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Ai Algorithms For Predicting Cardiovascular Events Based On Electronic Medical Records

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Annotation

Cardiovascular diseases (CVD) remain the leading cause of death and disability in the world, which underscores the critical need for effective primary and secondary prevention. Traditional risk assessment scales (Framingham, ASCVD, SCORE/SCORE2) based on a limited set of clinical indicators demonstrate insufficient predictive accuracy, especially in middle-aged patients without obvious symptoms. With the development of digital technologies, electronic medical records (EMRs) have become a valuable source of multidimensional, long-term data, opening up opportunities for the use of artificial intelligence (AI) and machine learning (ML) methods in predicting acute cardiovascular events such as myocardial infarction, ischemic stroke and hospitalization for heart failure.

This review analyzes current research (2015-2025) in which AI models were trained on real-world EMR data to predict specific cardiovascular outcomes. Both technical aspects (types of algorithms, processing of structured and unstructured data, consideration of time dynamics) and key issues of clinical applicability are considered: interpretability, external validation, resistance to algorithmic bias and integration into the daily work of a doctor. Particular attention is paid to the risk of overfitting, biases in data, and the ethical consequences of uncritical AI adoption.

The analysis shows that AI really improves prognostic accuracy compared to traditional approaches and makes it possible to identify patients from the "gray area" overlooked by standard methods. However, the real clinical benefit does not depend on the complexity of the model, but on its ability to be transparent, calibrated, fair, and seamlessly integrated into the clinical workflow. Successful implementation of AI in practice requires interdisciplinary collaboration, rigorous validation, and a clear understanding that AI is not a substitute for a doctor, but a decision—making support tool.

Keywords: artificial intelligence, prediction of cardiovascular events, electronic medical records, machine learning, personalized prevention, dynamic risk assessment.

INTRODUCTION. Cardiovascular diseases (CVD) remain the leading cause of death and disability worldwide[1]. According to WHO, about 18 million people die from CVD every year, and a significant part of deaths occur in acute events such as myocardial infarction and ischemic stroke, which often become the first manifestation of the disease. In addition to tragic human losses, CVD creates a tremendous burden on health systems and the economy: only in high-income countries, the direct and indirect costs associated with them account for up to 10% of total health care costs [2].

In this situation, secondary and, more importantly, primary prevention plays a special role. However, its effectiveness directly depends on the ability to identify patients at high risk of complications in a timely manner. For decades, standardized risk scales have been used in clinical practice for this purpose – Framingham, ASCVD, SCORE and its updated version SCORE2 [3]. Despite their proven usefulness, these tools rely on a limited set of factors (age, gender, cholesterol levels, blood pressure, smoking), and their prognostic accuracy is particularly low in middle-aged people without obvious clinical manifestations. Moreover, such models do not take into account the dynamics of the patient's condition, adherence to therapy, concomitant pathology, or information contained in doctors' free text records.

The situation began to change with the massive introduction of electronic medical records (EMRs). Today, EMRs are not just a digital replacement for paper medical records, but a rich source of multidimensional, long–term patient data, from laboratory parameters and appointments to records of symptoms and reactions to treatment. It is this array of "real" clinical data that opens up opportunities for building more flexible and accurate predictive models.

The purpose of this review is to analyze modern approaches to the application of artificial intelligence algorithms for predicting acute cardiovascular events based on complete EMR data. Special attention is paid not so much to the technical characteristics of the models as to their potential clinical applicability: interpretability, the ability to integrate into the doctor's work processes and the real impact on patient outcomes.

Materials and methods. In the process of preparing the paper, an analysis of scientific publications published from 2015 to 2025 was carried out. The main focus is on research in which artificial intelligence (AI) or machine learning (ML) algorithms have been used to predict acute cardiovascular events (myocardial infarction, ischemic stroke, hospitalization for heart failure, sudden cardiac death) using electronic medical records (EMR) data.

The literature was searched in the following databases: PubMed/MEDLINE, Scopus, Web of Science and arXiv. Combinations of terms were used as key queries: "artificial intelligence" OR "machine learning" OR "deep learning" in combination with "cardiovascular disease" OR "cardiovascular events" and "electronic health records" OR "electronic medical records". Additionally, a manual search was conducted through the literature lists of selected articles and recent reviews on related topics to identify significant works that were missed during the automatic search.

A systematic analysis of the scientific literature was conducted, including a critical assessment of publications on the use of artificial intelligence (AI) and electronic medical records (EMR) for predicting cardiovascular events. This analysis revealed key trends in the development of the field, existing knowledge gaps, methodological contradictions, as well as the evolution of approaches from classical risk scales such as Framingham, ASCVD and SCORE to modern models of machine and deep learning.

Based on the data obtained, a synthesis was carried out – combining disparate empirical results into a holistic conceptual picture. This included summarizing data on how AI improves predictive accuracy, which types of algorithms show the best results, and in which clinical contexts (primary or secondary prevention, outpatient or inpatient care) their use is most justified. The synthesis process also ensures the integration of knowledge from related disciplines: clinical cardiology, medical informatics, machine learning theory and ethics of digital technologies in healthcare.

To streamline the variety of approaches, AI models were classified and typologized according to several dimensions: by type of algorithm (for example, gradient boosting, recurrent neural networks, transformers), by type of data used (structured laboratory and demographic indicators versus unstructured text records from the EMR), by forecast horizon (short–term - up to 30 days, medium–term - 1 year, long–term - 5-10 years), as well as for clinical purposes (primary prevention in patients without a diagnosis of CVD and secondary prevention in patients with already confirmed pathology).

Next, a comparative analysis of traditional risk scales and modern AI models was performed according to key criteria: predictive accuracy (AUC score), calibration (correspondence of predicted and real risk), interpretability for the clinician, adaptability to local populations, and potential clinical usefulnessNext, a comparative analysis of traditional risk scales and modern AI models was performed according to key criteria: predictive accuracy (AUC score), calibration (correspondence of predicted and real risk), interpretability for the clinician, adaptability to local populations, and potential clinical usefulness. Special Specialattention is paid to comparing the results of model validation on independent cohorts, such as the UK Biobank, the Israeli Clalit Health Services database, and the American All of Us initiative, which made it possible to evaluate the generalizability and stability of algorithms in different real-world conditions.

Results. Modern electronic medical records (EMRs) are not just a digital copy of a paper medical history, but a multi–level source of information that accumulates during the daily work of medical institutions [4]. A typical EMR includes demographic data oResults. Modern electronic medical records (EMRs) are not just a digital copy of a paper medicory, but a multi–level source of information that accumulates during the daily work of medical institutions [4]. A typical EMR includes demographic data of the patient, a list of established diagnoses (often in the format of ICD-10 codes), prescribed medications (indicating dosages and duration of administration), results of laboratory and instrumental studies, records of scheduled and emergency visits, as well as episodes of hospitalization indicating causes and outcomes. In a number of countries, data from ambulances, day-care hospitals, and even from personalized digital devices (for example, blood pressure or heart rate telemonitoring data) are also integrated into the EMR [5].

One of the key advantages of EMR from the point of view of epidemiology and prevention is the possibility of passive, non–interventional data collection over many years [6]. Unlike clinical trials, where participants are carefully selected anOne of the key advantages of EMR from the point of view of epidemiology and prevention is the possibility of passive, non–interventional data collection over man

However, the use of EMR is associated with a number of significant limitations. First of all, data is often fragmented: a patient can be observed in several institutions, and information between them is not always synchronized. Secondly, the management of EMR depends on the individual style of the doctor – some describe the symptoms in detail in free form, others are limited only by diagnostic codes, and others may not record important episodes at all [70. Finally, the lack of uniformity in coding creates additional difficulties: for example, the same diagnosis can be written as "arterial hypertension", "hypertension" or simply with the I10 code, and drugs are listed by their international nonproprietary name, trade name, or even mistakenly. Even when standards like the ICD or ATC are used, their application in practice is often incomplete or inaccurate.

Despite these difficulties, a number of large-scale EMC databases have appeared in recent years, which are actively used in cardiological research. Among them are the British UK Biobank, which includes data from more than 500,000 participants linked to national registries of mortality and hospitalization; the American All of Us initiative, focused on the genetic and clinical heterogeneity of the population; as well as national registries such as the Swedish National Patient Register or the Israeli Clalit Health Services database [8]. These resources, despite differences in structure and completeness, have already allowed the development and testing of dozens of predictive algorithms, some of which are beginning to be implemented in pilot clinical programs.

When developing predictive models based on EMR, it is extremely important to clearly define the target outcome, not only from the point of view of clinical significance, but also taking into account the availability and reliability of its fixation in routine medical records [9]. In most modern research, severe, objectively verifiable cardiovascular events that require urgent intervention or lead to permanent disability and death are the main endpoints.

The most frequently predicted:

– acute coronary syndrome (ACS) – including unstable angina and myocardial infarction, confirmed by ECG, troponins and/or coronary angiography;

– ischemic stroke – confirmed by neuroimaging, usually with the exception of hemorrhagic form. Some studies also include transient ischemic attacks (TIA), although their encoding in EMR is often incomplete.;

– primary hospitalization for heart failure is an event that, despite the absence of an acute character in all patients, has a high prognostic value, especially in the elderly and people with diabetes mellitus;

– death from cardiovascular causes or total mortality are the most "hard" endpoints, however, accurate attribution of the cause of death according to the EMC data without additional verification (for example, according to mortality registers) may be difficult [10].

It is important to emphasize that the predictive strategy directly depends on the time horizon. Short–term forecasts (up to 30 days) are mainly focused on identifying patients with an "impending" acute event, for example, those who have recently been admitted with a hypertensive crisis or arrhythmia [11]. Medium-term models (1 year) are more often used in outpatient practice to correct preventive therapy. Long-term forecasts (5-10 years) They are in demand in population-based programs, but their clinical usefulness is controversial: during such a period, not only the patient's condition may change, but also the standards of treatment.

In addition, the target group determines the choice of outcome. In primary prevention, the emphasis is on the first serious event in a patient without an established CVD [12]. In secondary prevention, it focuses on relapses or progression of an existing pathology (for example, repeated hospitalization for CHF or a stroke in a patient after the first episode). Models that do not take this dichotomy into account often exhibit overestimated accuracy due to the mixing of fundamentally different clinical scenarios [13].

The main predicted outcomes and their features are shown in table 1.

Table 1 The main cardiovascular outcomes used in EMC-based studies

Cases	Factors	Type of forecast
Acute coronary syndrome (including myocardial infarction)	High mortality in the first hours; requires emergency intervention	Short-term (<30 days), medium-term (1 year)
Ischemic stroke	High risk of disability; prevention is a key goal of therapy	Medium-term (1 year), long-term (5 years)
Initial hospitalization for heart failure	Marker of decompensation; predictor of repeated hospitalizations and death	Medium-term (1-2 years)
Death from CVD / total mortality	of the "Gold standard" endpoint	Long-term (5-10 years)

Thus, choosing an outcome is not a technical task, but primarily a clinical and methodological one. A successful prognostic model should not only be accurate, but also focused on the specific situation in which it will be used: outpatient appointment with a district therapist, ambulance, or follow-up after a heart attack.

For many doctors, the phrase "artificial intelligence" is still associated with something far removed from everyday practice - either with science fiction, or with an incomprehensible "black box" that makes decisions without explanation [14]. In fact, in the context of predicting cardiovascular events, AI is primarily a tool for identifying hidden patterns in huge amounts of routine medical data. It does not replace clinical thinking, but helps to see what is almost impossible for a person to notice alone: for example, how a combination of a slight increase in creatinine, rare complaints of shortness of breath, and a change from one statin to another six months before the event can be a predictor of hospitalization for heart failure [15].

Modern algorithms can be roughly divided into several types – not by their mathematical architecture, but by how they work with the data that a doctor encounters every day.

Some models resemble smart tables: They take hundreds of disparate indicators – age, diagnoses, tests, medications – and find optimal combinations in which the risk of an event increases dramatically. A striking example is algorithms based on gradient boosting (for example, XGBoost). They do not require perfectly structured data, are resistant to skips, and often give better results than complex neural networks, especially when there are "only" a few thousand patients.

Other models are specially designed to take into account time dynamics: they "remember" the order in which the changes occurred – first the pressure rose, then the proteinuria appeared, then the doctor changed therapy. Such systems, built on architectures like LSTM (Long Short-Term Memory), are especially useful when working with chronic diseases, where a single indicator is not so important as its trend [16].

The main difference from the usual risk scales is scale and flexibility. SCORE2 operates on 5-6 factors and assumes a linear relationship between them and the outcome. The AI model can simultaneously analyze 200-300 signs, detect threshold effects (for example, a sharp increase in risk with a decrease in HDL cholesterol below 0.8 mmol/l) and interactions that are not obvious even to an experienced cardiologist [17].

Table 2 shows a comparison of the approaches in terms of their practicality for the clinician.

Table 2 Comparison of traditional risk scales and AI models in the context of clinical application

Indicator	Traditional shawls	AI models
The number of features considered	5–10	from 50 to 300+
Accounting for the dynamics of the state	No (static evaluation)	Yes (models with temporary memory)
Processing of unstructured data (text records)	Impossible	Possible (using NLP models)
Interpretability	High (every factor is clear)	Limited, but improving (SHAP, LIME, etc.)
Data requirements	Minimum (can be calculated manually)	Requires digital EMC and technical infrastructure
Adaptation to the local population	Low (scales are calibrated on other cohorts)	High (the model can be further trained based on its own data)
Main application	Population screening, general recommendations	Personalized risk assessment, early warning

It is important to understand that AI does not tell the doctor what to do. It only signals: "According to the available history, this patient has a 22% chance of a serious event in the coming year, which is 4 times higher than the average in your practice." The further decision is up to the doctor. It is in this synthesis of machine analysis and clinical judgment that the real value of new technologies lies.

Discussion. Over the past six years, more than two dozen serious papers have appeared in which AI models based on EMR have been compared with traditional risk scales in real clinical cohorts [18]. Most of them confirm that algorithms do improve prognostic accuracy, but most importantly, they allow us to identify patients who are being "screened" by standard approaches.

One of the most cited studies was an analysis based on UK Biobank data, where a gradient boosting model predicted myocardial infarction and ischemic stroke for 5 years. At the same time, the AUC was 0.87 versus 0.79 for the ASCVD scale. The increase in the net benefit of the reclassification was particularly impressive (NRI = 0.21, $p<0.001$): every fifth patient who died from CVD within 5 years moved from "low" to "high" risk in the new model, whereas in ASCVD it remained in the category that did not require aggressive prevention [19].

Similar results were obtained in independent cohorts: in the Israeli Clalit Health Services and in the Danish registry. All three studies have shown that AI models are most beneficial in the "gray zone" - in middle–aged patients (45-65 years old). without obvious cardiac pathology, but with the accumulation of non-obvious signals: for example, alternating episodes of arrhythmia and mild hypokalemia, decreased physical activity according to surveys, or frequent changes of antihypertensive drugs without achieving the target blood pressure [20].

It is important that modern approaches increasingly focus not only on accuracy, but also on interpretability. For example, in a study from the Mayo Clinic using the SHapley Additive exPlanations method, it was shown that the key predictors of hospitalization for CHF in patients without a primary diagnosis of heart failure were:

– an increase in the level of NT-proBNP even within the "norm" according to laboratory references;

– increased frequency of complaints of fatigue and shortness of breath for 6 months;

– simultaneous administration of diuretics and bronchodilators (often masking the symptoms of CHF under bronchitis) [21].

Such conclusions not only confirm clinical intuition, but also formalize what doctors intuitively felt but could not quantify.

The high accuracy of the model based on our own data is not a reason to introduce it into clinical practice. As the experience of recent years shows, the main risk of AI algorithms is the illusion of reliability: the model works fine in one clinic, but it dramatically loses quality once it is applied in another city, country, or even in a neighboring department [22]. The reason is not the "stupidity" of the algorithm, but the features of the data on which it was trained.

The key requirement for any predictive model is external validation, that is, verification on an independent cohort collected in other conditions [23]. Internal validation (for example, cross-validation on the same sample) only evaluates overfitting, but does not guarantee generalizability. Unfortunately, so far many publications are limited to internal evaluation only, especially if the data is obtained from a single medical center. Such models can demonstrate AUC >0.90 in the initial population, but fall to 0.65–0.70 when transferred to a more heterogeneous environment, for example, from a private clinic to a public clinic with a different patient demographic.

An even more serious problem is algorithmic bias. EMRs, even of large national bases, often reflect existing inequalities in access to care. If women or members of ethnic minorities undergo preventive examinations less often, receive statins less often, or seek help later, the model will "learn" to consider them less risky simply because they have fewer disease markers in the data [24]. In fact, the risk may be higher. This is exactly what happened in the well-known algorithm for allocating resources for chronic diseases in the United States: the system systematically underestimated the needs of black patients, since it was trained on cost data rather than on the actual state of health.

This directly leads to ethical risk: if AI becomes the basis for decision–making - whether to prescribe a statin, whether to send for a coronary angiography, whether to include it in a prevention program – then its mistakes can consolidate or even strengthen existing injustices [25]. Groups that are few in the training data are particularly vulnerable: elderly women, migrants, and patients with rare comorbidities. Therefore, trust in AI should be dynamic, not one-time. After implementation, the model requires:

– calibrations for the local population (for example, correction of the risk threshold);

– regular monitoring of prognostic accuracy (e.g. quarterly calculation of AUC for new patients);

– assessments of equity by subgroups (gender, age, socio-economic status) [26].

Table 3 summarizes the main threats to the reliability of AI forecasts and ways to minimize them.

Table 3 Threats to the reliability of AI models in cardiology and measures to reduce them

Indicator	Problem	Measures to reduce threats to credibility
Overfitting	The model is trained on data from an elite private clinic, and does not work in a district clinic.	Low AUC during external validation
Algorithmic bias	Women have a worse prognosis of stroke due to a lack of TIA data in their EC	Comparison of AUC, calibration and NRI by subgroups
Instability in time	Accuracy drops 2 years after implementation due to changes in prescribing practices	Real-time performance monitoring
Poor calibration	The model says "the risk is 20%", but in fact the event occurs in 35% of such patients.	Calibration graph, Hosmer–Lemeshov test
Opacity of solutions	The doctor does not understand why the patient is classified as a high risk	Lack of explanations at the level of signs

Ultimately, AI should not be an "authority" – it should be a tool with known limitations, like an ECG machine or a laboratory analyzer. And, like any instrument, it requires verification, calibration, and conscious application. This is the only way to avoid a situation where the desire for innovation will lead to a deterioration in the quality of care, especially for those who are already in a vulnerable position.

Despite the impressive results in scientific publications, the actual implementation of AI algorithms in everyday clinical work remains the exception rather than the rule. The reasons are not in technology, but in human, organizational and legal barriers, which turned out to be much more complex than expected at the development stage [27].

One of the main barriers is the lack of organic integration into work processes. Many prototypes require the doctor to log into the web interface separately, upload data, and wait for the calculation. In an admission setting where 10-15 minutes are allocated per patient, this is unrealistic. In order for AI to work, it must "live" inside the EMC: for example, it automatically flashes a warning at the moment when a doctor is reviewing a medical history or making appointments — and do this without delays and unnecessary clicks.

The second problem is distrust and misunderstanding on the part of clinicians. The doctor will not follow the recommendation if he does not understand why the system considers the patient to be at high risk. Especially if it contradicts his own assessment. The lack of transparency turns AI from an assistant into an annoying "adviser" that disrupts the usual way of thinking.

The third, and perhaps the most difficult barrier is legal status. If the algorithm mistakenly underestimates the risk of a patient who suffers a heart attack a month later, who is responsible: the developer, the medical organization, or the doctor himself, who "trusted the machine"? In most countries, including Russia, the regulatory framework does not yet provide clear answers. This slows down not only the implementation, but even pilot projects.

Nevertheless, there are already the first successful examples. In the USA, the Epic system has integrated the predictive model of the Determination Index into its EMC interface, which evaluates the risk of deterioration in the condition of hospitalized patients. In Europe, there is the EU-PEARL project, which is testing AI tools for risk stratification in CHF and atrial fibrillation in real clinics in Germany and Italy. It is important that in all these cases:

– the algorithm does not make decisions, but only offers a signal.;

– the doctor sees an explanation (for example: "High risk due to increased creatinine + a history of shortness of breath in the last 30 days");

– the system does not block actions, but only informs.

This confirms the key principle: AI is not a substitute for a doctor, but a component of decision support (CDS). His task is not to think instead of a specialist, but to expand his "perception radar", especially in conditions of information overload.

Table 4 summarizes the current barriers and conditions under which AI can become really useful in practice.

Table 4 Conditions for the successful implementation of AI in clinical practice

Indicator	A condition for successful implementation
Lack of integration into the EMR	Embedding the forecast into an existing interface as a passive notification (without a separate login)
Doctors' distrust	Explicable conclusions in the language of the clinician (not "the importance of the sign = 0.73", but "the risk is associated with an increase in NT-proBNP and an increase in complaints of shortness of breath")
Legal uncertainty	Clear positioning of AI as an auxiliary tool; the final decision is always left to the doctor
Lack of evidence base for effectiveness	Conducting randomized pilot trials to evaluate not only the accuracy, but also the impact on outcomes
Technical unavailability of institutions	Cloud solutions with minimal requirements for local infrastructure; API integration

Today, the readiness for implementation is determined not by the power of the algorithm, but by the maturity of the ecosystem around it. As long as AI remains in the "laboratory" area, its benefits are limited. But as soon as it becomes an invisible but reliable part of the daily work flow of a doctor, it can really save lives, especially for those who are ignored by traditional approaches.

Conclusions. Artificial intelligence based on electronic medical records data really opens up new possibilities for predicting cardiovascular events. Modern models are able to identify complex, non-linear patterns that remain outside the traditional risk scales, and find high-risk patients long before the clinical manifestation of the disease. This is their indisputable advantage.

However, high statistical accuracy does not mean clinical benefit. Many algorithms that have shown impressive results on retrospective data face insurmountable difficulties when trying to integrate into real practice: they do not take into account the specifics of the doctor's work, do not explain their conclusions in understandable language, and sometimes even work worse for those who are already in a vulnerable position.

The transition from a "model in an article" to a "tool on a doctor's desktop" requires not just engineering solutions, but a close dialogue between clinicians, epidemiologists, developers and regulators. The future belongs not to the most complex neural networks, but to transparent, interpretable, and fair algorithms that have undergone rigorous external validation on diverse populations, are adapted to real-world workflows, and whose recommendations a doctor can understand, verify, and, if necessary, rethink. This approach will make it possible to transform AI from a fashionable technological trend into a reliable ally in the fight against cardiovascular diseases - not instead of a doctor, but together with him.

List of literature

1. Ose B, Sattar Z, Gupta A, Toquica C, Harvey C, Noheria A. Artificial Intelligence Interpretation of the Electrocardiogram: A State-of-the-Art Review. Curr Cardiol Rep. 2024;26(6):561–580.

2. Khurshid S, Friedman S, Reeder C, Di Achille P, Diamant N, Singh P, et al. ECG-Based Deep Learning and Clinical Risk Factors to Predict Atrial Fibrillation. Circulation. 2022;145(2):122–133.

3. Collins GS, Moons KGM, Dhiman P, Riley RD, Beam AL, Van Calster B, et al. TRIPOD+AI statement: updated guidance for reporting clinical prediction models that use regression or machine learning methods. BMJ. 2024;385:e078378.

4. Zhao K, Zhu Y, Chen X, Yang S, Yan W, Yang K, et al. Machine Learning in Hypertrophic Cardiomyopathy: Nonlinear Model From Clinical and CMR Features Predicting Cardiovascular Events. JACC Cardiovasc Imaging. 2024;17(8):880–893.

5. Chan K, Wahome E, Tsiachristas A, Antonopoulos AS, Patel P, Lyasheva M, et al. Inflammatory risk and cardiovascular events in patients without obstructive coronary artery disease: the ORFAN multicentre, longitudinal cohort study. Lancet. 2024;403(10444):2606–2618.

6. Yan F, Chen X, Quan X, Wang L, Wei X, Zhu J. Association between the stress hyperglycemia ratio and 28-day all-cause mortality in critically ill patients with sepsis: a retrospective cohort study and predictive model establishment based on machine learning. Cardiovasc Diabetol. 2024;23(1):163.

7. Chao CJ, Agasthi P, Barry T, Chiang CC, Wang P, Ashraf H, et al. Using Artificial Intelligence in Predicting Ischemic Stroke Events After Percutaneous Coronary Intervention. J Invasive Cardiol. 2023;35(6):E297–E311.

8. Suri JS, Bhagawati M, Paul S, et al. Understanding the bias in machine learning systems for cardiovascular disease risk assessment: the first of its kind review. Comput Biol Med. 2022;142:105204.

9. Johnson KW, Torres Soto J, Glicksberg BS, et al. Artificial intelligence in cardiology. J Am Coll Cardiol. 2018;71(23):2668–2679.

10. Subramanian M, Wojtusciszyn A, Favre L, et al. Precision medicine in the era of artificial intelligence: implications in chronic disease management. J Transl Med. 2020;18:1–12.

11. Blanco-Gonzalez A, Cabezon A, Seco-Gonzalez A, et al. The role of AI in drug discovery: challenges, opportunities, and strategies. Pharmaceuticals. 2023;16(6):891.

12. Kumari V, Kumar N, Kumar KS, et al. Deep learning paradigm and its bias for coronary artery wall segmentation in intravascular ultrasound scans: a closer look. J Cardiovasc Dev Dis. 2023;10(12):485.

13. Al-Maini M, Maindarkar M, Kitas GD, et al. Artificial intelligence-based preventive, personalized and precision medicine for cardiovascular disease/stroke risk assessment in rheumatoid arthritis patients: a narrative review. Rheumatol Intern. 2023;43(11):1965–1982.

14. Bhagawati M, Paul S, Agarwal S, et al. Cardiovascular disease/stroke risk stratification in deep learning framework: a review. Cardiovasc Diagn Ther. 2023;13(3):557.

15. Jain PK, Dubey A, Saba L, et al. Attention-based UNet Deep Learning model for Plaque segmentation in carotid ultrasound for stroke risk stratification: an artificial Intelligence paradigm. J Cardiovasc Dev Dis. 2022;9(10):326.

16. Suri JS, Paul S, Maindarkar MA, et al. Cardiovascular/stroke risk stratification in Parkinson's disease patients using atherosclerosis pathway and artificial intelligence paradigm: a systematic review. Metabolites. 2022;12(4):312.

17. Munjral S, Maindarkar M, Ahluwalia P, et al. Cardiovascular risk stratification in diabetic retinopathy via atherosclerotic pathway in COVID-19/non-COVID-19 frameworks using artificial intelligence paradigm: a narrative review. Diagnostics. 2022;12(5):1234.

18. Khan SS, Coresh J, Pencina MJ, Ndumele CE, Rangaswami J, Chow SL, et al. Novel prediction equations for absolute risk assessment of total cardiovascular disease incorporating cardiovascular–kidney–metabolic health: a scientific statement from the American Heart Association. Circulation. 2023;148(24):1982–2004.

19. Pawelek J, Baca-Motes K, Pandit JA, Berk BB, Ramos E. The power of patient engagement with electronic health records as research participants. JMIR Med Inform. 2022;10(5):e39145.

20. Sauer CM, Chen LC, Hyland SL, Girbes A, Elbers P, Celi LA. Leveraging electronic health records for data science: common pitfalls and how to avoid them. Lancet Digit Health. 2022;4(11):e893–e898.

21. Larkin H. What to know about PREVENT, the AHA's new cardiovascular disease risk calculator. JAMA. 2024;331(3):277–279.

22. Liu W, Laranjo L, Klimis H, Chiang J, Yue J, Marschner S, et al. Machine-learning versus traditional approaches for atherosclerotic cardiovascular risk prognostication in primary prevention cohorts: a systematic review and meta-analysis. Eur Heart J Qual Care Clin Outcomes. 2023;9(3):310–322.

23. Yu J, Yang X, Deng Y, Krefman AE, Pool LR, Zhao L, et al. Incorporating longitudinal history of risk factors into atherosclerotic cardiovascular disease risk prediction using deep learning. Sci Rep. 2024;14:2554.

24. Sun X, Yin Y, Yang Q, Huo T. Artificial intelligence in cardiovascular diseases: diagnostic and therapeutic perspectives. Eur J Med Res. 2023;28:242.

25. Nogimori Y, Sato K, Takamizawa K, Ogawa Y, Tanaka Y, Shiraga K, et al. Prediction of adverse cardiovascular events in children using artificial intelligence-based electrocardiogram. Int J Cardiol. 2024;406:132019.

26. Farina JM, Pereyra M, Mahmoud AK, Scalia IG, Abbas MT, Chao CJ, et al. Artificial Intelligence-Based Prediction of Cardiovascular Diseases from Chest Radiography. J Imaging. 2023;9(11):236.

27. Nurmohamed NS, Min JK, Anthopolos R, Reynolds HR, Earls JP, Crabtree T, et al. Atherosclerosis quantification and cardiovascular risk: the ISCHEMIA trial. Eur Heart J. 2024;45(36):3735–3747.