms, while patients should know that a single alert does not always indicate a life-threatening situation, although some signals require diagnostic evaluation. Digital technologies should therefore be implemented selectively, with clear procedures, staff responsibility, data security, and outcome evaluation.

7. Discussion

The literature analysis indicates that modern technologies can support the prevention, diagnosis, and monitoring of cardiovascular diseases when they address a clearly defined clinical problem. Their main value lies in earlier risk detection, systematic patient observation, and better tailoring of interventions to the patient's health status.

In prevention, the transition from one-time risk assessment to dynamic monitoring is important. Classical scores such as SCORE2, QRISK, and ACC/AHA calculators are useful, but they rely mainly on data from a single point in time. Models based on electronic health records can analyze more variables and account for changes over time, which may help identify patients requiring earlier intervention (Rajkomar et al., 2019; Weng et al., 2017; Liu et al., 2024). Their usefulness, however, depends on data quality, validation, and linking the result to a specific clinical action.

In diagnostics, the most important applications involve AI-based ECG analysis and cardiac imaging. Algorithms can detect arrhythmias, identify subtle ECG patterns, and support the assessment of cardiac function in echocardiography, CCTA, and cardiac magnetic resonance imaging (Hannun et al., 2019; Ribeiro et al., 2020; Attia et al., 2019a; Ouyang et al., 2020; Wang et al., 2024). However, such systems should support physicians' decisions rather than replace clinical assessment.

In chronic disease monitoring, the effectiveness of technology depends on the organization of the entire care process. The TIM-HF2 study showed benefits of remote management in patients with heart failure, whereas BEAT-HF did not confirm a significant reduction in rehospitalizations after remote monitoring alone (Koehler et al., 2018; Ong et al., 2016). This means that measurement alone is insufficient; data interpretation, alert prioritization, and the possibility of treatment modification are necessary.

Wearable and consumer devices allow data to be recorded in the patient's everyday environment. Smartwatches and PPG sensors may support screening for atrial fibrillation, as confirmed in large population studies (Perez et al., 2019; Lubitz et al., 2022). Their results, however, require clinical confirmation because of the risk of false alarms and variable signal quality.

Digital technologies may also improve risk factor control. Blood pressure telemonitoring combined with support from a pharmacist or primary care team improved blood pressure control in the HyperLink and TASMINH4 studies (Margolis et al., 2013; McManus et al., 2018). Similar solutions may support lipid control, laboratory testing, and treatment adherence (Persell et al., 2013; Miao et al., 2024).

The evaluation of medical technologies should not be limited to sensitivity, specificity, or AUC. Their impact on clinical decisions, patient safety, staff workload, costs, quality of life, and user acceptance is also important. From a social perspective, data privacy, equity of access, and preservation of the physician–patient relationship remain crucial.

In summary, digital technologies have the greatest value when they are validated, address a specific clinical problem, are integrated into a clear care pathway, and are interpreted by medical personnel. The future of digital cardiology should be based on the model of “technology plus process”: measurement, interpretation, decision, and clinical response.

8. Conclusions

Modern technologies can provide real support for the prevention, diagnosis, and monitoring of cardiovascular diseases. However, their value depends on whether they address a specific clinical problem. They are most important in areas where they help detect arrhythmias more quickly, improve blood pressure control, reduce hospitalizations in heart failure, increase access to rehabilitation, or improve the analysis of imaging studies.

Artificial intelligence can support the assessment of ECG, echocardiography, computed tomography, and cardiac magnetic resonance imaging. It enables the detection of subtle patterns and the automation of repetitive measurements. However, it should not replace the physician. The algorithm’s result should be treated as additional information that must be interpreted in relation to the patient’s symptoms, medical history, test results, and overall clinical situation.

Wearable devices, mobile applications, and telemonitoring make it possible to observe the patient outside the doctor’s office. As a result, deterioration in health can be noticed earlier, risk factors can be better controlled, and the patient’s participation in treatment can be increased. This is particularly important in chronic diseases such as heart failure, hypertension, atrial fibrillation, and coronary artery disease.

Data collection alone is not sufficient. The effectiveness of technology depends on whether the data are of good quality, whether someone analyzes them, whether clear response thresholds exist, and whether the patient has the possibility of contact with medical personnel. A system that only collects results but does not lead to a clinical decision has limited value.

The implementation of digital technologies requires further research, safety assessment, cost analysis, and testing in different patient groups. It is important that algorithms are also evaluated in older adults, women, patients with multimorbidity, and groups that are underrepresented in studies. Without this, there is a risk of errors, inequalities, and limited trust in new solutions.

Digital cardiology should be developed in an ethical and responsible way. This includes the protection of patient data, transparency of algorithm operation, clear definition of clinical responsibility, and accessibility of technologies for people with different levels of digital competence and financial resources. Modern solutions can reduce inequalities in care, but only if they are designed with different patient groups in mind.

In summary, digital technologies should support the physician and the patient, rather than replace the clinical relationship. They have the greatest value when they combine reliable data, medical knowledge, clear organization of care, and the patient’s informed participation. Only such an approach can improve the prevention, diagnosis, and monitoring of cardiovascular diseases.

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