ISSN 2304-3415, Russian Open Medical Journal
2025. Volume 14. Issue 4 (December). Article CID e0410
DOI: 10.15275/rusomj.2025.0410

Review

The Transformation of Cardiovascular Medicine Under the Influence of Artificial Intelligence: History, Achievements, and Prospects

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Received 19 June 2025, Revised 16 July 2025, Accepted 23 September 2025

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Abstract: *Background* — This comprehensive literature review aims to examine key milestones in the development of artificial intelligence (AI) in cardiology, highlight current advances, and identify significant challenges associated with AI integration that are underrepresented in the literature. Using a rigorous methodological approach, this review provides a detailed understanding of the transformative potential and practical limitations of AI technologies in cardiovascular medicine.
Methods — A thorough search of e-Library, PubMed, and Scopus databases was conducted using a carefully selected set of keywords, including *'artificial intelligence'*, *'expert systems'*, *'personalized medicine'*, *'polygenic risk assessment'*, *'neural networks'*, *'large language models'*, *'deep learning'*, *'cardiovascular disease'*, and *'prevention'*. The search encompassed publications from 1995 to June 2025, resulting in a total of 268 articles that were systematically reviewed and analyzed. A subset of 65 articles was subsequently selected for in-depth review to ensure a comprehensive and representative sample of the current state of research in this field.
Results — This article provides a comprehensive analysis of the AI application in cardiology, tracing the historical evolution of technological advances, current achievements, existing challenges, and prospects for integration. The development of AI in cardiology is described in detail from the development of the first expert systems to the emergence of sophisticated neural network models that have demonstrated exceptional accuracy in the diagnosis and prognosis of cardiovascular diseases (CVD). Particular attention is paid to the use of AI for cardiovascular risk prediction, including the integration of polygenic risk scores (PRS) with patient clinical data. The main drivers of AI adoption are revealed, including a chronic shortage of medical specialists, economic demands, and rapid technological innovation. Additionally, the article identifies significant barriers, such as patient and healthcare professional resistance, legal and ethical considerations, data quality issues, and cybersecurity challenges.
Conclusion — It is emphasized that modern AI systems are shifting from human-dependent learning paradigms to autonomous self-learning models, which facilitates their accelerated development and integration into clinical practice. In conclusion, it should be noted that the successful and safe implementation of AI in cardiology depends on the readiness of the medical community, patients, and healthcare systems to engage in collaborative transformation, as well as on the improvement of the regulatory framework and quality control mechanisms for AI technologies.

Keywords: artificial intelligence, neural networks, large language models, deep learning, cardiovascular diseases, prevention, personalized medicine, polygenic risk assessment.

Cite as Shvarts YuG, Akimova NS, Konshina LE, Runnova AE, Parkhoniuk EV, Kiselev AR. The transformation of cardiovascular medicine under the influence of artificial intelligence: History, achievements, and prospects. *Russian Open Medical Journal* 2025; 14: e0410.

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Introduction

Artificial intelligence (AI) is one of the most important challenges and opportunities in modern medicine, including cardiology. The integration of AI technologies has shown significant promise in improving diagnostic accuracy, predictive analytics, patient monitoring, therapy planning, pharmaceutical research, and personalized approaches to disease prevention and treatment [1-3]. The transformative potential of AI in cardiovascular medicine is becoming increasingly clear [4-6]. However, along with the benefits, there are also significant challenges and risks associated with the rapid development of AI in healthcare. These risks affect both healthcare professionals and patients. Some of these challenges are already well documented and widely discussed [7, 8]. Others, however, remain less visible and require further study. It is not the scope of this article to comprehensively analyze individual technical aspects of AI, including the generalizability of machine learning models, the phenomenon of AI hallucinations, potential errors, and the risks of harm from AI to patients and healthcare professionals. This review also does not address the legal, ethical, and moral aspects of AI

application in cardiology, which are often discussed in similar reviews [9-11].

This review, unlike other publications of undeniable scientific and practical significance, is characterized by a multifaceted interdisciplinary approach, historical breadth, and comprehensive analysis of both the technical and social aspects of AI application in cardiology. It provides a historical overview of the development of analytical systems for processing cardiac patient data, including domestic and international examples. It also highlights advances in the application of AI knowledge in cardiology and medicine in general. The high prognostic value of AI-based inferences for predicting cardiovascular events in patients with and without cardiovascular diseases (CVD) is discussed in detail. Specific examples of AI application in this context are examined in detail, followed by an analysis of the challenges associated with implementing AI in real-world clinical practice. The ethical and moral aspects of integrating AI into medical practice are also considered, including the perspectives of patients, healthcare professionals, and educators. Furthermore, an assessment of the potential for predicting future developments and expanding the use of AI capabilities in cardiology is presented. The goal of this review is to provide a balanced and objective assessment of the current state and future prospects of AI in cardiovascular medicine.

Review algorithm

This analytical literature review attempts to clarify key stages in the development of AI in cardiology, describe current achievements, and identify important challenges related to AI integration that are rarely discussed. It also assesses the potential of solutions and the immediate prospects of these technologies. A comprehensive search of e-Library, PubMed, and Scopus databases was conducted using the following keywords: *'artificial intelligence'*, *'expert systems'*, *'personalized medicine'*, *'polygenic risk assessment'*, *'neural networks'*, *'large language models'*, *'deep learning'*, *'cardiovascular disease'*, and *'prevention'*. Publications from 1995 to June 2025 were included; a total of 268 articles were reviewed and analyzed. A subset of 65 articles was selected for in-depth review. In some cases, references to non-medical sources on general AI issues were included to ensure a holistic view.

History

Conventionally, two areas of digitalization can be considered precursors of AI in medicine: PubMed, an analytical and search engine created in the 1960s; and clinical information databases – medical documentation systems – that emerged later. These laid the foundation for future developments in AI. Other precursors include prognostic and diagnostic algorithms based on multivariate statistical analysis, developed in the 1960s and 1980s. In particular, systems such as the Framingham Risk Score and Duke Treadmill Score, and later TIMI, SCORE, and EuroSCORE, are well-known in cardiology.

Since the 1970s, AI systems have begun to emerge, such as programs demonstrating intelligent properties. These are expert systems (ES), which utilize formalized expert expertise. MYCIN was one of the first medical systems to use a knowledge base containing approximately 600 expert rules for recommending antibacterial therapy. MYCIN formed the basis of later rule-based systems such as EMYCIN ("essential MYCIN"). INTERNIST-I was later developed, using the same framework as EMYCIN but with a more extensive medical knowledge base to assist primary care physicians in diagnosis, including in cardiology. INTERNIST became a pioneer in structuring medical knowledge. In the 1980s, DXplain, a medical decision support system, was released [12].

In the late 1990s, the field of AI experienced a resurgence of interest in its application to cardiology. However, early AI systems developed during this period often demonstrated limited capabilities, solving highly specialized problems [13] or making errors in complex clinical situations [13, 14]. Most of these AI systems were primarily used for diagnostic purposes, and some were used in emergency cardiology, such as ANGINE, EMERGENCY, and Predictive Instrument. In emergency cardiology, these systems were used to differentiate patients with chest pain into those requiring intensive care and those who could be managed without it. Based on existing knowledge of disease pathogenesis, the KORDEX expert system was developed, the first industrial version of which was released in 1995 [15]. KORDEX was designed to generate short-term prognoses of adverse outcomes in patients with unstable angina and provide treatment recommendations based on expert mechanisms. Despite these achievements, widespread implementation of KORDEX in cardiology remained problematic due to a number of persistent challenges inherent in AI systems, many of which remain relevant today. These challenges include technical limitations, skepticism among physicians and healthcare leaders, and ethical and legal issues. The advent of neural networks at the beginning of the 21st century breathed new life into the application of AI in medicine, and cardiology was one of the first fields to take advantage of this technological advancement. This was largely due to the availability of large volumes of structured data, such as electrocardiograms (ECGs) and echocardiograms, which neural networks can process and analyze with high efficiency.

Currently, a significant number of AI systems have been developed and are being used in the field of practical cardiology, both in Russia and worldwide [4]. A detailed analysis of these systems can be found in review articles written, among others, by experts such as Belenkov [16] and Meder [9]. It is worth noting that algorithms designed to analyze medical images (e.g., computed tomography [CT], ultrasonography, etc.) and physiological signals (such as electrocardiograms [ECGs]) predominate in both quantity and quality. Hundreds of such systems have already been created, and this trend is due to several factors. Instrumental data are characterized by well-structured and abundant data; images are organized pixel-wise or voxel-wise; ECG recordings and pulse waveforms represent time series data that can be efficiently processed by neural networks, thereby facilitating the training of AI systems [17, 18]. Furthermore, standardized testing procedures exist, results are easily verified, and legal and ethical issues are minimized. These characteristics make cardiology a model field for the validation and implementation of medical AI technologies.

Recently developed automated systems for interpreting echocardiographic and (CT) data using large datasets from multiple centers have demonstrated impressive performance. These systems enable the extraction of valuable information, facilitating evidence-based decision-making and optimization of patient treatment strategies [19]. There is growing evidence supporting the successful application of AI to analyze biological signals using wearable devices and smartphones, particularly in the context of remote patient monitoring [9]. Furthermore, the use of smart apps for a smartphone for patient self-monitoring has shown promise,

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as demonstrated by a multicenter randomized controlled trial evaluating the effectiveness of mobile health technologies integrating telemonitoring and teleintervention in the treatment during the vulnerable phase of heart failure [20].

AI systems have demonstrated significant advances in the design and execution of clinical trials in cardiology, pharmaceutical research, and protein engineering. Some models, such as ESM3 and AlphaFold 3, have significantly improved the accuracy of predicting the structures of biological molecules, thereby contributing to a deeper understanding of pathological mechanisms and revolutionizing the drug development process.

AI is increasingly integrated into medical practice, with AI agents performing routine tasks such as text content creation, thereby freeing up physician time and potentially reducing professional burnout by 26%. Research shows that discharge summaries generated by large language models (LLMs) are comparable in quality to those generated by physicians [21]. Voice communication with patients, replacing manual data entry (e.g., typing), has already become a reality in some cases, although the degree of its implementation varies across countries. In the Russian Federation, the DIALOG study is being conducted to evaluate the effectiveness of voice assistants in monitoring the progression of various diseases [16]. An AI-based service that analyzes patient-physician conversations, automates medical documentation, and provides recommendations on diagnostic approaches, treatment strategies, and referrals for laboratory tests has been developed and is gradually implemented [22].

There is evidence that AI systems trained to conduct medical interviews have demonstrated performance comparable to or even superior to that of human physicians when interacting with simulated patients and generating lists of potential diagnoses from patient records. In particular, LLMs have achieved impressive results in clinical diagnosis [23]. The OpenAI model scored 96% on a MedQA test assessing answers to medical questions, an improvement of 28.4% over the 2022 Benchmark. GPT-4.0 has also demonstrated superior diagnostic performance compared to physicians in some complex cases, although the combined human-AI approach remains more effective than either method alone [24]. As of early March 2025, at least 300 hospitals in China have begun using DeepSeek LLMs for clinical diagnosis and medical decision support [25]. This trend has created the potential for AI to replace human doctors in certain medical contexts. Ant Group has integrated nearly 100 AI doctor agents into its Alipay app, each modeled after renowned medical experts from leading Chinese hospitals. Patients can communicate with these AI doctors via text or audio messages and access medical data for 24/7 analysis.

Predicting cardiovascular risk

One of the most important and illustrative areas of AI application in medicine, particularly in cardiology, is prognostication. Machine learning-based methods, including advanced deep learning algorithms, are actively employed to predict cardiovascular risk [26, 27]. Neural network models have been trained to recognize complex patterns in ECG data, enabling the identification of patients at increased risk of sudden cardiac death, even in the absence of overt clinical manifestations of cardiovascular pathology [28, 29]. In a comprehensive multicenter prospective study, AI systems using ECG analysis demonstrated diagnostic accuracy and predictive ability not only in diagnosing acute myocardial infarction but also in generating a 30-day prognosis. The performance of these AI systems was comparable to or even superior to traditional risk stratification methodologies and emergency department physician assessments [30]. There is currently a significant body of literature dedicated to predicting cardiovascular risk through the analysis of images and biosignals. AI-based analyses are becoming increasingly accurate and reliable [30]. The above discussion illustrates this trend.

Nevertheless, there are well-known examples of using alternative types of medical data for prediction. AI has made it possible to assess the risk of decompensation in heart failure, ventricular fibrillation, and sudden cardiac death. A study by IBM WatsonHealth used a machine learning model to predict the likelihood of hospitalization for heart failure among patients already suffering from the disease. The model included data on comorbidities, medication regimens, frequency of medical consultations, and other important variables. Neural networks can analyze virtually any text and electronic medical record data to predict treatment outcomes and identify patients who may benefit from targeted interventions [31]. AI-based algorithms have been refined to identify patients with an increased likelihood of developing acute coronary syndrome (ACS). The aforementioned predictive AI systems can perform a comprehensive analysis not only of ECG data but also of medical records, laboratory parameters, and imaging methods. Machine learning algorithms, such as the Deep Patient model [32], utilize extensive datasets from electronic patient records, covering variables such as age, weight, blood pressure, cholesterol levels, lifestyle factors, and family history. These algorithms are capable of predicting the development of various diseases, including CVDs.

In recent years, the field of preventive cardiology has increasingly shifted toward a personalized approach to cardiovascular risk assessment. One of the most promising approaches in this regard is the use of polygenic risk scores (PRS), which are quantitative metrics reflecting the cumulative influence of multiple genetic variants on predisposition to CVDs. PRS can identify individuals at increased risk of CVD, independent of the presence of traditional risk factors [1]. They demonstrated significant prognostic value for conditions such as coronary artery disease, myocardial infarction, atrial fibrillation, and hypertension. For example, a study by Khera et al. (2018) using data from the UK Biobank found that individuals with a high PRS were four times more likely to develop coronary artery disease than the general population [33]. Although initial experiments using PRS were generally successful, most did not outperform models based on traditional risk factors. One of the main reasons for this limitation was the primary reliance on statistical analysis methods. This approach presents significant challenges in identifying complex and sometimes unanticipated interactions between genes in the genome, as well as the relationships of genetic variants with environmental factors and disease prognosis.

At the same time, the integration of PRS with AI is rapidly becoming a powerful tool for the early detection and prevention of CVDs. A study by Liu et al. (2023) demonstrated that the combination of PRS with clinical data and machine learning algorithms can significantly improve the accuracy of coronary event prediction in patients from the UK Biobank database [34]. The potential for improved prediction through the integration of PRS with AI was substantiated [35]. The combined approach facilitated more accurate stratification of patients according to the risk of developing coronary events compared with traditional risk assessment scales [4]. Furthermore, it has been demonstrated that

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by integrating genomic risk factors for CVD with traditional socioeconomic, behavioral, and environmental factors, machine learning can facilitate the development of accurate risk prediction models and personalized treatment strategies for patients with hypertension [36-38].

The integration of PRS with AI capabilities has significantly advanced the field of preventive cardiology. In addition to predictive accuracy, AI has demonstrated potential in developing evidence-based recommendations for CVD prevention. Experts rated 84% of AI-generated responses regarding CVD prevention and risk factors as reasonable and comprehensive [39]. The National University Health System in Singapore has successfully implemented AI in a real-time cardiovascular risk management platform. This innovation enables healthcare professionals to monitor cardiovascular risk factors at the community level and allocate medical resources and educational interventions accordingly [40]. Contemporary AI systems are actively contributing to the development of preventive cardiology by facilitating the early identification of high-risk individuals and the timely implementation of personalized intervention programs. The rapid advancement of AI capabilities in recent years has been a key driver of progress in this and other areas of medicine. It is appropriate to focus on the fundamental characteristics of current AI technology [41, 42].

Prospects for the application of contemporary medical technologies based on artificial intelligence

What capabilities exist at this stage that make AI a promising tool for predictive analytics and other areas of cardiology? The field of AI encompasses many subdisciplines, including machine learning, deep learning, and natural language processing (NLP) [43]. Medical expert systems (MES) remain an important component of AI applications in healthcare. Their primary goal is to transform and systematize the knowledge of medical experts into algorithms that mimic their clinical reasoning. MES primarily rely on human expertise and operate based on established rules. Proponents of MES emphasize that, despite recent advances in explainable AI, machine learning algorithms are still often perceived as black boxes that are too distant from human cognition. Moreover, machine learning algorithms require significant amounts of data for training. Comparative studies have demonstrated examples where MES outperformed neural networks in certain applications [44, 45].

In the context of testing on extensive clinical data, specialized MES demonstrated a higher rate of accurate diagnoses and provided a more accurate list of potential diagnoses than LLMs. The latter demonstrated commendable performance as well [46].

However, it is important to recognize that the development of LLMs and their ability to overcome associated limitations proceeds at a rate significantly exceeding the progress of MES. Furthermore, the problem of finding qualified experts to contribute to the creation of knowledge bases remains critical [13]. The development of ES to address common but complex problems beyond the capabilities of typical cardiologists, or in areas where there is a lack of empirical data for training neural networks and a lack of systematic organization of information, remains relevant. This is particularly true in scenarios involving the coexistence of multiple pathologies or the emergence of new diseases, such as the COVID-19 pandemic in 2020. Integrating MES components with neural network-based models, in particular LLMs, clearly offers the most promising approach. For example, an AI system (MAI-DxO) specially trained with the participation of healthcare professionals demonstrated the ability to perform iterative (clinical) reasoning and make informed decisions. When analyzing medical records of patients with complicated anamneses, the system achieved an more then 80% correct diagnosis rate, i.e., four times higher than a group of experienced physicians [47].

As noted earlier, neural networks offer several advantages over traditional statistical methods, including regression analysis and expert methodologies. They demonstrate excellent capabilities in processing large volumes of AI data, especially complex and multivariate datasets such as genotyping information, electronic medical records, laboratory parameters, and anamnestic data. Due to these capabilities, neural networks are able to identify subtle patterns and interdependencies that may be missed using traditional statistical methods. Neural networks are arguably well suited for modeling complex nonlinear relationships between genetic variations, environmental factors, and patient phenotypes, making them particularly effective for analyzing medical data [3]. This, in turn, contributes to their excellent predictive accuracy and effectiveness in classifying and segmenting complex cases, as demonstrated by Manlhiot et al. [48]. An additional advantage of neural networks, particularly in the context of deep learning, is their ability to automatically extract features from flawed data without the need for manual variable selection. Furthermore, neural networks exhibit higher robustness to noisy data, allowing to generate more reliable predictions under conditions of uncertainty, which are common in medical applications.

Another important characteristic of AI is the gradual reduction in dependence on human intervention in the learning process. Current AI models are trained not by a large team of specialists, but by using previous versions of AI systems. Contemporary AI has evolved into self-learning systems capable of autonomously improving their algorithms. Research has shown that contemporary AI algorithms [48] exhibit significant independence in processing data and signals, apparently requiring minimal involvement of programmers and medical supervision. In this context, neural network models have the potential to adapt to new data and changing clinical realities, primarily through recursive learning, which contributes to improved prediction accuracy as new information becomes available [48]. This advancement enables the integration of AI into real-time monitoring systems for event prediction, which can be crucial for informed clinical decision-making in various areas of cardiology.

Consequently, we are witnessing the gradual end of the era of human data and the transition to the era of experience. The core concept of the latter envisions AI agents learning through autonomous interaction with their environment, gradually accumulating experience and developing their own ideas, goals, and strategies. This paradigm shift not only addresses the data shortage problem but also brings us closer to the concept of artificial general intelligence (AGI). According to leading experts, AGI presumes that machines can surpass human capabilities, including those of healthcare professionals [49]. Despite substantial progress and the accelerated development and adoption of AI technologies, significant challenges remain in refining these models. We believe it is necessary to focus on certain challenges that are particularly relevant to the healthcare field.

Data-related problem

AI systems demonstrate an unprecedented capacity for rapid learning and adaptation due to their ability to process massive amounts of data in real time and under uncertainty. This ability significantly improves their performance, leading to exponential growth in efficiency [50]. On the other hand, the quality of modern medical data, with the exception of images and biosignals, imposes serious limitations on the improvement of AI systems [51]. This limitation applies to both primary data sources (such as medical records, registries, and scientific articles) and secondary data used by AI in the era of experience and in self-learning processes. Below are some of the main issues with the quality of medical data that can negatively impact the training of AI systems.

The data under consideration may initially be characterized by incompleteness or absence, inaccuracies, or distortions, including misdiagnoses (e.g., a diagnosis made as a result of physician's error, lack of standardization, or dictated by institutional interests). Data biases are also common, including demographic, institutional, and, most importantly, temporal biases associated with data aging.

The problem of data imbalance poses a serious challenge. This problem is characterized by a lack of information on rare diseases and an underrepresentation of healthy individuals, as well as data selectivity. The latter typically reflects only the most important aspects of medical practice, while ignoring cases from rural hospitals or economically disadvantaged regions. These difficulties are particularly relevant to the representativeness of data obtained from clinical trials. For instance, in the case of ACS, the choice of strict inclusion and exclusion criteria can result in the exclusion of a large proportion of patients from the AI training database [52]. Consequently, AI-generated prognostic models and treatment recommendations may have limited applicability to this subgroup of patients. Examples include anemia, chronic obstructive pulmonary disease, chronic hepatitis, recent COVID-19), and other comorbidities in patients with ACS. In such cases, training AI models may be insufficient, as these conditions can significantly impact prognosis, value of diagnostic tests, and treatment efficacy. Furthermore, there is a significant lack of extensive studies and registries specifically focused on patients with such comorbidities.

In practical medicine, data quality issues remain a serious concern. To illustrate this issue, let us consider the hospital mortality rate in some regions of Russia for 2024, as presented in publicly available data from the Medical Information System (MIS). For example, in the Leningrad Oblast, the mortality rate ranges from 6% to 8.8%, while in St. Petersburg it ranges from 14% to 21%. Similarly, in the Bryansk Oblast, this rate ranges from 5.7% to 8.7%, while in the neighboring Smolensk Oblast, from 15.3% to 16.4%. These differences are also observed in many other regions of the country. The reasons for these seemingly inconsistent differences, both understandable and difficult to explain, are unlikely to be resolved in the foreseeable future, indicating serious issues with the quality of primary data. Despite the advantages of existing registries, they are insufficient to comprehensively address this issue [53].

Furthermore, there is evidence that current morbidity assessment methodology may be unable to detect all cases of some disease (for example, myocardial infarction). Furthermore, there is a high risk of inappropriate use of International Classification of Diseases (ICD) codes (not consistent with ICD recommendations) [54, 55]. Training new AI systems on previous systems may lead to the transfer of erroneous data to new models, thereby exacerbating already existing problems. Also noteworthy is the risk of so-called model collapse – a scenario in which AI is increasingly trained not on primary unprocessed data, but on data generated by other AI systems [56]. This phenomenon can gradually reduce the quality and reliability of AI performance over time. While the potential of advanced AI and AGI to handle ambiguous data may eventually drive progress in this field, it is expected that the accuracy of AI predictions may not be at a consistently high level in the near future.

Healthcare professionals

The influence of healthcare administrators and practicing physicians on the pace of AI adoption is the subject of ongoing research, debate, and comprehensive surveys. According to a survey conducted by the Center for Connected Medicine at the University of Pittsburgh Medical Center, healthcare executives in the USA have named AI as the most promising emerging technology in healthcare for the fourth consecutive year. Notably, both the European Society of Cardiology and the American Heart Association support the integration of AI into medical practice [57, 58].

Two-thirds of medical association representatives disagree with the statement that "AI tools in healthcare constitute the primary solution to the scarcity of medical personnel." However, none believe that "AI will have an insignificant on healthcare" [4]. A survey conducted in the USA found that two-thirds of physicians use AI in their practices for billing, medical record keeping, treatment planning, patient discharge recommendations, and diagnostic support, among others. The vast majority of physicians express confidence that their profession will not be displaced by AI tools [4]. One of the survey questions asked about physicians' perceptions of the role of AI in medicine over the next decade. Two-thirds of respondents selected the statement, "AI will radically transform medicine, but the role of physicians will remain paramount." Only 6.6% of medical survey participants in Russia agreed that AI could replace them, while 76% of respondents believe that in the future, physicians who use AI will displace those who do not [59].

There are certain risks associated with the social consequences in the medical community associated with the use of AI tools. Professionals who use AI tools may face negative assessments of their competence and motivation from their colleagues. This can lead to both expected and actual social sanctions, creating a paradox where AI tools can improve overall productivity while simultaneously affecting professional reputation [60]. These observations are based on existing perceptions and concerns identified during surveys of healthcare professionals. In contrast, interviews with experts at various levels reveal a different perspective. Many experts argue that physicians who perceive AI as a collaborative partner rather than a threat will achieve greater professional success and effectiveness in a rapidly changing environment where AI is advancing at an unprecedented pace. Senior information technology (IT) industry executives assert that AI has the potential to replace a significant portion of medical functions. The spread of generative AI is expected not only to augment human capabilities but also to replace many traditional medical functions. The most successful physicians will not only

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possess extensive medical knowledge but also be able to effectively utilize AI to access additional information and apply it productively. Consequently, there is a pressing need to revise medical education programs to reflect the new realities of the healthcare system.

Medical education

Gradual changes in medical education are likely to occur. As AGI and AI are gradually integrated into medical practice, new qualities and competencies will be required of healthcare professionals. Historically, medical education has focused primarily on the acquisition of factual medical knowledge. However, students and practitioners are now being encouraged to shift their perspective on AI, viewing it not simply as a tool but as a mechanism for developing cognitive abilities. The degree of integration of AI into medical practice is expected to lead to exponential growth in healthcare professionals' competencies. It is crucial to find a balance between preserving the core achievements of traditional medical education and mastering interdisciplinary workflows, as well as acquiring strategic meta skills such as synthesis, abstraction, and emotional intelligence, which are necessary to achieve new levels of quality and safety in medical practice. Integrating feedback-based learning into medical education is considered a promising approach in this regard. This involves using AI for real-time critique and workflow improvement. However, a number of important questions remain unanswered. For example, as AI becomes increasingly integrated into medical practice, the importance of memorizing numerous facts, such as reference values for blood tests and drug doses, is declining. Therefore, it is necessary to determine whether and to what extent the emphasis on factual knowledge in medical education should be reduced [61].

Patients

Patient reluctance to use AI in medical practice poses a significant challenge to its integration into healthcare systems. According to current data from Russia, only 1% of respondents are willing to undergo treatment directly with AI. A significant proportion of respondents (38%) oppose the use of AI in medicine, while 51% express openness to AI-assisted diagnosis and treatment. Forty-eight percent of respondents believe that AI can perform some tasks traditionally executed by doctors, and only 3% claim that AI can completely replace healthcare professionals [62]. Despite these conservative views, there is a growing trend for patients to seek medical care through AI platforms, including ChatGPT, which is frequently observed. Moreover, in a large-scale American study, patients expressed a preference for communication via AI-generated messages, although their satisfaction level decreased slightly when they learned about the involvement of AI in this process [63].

Overall, most proponents of the use of AI in medical practice favor its role as a complementary tool to augment physicians' capabilities, rather than as a replacement for healthcare professionals. Patients continue to prefer human-to-human interaction, and the current limitations of AI in fully understanding and integrating patients' psychological profiles are a significant factor contributing to skepticism regarding its ability to provide personalized care [64]. However, as AI becomes more integrated into patient care processes, many of its current shortcomings are expected to be addressed. Patients may gradually become accustomed to AI's involvement in monitoring their health, potentially leading to the normalization of its use [65]. There is also the possibility that patients will eventually come to expect AI-based treatments as the standard of care. How to meet these expectations remains to be determined, as AI has the potential to pose a key challenge to the healthcare system [66].

Risk-benefit analysis, as well as an assessment of potential hazards and safety measures for patient self-use of AI-based tools, have not been fully studied. Furthermore, it remains unclear how the healthcare system should appropriately respond to the needs and requests of such patients.

The future of artificial intelligence in cardiology

Forecasts regarding the development of AI in medicine, particularly in cardiology, are numerous and varied, which presents a significant challenge. A significant limitation is the heterogeneity of the experts involved in these forecasts. A fundamental problem arises when many forecasts, including those mentioned above, are based on linear extrapolation of past technological advances over the past five to twenty years. These forecasts are often overly conservative because they do not fully account for the accelerated pace of AI development. Advances in neural networks over the past two years have exceeded expectations, and over the next five to ten years, we expect a significant and rapid expansion of both AI capabilities and its potential applications in cardiology and medicine in general [67]. This general forecast appears reasonable for several reasons. First, the integration of AI with robotics and smart devices may provide the basis for the creation of autonomous systems for initial patient hospitalization and medical examination, especially in conditions of medical staff shortage.

Leading manufacturers are now integrating a variety of sensors (such as ECG monitors, temperature sensors, sleep analysis tools, and even voice recognition systems) with AI capabilities [68]. The implementation of AI agents capable of providing personalized recommendations in real time is becoming increasingly feasible. Many of these devices are designed for self-use by patients and demonstrate minimal dependence on regulation, while the rapid development of AI for image signal processing is particularly noteworthy. Similar trends are also emerging in the field of healthcare professional – patient interactions. Breakthroughs in multimodal models such as GPT-5 and Gemini 2.0 demonstrate preliminary capabilities in the field of clinical reasoning. It is possible that these systems will be able to achieve and exceed the diagnostic accuracy of the average physician (including specialists such as internists and cardiologists) within the next few years. For example, Google's Med-PaLM 2 AI system has already demonstrated a level of proficiency equivalent to that of a physician examiner on the American Medical Licensing Examination (AMLE) as of 2023. Further refinement is expected to take 3-5 years before these advanced systems are ready for widespread medical use. A prime example is Alibaba Health, where AI-powered virtual therapists currently handle 90% of routine inquiries made by patients. In this context, challenges related to voice communication and psychological aspects are seen as solvable [69, 70].

The accelerated adoption of AI to support healthcare professionals in patient interactions, potentially even replacing some functions, is a topic of significant interest and active

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discussion in the healthcare sector. The ongoing shortage of primary care physicians – a complex issue that has yet to be effectively addressed – could be mitigated through the implementation of AI technologies. It is quite possible that AI implementation could prove more effective and cost-effective than traditional human resource-based solutions. Consequently, the reluctance of healthcare authorities to adopt AI may be surprisingly minimal. Regarding the often-cited quality of medical empathy, it is important to recognize that in modern practice, many patients receive only a superficial examination from their general practitioners for a limited time (5-7 minutes). An AI system equipped with a friendly interface and the ability to memorize a patient's medical history could potentially provide a comparable level of patient engagement.

A gradual generational shift could significantly accelerate the adoption of AI technologies, which is particularly beneficial for private healthcare organizations, pharmaceutical corporations, and IT conglomerates. For these organizations, the capabilities of neural networks are already a reality. However, it is crucial to distinguish between the development of AI and its actual implementation in healthcare practice. The latter process largely depends on human intervention. It is difficult to predict the extent to which the medical community will facilitate or hinder the integration of AI technologies. It is even more difficult to predict the role of healthcare system leadership in the implementation of AI. While the initial phase of AI implementation is primarily focused on automating routine medical tasks and streamlining workflows, subsequent stages may involve replacing entire healthcare systems.

Methodologies for assessing the quality of AI systems, particularly those designed to support clinical decision-making, are currently controversial. There is no consensus on the need for full-scale randomized clinical trials to evaluate the effectiveness and safety of AI technologies. Furthermore, it is unclear whether specialized assessment systems, such as HealthBench, which offers a comprehensive open assessment of AI systems based on 48,562 different criteria in various healthcare contexts and the behavioral characteristics of neural networks, are adequate.

Conclusion

The advent of AI is ushering in a new era of revolutionary advances in healthcare, including cardiovascular medicine. Recent advances in AI technologies are highly sophisticated and enable paradigm shifts in the analysis of medical images, biosignals, remote patient monitoring, and the prediction and personalization of interventions based on genomic analysis, environmental factors, and phenotypic characteristics. Current AI systems are increasingly capable of processing vast amounts of medical data, identifying subtle patterns in the development and prognosis of diseases, including those with hereditary components. The *era of expertise* for AI is rapidly approaching, with learning and improvement processes becoming increasingly autonomous and accelerating exponentially.

The primary drivers for integrating AI into cardiology are clearly the shortage of medical professionals, economic considerations, senior management support, and the rapid advancement of technological capabilities. However, key barriers may include concerns about potential job losses among healthcare workers, resistance from elderly patients, who constitute a significant portion of the general population, legal and ethical concerns, and cybersecurity vulnerabilities.

Despite the growing potential of AI and the gradual elimination of numerous technical limitations, a number of challenges remain, particularly those related to the quality of medical data. The issue of data integrity and, consequently, the training of AI models poses a significant obstacle to improving the accuracy of prognostication and other AI-based decisions.

Published data demonstrate that AI systems can function not only as a tool but also as a surrogate physician in several areas of cardiology. The approach of healthcare professionals and administrators to AI integration, as well as patient perceptions, remain relatively conservative. However, change is likely, perhaps in various directions. Therefore, we expect the most challenging aspects to be related to human factors rather than technological progress. At the same time, AI development in medicine is proceeding rapidly. The interaction between healthcare professionals and AI is undergoing significant changes, and future progress depends on numerous variables, which themselves are undergoing accelerated change. Consequently, making a relatively accurate forecast even for the next five to ten years is becoming virtually impossible. We hope that medical societies and associations will play a key role in assessing and regulating this process. This will facilitate the seamless integration of AI into medical practice, ensuring minimal costs and maximum effectiveness.

Author contributions

Conceptualization, Y.S., N.A. and A.K.; methodology, Y.S.; validation, Y.S., A.R. and L.K.; formal analysis, Y.S.; investigation, Y.S.; resources, Y.G., E.P.; writing – original draft preparation, Y.S.; writing – review and editing, Y.S. and N.A.; funding acquisition, N.A. and L.K. All authors have read and approved the published version of the manuscript.

Funding

This review was completed within the framework of the government procurement to the Russian Federation Ministry of Healthcare, *Development of a Computer Appliance for Noninvasive Monitoring and Prediction of Circulatory Decompensation in Patients with Chronic Heart Failure*, No. 056-00059-25-21 of January 10, 2025.

Data availability statement

This study is based on the analysis of published sources. The data presented in this study are available in the e-Library, PubMed, and Scopus databases. These data were obtained from the following publicly available domains: https://www.elibrary.ru, https://pubmed.ncbi.nlm.nih.gov/, https://www.scopus.com.

Conflict of interest

The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript: AI, artificial intelligence; ES, expert systems; TIMI, thrombolysis in myocardial infarction; SCORE, Systematic Coronary Risk Evaluation; EuroSCORE, European System for Cardiac Operative Risk Evaluation; ECGs, electrocardiograms; CT, computed tomography; LLMs, large language models; PRS, polygenic risk scores; CVD, cardiovascular disease; NLP, natural language processing; MES, medical expert systems; AGI, artificial general intelligence; IT, information technology; ACS, acute coronary

syndrome; MIS, medical information system; ICD, international classification of diseases.

References

1. Topol EJ. High-performance medicine: The convergence of human and artificial intelligence. *Nat Med* 2019; 25(1): 44-56. https://doi.org/10.1038/s41591-018-0300-7.
2. Esteva A, Robicquet A, Ramsundar B, Kuleshov V, DePristo M, Chou K, et al. A guide to deep learning in healthcare. Nat Med. 2019; 25(1): 24-29. https://doi.org/10.1038/s41591-018-0316-z.
3. Lüscher TF, Wenzl FA, D'Ascenzo F, Friedman PA, Antoniades C. Artificial intelligence in cardiovascular medicine: clinical applications. *Eur Heart J* 2024; 45(40): 4291-4304. https://doi.org/10.1093/eurheartj/ehae465.
4. Shabeer H, Haider HMA, Khatri T, Khan N, Rafique AA, Anjam F. The role of artificial intelligence in early diagnosis and management of cardiovascular diseases. *Indus Journal of Bioscience Research* 2025; 3(2): 213-224. https://doi.org/10.70749/ijbr.v3i2.667.
5. Khan Mamun MMR, Elfouly T. AI-Enabled Electrocardiogram Analysis for Disease Diagnosis. *Appl Syst Innov* 2023; 6(5): 95. https://doi.org/10.3390/asi6050095.
6. Rao SJ, Iqbal SB, Isath A, Virk HUH, Wang Z, Glicksberg BS, Krittanawong C. An update on the use of artificial intelligence in cardiovascular medicine. *Hearts* 2024; 5(1): 91-104. https://doi.org/10.3390/hearts5010007.
7. Callahan A, McElfresh D, Banda JM, Bunney G, Char D, Chen J, et al. Standing on FURM ground: a framework for evaluating fair, useful, and reliable AI models in health care systems. *NEJM Catalyst Innovations in Care Delivery* 2024; 5(10): CAT-24. https://doi.org/10.1056/CAT.24.0131.
8. Warrington DJ, Holm S. Healthcare ethics and artificial intelligence: a UK doctor survey. *BMJ Open* 2024; 14(12): e089090. https://doi.org/10.1136/bmjopen-2024-089090.
9. Meder B, Asselbergs FW, Ashley E. Artificial intelligence to improve cardiovascular population health. *Eur Heart J* 2025; 46(20): 1907-1916. https://doi.org/10.1093/eurheartj/ehaf125.
10. Mamedov MN, Savchuk EA, Karimov AK. Artificial intelligence in cardiology. *International Heart and Vascular Disease Journal* 2024; 12(43): 4-8. https://doi.org/10.24412/2311-1623-2024-43-5-11.
11. Sethi Y, Patel N, Kaka N, Kaiwan O, Kar J, Moinuddin A, et al. Precision Medicine and the future of Cardiovascular Diseases: A Clinically Oriented Comprehensive Review. *J Clin Med* 2023; 12(5): 1799. https://doi.org/10.3390/jcm12051799.
12. Kaul V, Enslin S, Gross SA. History of artificial intelligence in medicine. *Gastrointest Endosc* 2020; 92(4): 807-812. https://doi.org/10.1016/j.gie.2020.06.040.
13. Shvarts YG, Dolinina O, Karimov RN. Problems of developing medical expert systems. *Zdravookhranenie Rossiiskoi Federatsii* 1994; (1): 7-9. (In Russian).
14. Shvarts YG. The immediate prognosis is at the stages of intensive therapy for unstable angina and paroxysmal supraventricular tachyarrhythmias. DSc Thesis. Saratov. 1996.
15. Dolinina O, Kaner A, Shvarts Y. Expert System KORDEX for Solving of Urgent Cardiology Problems. In: Dolinina O, Bessmertny I, Brovko A, Kreinovich V, Pechenkin V, Lvov A, et al. Artificial Intelligence in Models, Methods and Applications. AIES 2022. Studies in Systems, Decision and Control, vol 457. Springer, Cham. 2023: 617-634. https://doi.org/10.1007/978-3-031-22938-1_42.
16. Belenkov YN, Kozhevnikova MV, Khabarova NV, Ilgisonis IS, Korobkova EO. The Role of Artificial Intelligence in Cardiology. *Kardiologiia* 2025; 65(2): 3-16. Russian, English. https://doi.org/10.18087/cardio.2025.2.n2879.
17. Lee MS, Shin TG, Lee Y, Kim DH, Choi SH, Cho H, et al; ROMIAE study group. Artificial intelligence applied to electrocardiogram to rule out acute myocardial infarction: the ROMIAE multicentre study. *Eur Heart J* 2025; 46(20): 1917-1929. https://doi.org/10.1093/eurheartj/ehaf004.
18. Lin C, Liu WT, Chang CH, Lee CC, Hsing SC, Fang WH, et al. Artificial intelligence-powered rapid identification of ST-elevation myocardial infarction via electrocardiogram (ARISE) – a pragmatic randomized controlled trial. *NEJM AI* 2024; 1(7): AIoa2400190. https://doi.org/10.1056/AIoa2400190.
19. Hagopian R, Strebel T, Bernatz S, Myers GA, Offerman E, Zuniga E, et al. Opportunistic Coronary Calcium Screening at Veterans Affairs Hospitals. *NEJM AI* 2025; 2(6): AIoa2400937. https://doi.org/10.1056/AIoa2400937.
20. Yun S, Comín-Colet J, Calero-Molina E, Hidalgo E, José-Bazán N, Cobo Marcos M, et al; HERMeStrialinvestigatorsgroup. Evaluation of mobile health technology combining telemonitoring and teleintervention versus usual care in vulnerable-phase heart failure management (HERMeS): a multicentre, randomised controlled trial. *Lancet Digit Health* 2025; 7(5): 100866. https://doi.org/10.1016/j.landig.2025.02.006.
21. Williams CYK, Subramanian CR, Ali SS, Apolinario M, Askin E, Barish P, et al. Physician- and Large Language Model-Generated Hospital Discharge Summaries. *JAMA Intern Med* 2025; 185(7): 818-825. https://doi.org/10.1001/jamainternmed.2025.0821.
22. AI assistant for doctors: how do we automate patient admission based on speech and NLP analysis. 2025. Russian. https://habr.com/ru/articles/915330.
23. Goh E, Gallo R, Hom J, Storng E, Weng Y, Kerman H, Parsons AS, Ahuja N, Horvitz E, Yang D, Milstein A, Olson APJ, Rodman A, Chen JH Large Language Model Influence on Diagnostiic Reasoning A Randomized Trial. *JAMA Netw Open* 2024; 7(10): e2440969. https://doi.org/10.1001/jamanetworkopen.2024.40969.
24. Hswen Y, Rubin R. An AI Chatbot Outperformed Physicians and Physicians Plus AI in a Trial-What Does That Mean? *JAMA* 2025; 333(4): 273-276. https://doi.org/10.1001/jama.2024.23860.
25. DeepSeek recruits medical interns to boost AI healthcare data quality as 300 hospitals adopt open-source models in China. 2025. https://completeaitraining.com/news/deepseek-recruits-medical-interns-to-boost-ai-healthcare.
26. Mpanya D, Celik T, Klug E, Ntsinjana H. Predicting mortality and hospitalization in heart failure using machine learning: A systematic literature review. *Int J Cardiol Heart Vasc* 2021; 34: 100773. https://doi.org/10.1016/j.ijcha.2021.100773.
27. Gao H, Wang Q, Li K, Zhou J, Wang X, Yu C. Deep Learning-Enabled Non-Invasive Human ECG and Long-Term Heart Rate Variability Monitoring and Matching with Sleep Stages Based on an Optical Fiber Sensor System. *IEEE Sensors Journal* 2025; 25(7): 11131-11147. https://doi.org/10.1109/JSEN.2025.3543869.
28. Fang R, Pouyanfar S, Yang Y, Chen SC, Iyengar SS. Computational health informatics in the big data age: a survey. *ACM Computing Surveys (CSUR)* 2016; 49(1): 1-36. https://doi.org/10.1145/2932707.
29. Fan J, Jiajun C, Youjun G, Changyin S. Research on ECG classification based on transfer learning. *Journal of China Universities of Posts and Telecommunications* 2022; 29(6): 83-96. https://doi.org/10.19682/j.cnki.1005-8885.2022.1008.
30. Lee MS, Shin TG, Lee Y, Kim DH, Choi SH, Cho H, et al; ROMIAE study group. Artificial intelligence applied to electrocardiogram to rule out acute myocardial infarction: the ROMIAE multicentre study. *Eur Heart J* 2025; 46(20): 1917-1929. https://doi.org/10.1093/eurheartj/ehaf004.
31. Movsisyan NK, Vinciguerra M, Medina-Inojosa JR, Lopez-Jimenez F. Cardiovascular Diseases in Central and Eastern Europe: A Call for More Surveillance and Evidence-Based Health Promotion. *Ann Glob Health* 2020; 86(1): 21. https://doi.org/10.5334/aogh.2713.
32. Miotto R, Li L, Kidd BA, Dudley JT. Deep Patient: An Unsupervised Representation to Predict the Future of Patients from the Electronic

Health Records. *Sci Rep* 2016; 6: 26094. https://doi.org/10.1038/srep26094.

33. Khera AV, Chaffin M, Aragam KG, Haas ME, Roselli C, Choi SH, et al. Genome-wide polygenic scores for common diseases identify individuals with risk equivalent to monogenic mutations. *Nat Genet* 2018; 50(9): 1219-1224. https://doi.org/10.1038/s41588-018-0183-z.
34. Liu T, Krentz A, Lu L, Curcin V. Machine learning based prediction models for cardiovascular disease risk using electronic health records data: systematic review and meta-analysis. *Eur Heart J Digit Health* 2024; 6(1): 7-22. https://doi.org/10.1093/ehjdh/ztae080.
35. Shanmugasundaram, S. Agentic AI in Predictive AIOps: Enhancing IT Autonomy and Performance. *International Journal of Scientific Research and Management (IJSRM)* 2024; 12(11): 1631-1638. https://doi.org/10.18535/ijsrm/v12i11.ec01.
36. Layton AT. AI, Machine Learning, and ChatGPT in Hypertension. *Hypertension* 2024; 81(4): 709-716. https://doi.org/10.1161/HYPERTENSIONAHA.124.19468.
37. Chaikijurajai T, Laffin LJ, Tang WHW. Artificial Intelligence and Hypertension: Recent Advances and Future Outlook. *Am J Hypertens* 2020; 33(11): 967-974. https://doi.org/10.1093/ajh/hpaa102.
38. Kim SE, Lee CJ. Can Artificial Intelligence Change the Practice of Managing Hypertension? *Korean Circ J* 2022; 52(10): 795-796. https://doi.org/10.4070/kcj.2022.0254.
39. Sarraju A, Bruemmer D, Van Iterson E, Cho L, Rodriguez F, Laffin L. Appropriateness of Cardiovascular Disease Prevention Recommendations Obtained From a Popular Online Chat-Based Artificial Intelligence Model. *JAMA* 2023; 329(10): 842-844. https://doi.org/10.1001/jama.2023.1044.
40. Dalakoti M, Wong S, Lee W, Lee J, Yang H, Loong S, et al. Incorporating AI into cardiovascular diseases prevention-insights from Singapore. *Lancet Reg Health West Pac* 2024; 48: 101102. https://doi.org/10.1016/j.lanwpc.2024.101102.
41. 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(4): 310-322. https://doi.org/10.1093/ehjqcco/qcad017.
42. Martin AR, Kanai M, Kamatani Y, Okada Y, Neale BM, Daly MJ. Clinical use of current polygenic risk scores may exacerbate health disparities. *Nat Genet* 2019; 51(4): 584-591. https://doi.org/10.1038/s41588-019-0379-x.
43. Uspenskiy VE, Saprankov VL, Mazin VI, Filippov AA, Boyarskaya NV, Malashicheva AB, et al. Machine learning and artificial intelligence in the prediction, diagnosis and treatment of thoracic aortic diseases. (Literature review). Part 1. *Russian Journal for Personalized Medicine* 2023; 3(3): 118-131. Russian. https://doi.org/10.18705/2782-3806-2023-3-3-118-131.
44. Vianello A, Olivelli M, Donati M, Fanucci L, Bechini A, Petrucci I, et al. Medical expert system for intelligent telemonitoring of patients with chronic heart failure: Preliminary validation and perspectives. *Circ Heart Fail* 2025; 18(1): e012478. https://doi.org/10.1161/CIRCHEARTFAILURE.124.012478.
45. Gusev AV, Gavrilov DV, Novitsky RE, Kuznetsova TYu, Boytsov SA. Improvement of cardiovascular risk assessment using machine learning methods. Russian Journal of Cardiology. 2021; 26(12): 4618. Russian. https://doi.org/10.15829/1560-4071-2021-4618.
46. Feldman MJ, Hoffer EP, Conley JJ, Chang J, Chung JA, Jernigan MC, et al. Dedicated AI expert system vs Generative AI with large language model for clinical diagnoses. *JAMA Netw Open* 2025; 8(5): e2512994. https://doi.org/10.1001/jamanetworkopen.2025.12994.
47. Nori H, Daswani M, Kelly C, Lundberg S, Ribeiro MT, Wilson M. Sequential Diagnosis with Language Models. *arXiv* 2025: 2506.22405. https://doi.org/10.48550/arXiv.2506.22405.
48. Manlhiot C, van den Eynde J, Kutty S, Ross HJ. A Primer on the Present State and Future Prospects for Machine Learning and Artificial Intelligence Applications in Cardiology. *Can J Cardiol* 2022; 38(2): 169-184. https://doi.org/10.1016/j.cjca.2021.11.009.
49. Masters K, Herrmann-Werner A, Festl-Wietek T, Taylor D. Preparing for Artificial General Intelligence (AGI) in Health Professions Education: AMEE Guide No. 172. *Med Teach* 2024; 46(10): 1258-1271. https://doi.org/10.1080/0142159X.2024.2387802.
50. Krishnan G, Singh S, Pathania M, Gosavi S, Abhishek S, Parchani A, et al. Artificial intelligence in clinical medicine: catalyzing a sustainable global healthcare paradigm. *Front Artif Intell* 2023; 6: 1227091. https://doi.org/10.3389/frai.2023.1227091.
51. Moor M, Banerjee O, Abad ZSH, Krumholz HM, Leskovec J, Topol EJ, et al. Foundation models for generalist medical artificial intelligence. *Nature* 2023; 616(7956): 259-265. https://doi.org/10.1038/s41586-023-05881-4.
52. Rothwell PM. External validity of randomised controlled trials: "to whom do the results of this trial apply?". *Lancet* 2005; 365(9453): 82-93. https://doi.org/10.1016/S0140-6736(04)17670-8.
53. Official statistics. https://www.fedstat.ru/.
54. Kakorina EP, Samorodskaya IV, Martsevich SYu. Topical issues of myocardial infarction incidence statistics. *Russian Journal of Cardiology* 2024; 29(9): 5928. https://doi.org/10.15829/1560-4071-2024-5928.
55. Wiest IC, Leßmann ME, Wolf F, Ferber D, Treeck MV, Zhu J. Deidentifying Medical Documents with Local, Privacy-Preserving Large Language Models: The LLM-Anonymizer. *NEJM AI* 2025; 2(4): 2400537. https://doi.org/10.1056/AIdbp2400537.
56. Shumailov I, Shumaylov Z, Zhao Y, Papernot N, Anderson R, Gal Y. AI models collapse when trained on recursively generated data. *Nature* 2024; 631(8022): 755-759. https://doi.org/10.1038/s41586-024-07566-y.
57. Armoundas AA, Narayan SM, Arnett DK, Spector-Bagdady K, Bennett DA, Celi LA, Friedman PA, et al. Use of Artificial intelligence in improving outcomes in heart disease: a scientific statement from the American Heart Association. *Circulation* 2024; 149(14): e1028-e1050. https://doi.org/10.1161/CIR.0000000000001201.
58. Leclercq C, Witt H, Hindricks G, Katra RP, Albert D, Belliger A, et al. Wearables, telemedicine, and artificial intelligence in arrhythmias and heart failure: Proceedings of the European Society of Cardiology Cardiovascular Round Table. *Europace* 2022; 24(9): 1372-1383. https://doi.org/10.1093/europace/euac052.
59. Orlova IA, Akopyan ZA, Plisyuk AG, Tarasova EV, Borisov EN, Dolgushin GO, et al. Opinion research among Russian Physicians on the application of technologies using artificial intelligence in the field of medicine and health care. *BMC Health Serv Res* 2023; 23(1): 749. https://doi.org/10.1186/s12913-023-09493-6.
60. Reif JA, Larrick RP, Soll JB. Evidence of a social evaluation penalty for using AI. *Proc Natl Acad Sci U S A*. 2025; 122(19): e2426766122. https://doi.org/10.1073/pnas.2426766122.
61. Maddox TM, Embí P, Gerhart J, Goldsack J, Parikh RB, Sarich TC. Generative AI in Medicine – Evaluating Progress and Challenges. *N Engl J Med* 2025; 392(24): 2479-2483. https://doi.org/10.1056/NEJMsb2503956.
62. Portal Research Center Superjob.ru. Every second Russian admits the use of AI in medicine, but only 1 out of 100 is ready to fully trust AI in case of illness. Opinion polls. April 29, 2025. Available at: https://www.superjob.ru/research/articles/115286/kazhdyj-vtoroj-rossiyanin-dopuskaet-ispolzovanie-ii-v-medicine/. Accessed June 26, 2025.
63. Cavalier JS, Goldstein BA, Ravitsky V, Bélisle-Pipon JC, Bedoya A, Maddocks J, et al. Ethics in Patient Preferences for Artificial Intelligence-Drafted Responses to Electronic Messages. *JAMA Netw Open* 2025; 8(3): e250449. https://doi.org/10.1001/jamanetworkopen.2025.0449.

64. Mafi A. The risks and benefits of AI therapy tools. *BMJ* 2025; 389: r821. https://doi.org/10.1136/bmj.r821.
65. Sharko M, Cole CL. Integrating Artificial Intelligence Support in Patient Care While Respecting Ethical Principles. *JAMA Netw Open* 2025; 8(3): e250462. https://doi.org/10.1001/jamanetworkopen.2025.0462.
66. Stokel-Walker C. How patients are using AI. *BMJ* 2024; 387: q2393. https://doi.org/10.1136/bmj.q2393.
67. Phipps J, Passage B, Sel K, Martinez J, Saadat M, Koker T, et al. Early adverse physiological event detection using commercial wearables: challenges and opportunities. *NPJ Digit Med* 2024; 7(1): 136. https://doi.org/10.1038/s41746-024-01129-1.
68. Shour AR, Anguzu R, Onitilo AA. Speech Recognition Technology and Documentation Efficiency. *JAMA Netw Open* 2025; 8(3): e251526. https://doi.org/10.1001/jamanetworkopen.2025.1526.
69. Luo X, Zhou L, Adelgais K, Zhang Z. Assessing the Effectiveness of Automatic Speech Recognition Technology in Emergency Medicine Settings: A Comparative Study of Four AI-powered Engines. *Res Sq [Preprint]* 2024: rs.3.rs-4727659. https://doi.org/10.21203/rs.3.rs-4727659/v1.
70. Alotaibi JO, Alshahre AS. The role of conversational AI agents in providing support and social care for isolated individuals. *Alexandria Engineering Journal* 2024; 108: 273-284. https://doi.org/10.1016/j.aej.2024.07.098.

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