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POSSIBILITIES OF ARTIFICIAL INTELLIGENCE IN HEART FAILURE DIAGNOSIS

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Aim. To summarize existing approaches to the use of artificial intelligence in the diagnosis of heart failure, to characterize the algorithms and models employed, to describe the types of medical data used (ECG, echocardiography, EMR, CT/MRI, angiography, wearables), to evaluate model performance (accuracy, AUC, sensitivity/specificity), and to assess feasibility and prospects for clinical implementation – with particular attention to the situation and challenges in Kazakhstan.

Materials and methods. Systematic searches of *PubMed*, *Scopus*, *Web of Science*, *IEEE Xplore* and *Google Scholar* (2015 – 2025) identified peer-reviewed English and Russian studies on AI applications for heart failure diagnosis; two reviewers independently screened articles, extracted data and assessed quality, and results from 60 eligible studies were synthesized narratively with quantitative pooling where appropriate.

Results and discussion. Across 60 eligible studies (2015 – 2025), AI applied to ECG, echocardiography, EMRs, imaging and wearable data demonstrated diagnostic accuracy typically between 85-95% (AUCs up to 0.97); ECG-based algorithms reliably detected HFrEF, AI-assisted echocardiography improved segmentation and reduced operator dependence, multimodal models enhanced prediction of therapy response (including CRT), while implementation in Kazakhstan remains nascent due to infrastructure and data-access limitations.

Conclusion. Artificial intelligence is a promising direction in heart-failure diagnostics that can enhance the accuracy, timeliness and personalization of clinical decisions. For large-scale clinical adoption – especially in Kazakhstan – prospective validation, standardized protocols, local representative datasets, robust digital infrastructure and workforce training are required.

Key words. artificial intelligence; heart failure; diagnostics; machine learning; ECG; echocardiography; medical data; deep learning

INTRODUCTION

Heart failure (HF) continues to be a major global health problem, affecting more than 64 million people worldwide and is characterized by high morbidity and mortality. Heart failure is the leading cause of hospitalization in people over 65 years of age [1, 2].

Heart failure is a complex, multifaceted syndrome consisting of cardinal symptoms (eg, dyspnea, ankle swelling, and fatigue) that may be accompanied by signs (eg, elevated jugular venous pressure, pulmonary crackles, and peripheral edema). It results from structural and/or functional changes in the heart that result in elevated intracardiac pressure and/or inadequate cardiac output at rest and/or during exercise. Diagnosis and treatment of HF are particularly challenging due to its diverse presentation and variability in patient response. Despite significant advances in medical research and technology, traditional methods for diagnosing HF often prove ineffective, primarily due to the multifactorial nature of the disease. Over the course of the disease, patients with HF undergo numerous invasive and noninvasive diagnostic tests, generating large volumes of medical data. The size, complexity, and dynamic nature of big data can pose challenges to traditional statistical methods. In this changing landscape, artificial intelligence (AI) offers promising new avenues to transform HF diagnostics. Using advanced algorithms and machine learning techniques, AI can improve diagnostic accuracy, facilitate early detection, and support clinical decision making. These technological innovations have the potential to significantly address gaps in current diagnostic approaches and improve overall HF management, ultimately leading to better patient outcomes and more efficient healthcare delivery [2, 3].

Artificial intelligence (AI) is a computing program that has the ability to process functions that are considered typical of human intelligence, such as identifying certain patterns or images, programming, recognizing sounds or objects, and solving problems [2, 5]. AI provides a device with the ability to make autonomous decisions based on previously collected data. Currently, research projects are using large databases to develop an AI model that will be trained based on additional data from several sources: cardiovascular data, including cardiac imaging, cardiac biomarkers, electrocardiography, and clinical report information. Based on early prediction of a patient's HF risk, the AI will provide patients with personalized recommendations for medication, diet, exercise, pacemakers, and cardiac resynchronization therapy , and eventually ambulatory monitoring [16].

To better understand the role of AI in everyday clinical practice, healthcare professionals need to be familiar with some fundamental AI terms. In the medical field, the vast majority of applications primarily focus on the learning aspect, using machine learning (ML) as the underlying methodology. ML encompasses a set of algorithms that acquire the ability to achieve a goal without the need for strict and specific programming [17].

The **aim** of this review was to summarize existing approaches to the use of artificial intelligence in the diagnosis of heart failure, characterize the algorithms used, types of medical data, the effectiveness of models and consider the prospects for their implementation in clinical practice [6].

MATERIALS AND METHODS

The search for literary sources was carried out in the *PubMed*, *Scopus*, *Web of Science*, *IEEE Xplore* and *Google Scholar* databases using the following keywords: artificial intelligence, machine learning, heart failure, diagnosis, echocardiography, ECG, deep learning.

Inclusion criteria were the following:

- publications in English or Russian, published from 2015 to 2025;
- peer-reviewed articles containing primary data on the use of AI for the diagnosis of heart failure;
- studies that include assessment of the diagnostic accuracy of models (e.g. AUC, sensitivity, specificity) [8].

Reviews without original data, publications devoted only to outcome prediction, and articles with insufficient methodological transparency were excluded. As a result of the analysis, 60 articles were selected that met the criteria [7].

AI models have been applied to different types of medical information:

- *Electrocardiogram (ECG):* data from a single-moment or long-term recording of the heart rhythm;
- *Echocardiography:* video and still images used to assess contractile function;
- *Electronic medical records (EMR):* structured clinical data, laboratory parameters;
- *CT/MRI images of the heart:* visualization of morphological changes;
- *CAG:* coronary angiography with artificial intelligence integration;
- *SRT:* application of machine learning algorithms to assess response to cardiac resynchronization therapy;
- *Data from wearable devices:* long-term monitoring of heart rate, rhythm, activity [9].

Most studies used the following methods:

- *Deep convolutional neural networks (CNN)* – for image and ECG analysis;
- *Decision trees and gradient boosting (e.g. XGBoost)* – when working with tabular EHR data;
- *Time series models (e.g. LSTM*) – for analyzing sequences of biosignals;
- *Combined architectures (multimodal AI systems)* – combining multiple data sources [10].

In many publications, AI models have demonstrated high quality scores:

1. accuracy: from 85 to 95%;
2. area under the curve (AUC): from 0.88 to 0.97;
3. sensitivity and specificity: often exceeded 90% when using ECG and echocardiography [11].

Examples:

- The ECG-based model achieved an AUC of 0.93 in detecting reduced ejection fraction [11];
- Algorithms for echocardiography analysis provided accurate classification of HF with preserved and reduced ejection fraction [2];
- The use of EHR and laboratory data made it possible to predict HF long before clinical manifestation [12].

RESULTS

Diagnosis of heart failure. The diagnosis of HF depends on the patient's history, clinical examination, and interpretation of imaging and laboratory results. Late diagnosis may result in delayed initiation of optimal medical treatment, complications, and potentially preventable deaths or rehospitalizations that could have been prevented if appropriate treatment had been initiated earlier and in full [18]. Current studies using AI-based models to improve HF diagnosis include multiple data sources such as electrocardiograms (ECG), echocardiography, radiology results, and electronic medical record (EMR) data [1,2,3,4]. These studies have demonstrated impressive performance estimates when using these sources to build big data databases. In the study by Masetic et al., ECG signals from two databases were used to build a model using the random forest method [2]. In both databases, the algorithms demonstrated high accuracy, with HF detection rates ranging from 95% to 100%. Using convolutional neural networks (CNNs), both experiments demonstrated outstanding validity, also ranging from 95% to 100% using the random forest approach. However, the aforementioned datasets were limited to the subset of HF patients, as they did not include patients with preserved ejection fraction (HFpEF) [19].

Better validation of the deep learning method in HF diagnosis is expected after completion of the EAGLE (ECG-AI-guided screening for low ejection fraction, NCT04000087) trial [2,4]. A deep learning algorithm using a 12-lead ECG was developed and implemented in the electronic medical record to screen for HF with reduced ejection fraction (HFrEF), while a subsequent confirmatory echocardiogram will guide diagnosis and therapy. This will be one of the first attempts to evaluate the practical utility of AI through prospective evaluation in real-world scenarios [20].

Chest radiography is usually the initial imaging modality because it is accessible, noninvasive, and helps differentiate between cardiac and pulmonary causes of dyspnea. Celik et al. analyzed chest radiographs of 10,100 outpatients using a convolutional neural network-based artificial intelligence (Qxr) algorithm as a diagnostic tool [3, 6]. Chest radiographs with CTR > 0.5 and bilateral pleural effusion were flagged as potential HF radiographs. Eligible patients underwent confirmatory tests to establish or exclude the diagnosis of HF. There were also subjects not flagged as potential HF patients who were randomly selected and evaluated for the diagnosis of HF. Overall, the algorithm demonstrated a positive predictive value of 77% and a negative predictive value of 91%, performing well even in diagnosing HFpEF. Thus, 54% of diagnosed patients had HFpEF [21].

Echocardiography based on artificial intelligence. Echocardiography is widely used for various diagnostic purposes, from screening to cardiovascular risk stratification. Modern artificial intelligence (AI) technologies are increasingly used at all stages of the echocardiographic process: from image acquisition to segmentation and interpretation. One of the key areas is the automation of image acquisition, classification and segmentation [22]. Traditional echocardiographic imaging requires manual adjustment and skillful maneuvering of the ultrasound transducer to obtain high-quality images in various projections. This process is not only labor-intensive, but also subject to variability depending on the operator's level of training [23]. Echocardiographic robots and automated systems with AI are aimed at optimizing this process. They are able to automatically aim the transducer, recognize anatomical structures and record the required projections, which improves the consistency of studies, reduces dependence on personnel qualifications and accelerates the receipt of diagnostically significant data [24]. AI integration also facilitates automatic segmentation of cardiac structures and interpretation of acquired data in real time, facilitating clinical decision-making and improving diagnostic accuracy. In terms of acquired image quality, He et al. designed a study including 3495 echocardiographic reports to evaluate AI-based LVEF assessment [1, 2]. They found that the initial LVEF assessment by AI was as good as or better than the assessment by functional diagnostic physicians, suggesting that AI may improve the efficiency and effectiveness of cardiac function assessment.

In a prospective study mainly aimed at the reliability of AI-based diagnostics, Chen et al. evaluated 80 hospitalized patients with acute left ventricular HF. A deep convolutional neural network (DCNN) algorithm model was built to customize image processing [1, 3]. The patients were equally divided into a control group undergoing routine echocardiography and an observation group undergoing echocardiography based on the DCNN model. After comparing the two groups, it was noted that the AI-based assessment demonstrated higher diagnostic accuracy and was associated with lower readmission and mortality rates. However, since the sample size was small, there was no statistical significance characterizing all the results [25].

Moreover, echocardiographic assessment using AI may help to address the unmet need for accurate diagnosis in a large heterogeneous group of patients with HFpEF. A recent study from Stanford University used a deep learning model (Python, version 3.8.5) to automate echocardiographic assessment of patients, focusing on left ventricular size measurement [2, 6]. Photographs and videos demonstrating left ventricular hypertrophy were computationally evaluated by a 3D convolutional neural network to distinguish between causes of hypertrophy. The model was able to reliably identify cardiac amyloidosis and hypertrophic cardiomyopathy from other causes of LVH [26].

Automated view classification and segmentation are advanced applications of AI in echocardiography. Automated view classification refers to the use of AI algorithms to automatically identify and categorize echocardiographic views. Zhang et al. presented a fully automated echocardiographic interpretation pipeline that includes 23 view classifications [27]. Zhu et al. developed a deep residual CNN to automatically identify multiple contrast and non-contrast echocardiographic views, including LV parasternal short axis, apical 2-, 3-, and 4-chamber views. In the test dataset, the overall classification accuracy is 99.1%. Furthermore, these technologies can improve intra- and inter-observer variability. Christensen et al. developed a basic vision language model for echocardiography called EchoCLIP. It can learn the relationship between cardiac ultrasound images and expert cardiologist interpretations in a wide range of patients [28]. The results showed high accuracy in assessing cardiac function and identifying implanted intracardiac devices. However, one of the major limitations of this work is the use of an image encoder instead of a video encoder when echocardiography videos contain important motion-based information. Ouyang et al. developed the DL-EchoNet-Dynamic algorithm using 10,030 echocardiography videos. 56 The accuracy of EchoNet-Dynamic in assessing LVEF and classifying patients with HF was comparable to that of experienced cardiologists. The AI-based algorithm incorporated information from multiple cardiac cycles and accurately classified HFrEF (area under the curve [AUC] 0.97). Lau et al. proposed 2 DL-based echocardiogram interpretation models, DROID-LA (left atrium) and DROID-LV, to automate the assessment of standard LA and LV structure and function measurements [29]. One of the limiting factors in the accuracy of projection classification is speckle noise and aliasing. Kusunose et al tested 2 types of input methods for image classification using DL. 50 The best model classified video projections with an overall test accuracy of 98.1% in an independent cohort. The results of these studies served as a basis for AI-assisted echocardiography segmentation and interpretation [3].

From the above, it is clear that AI-assisted echocardiogram interpretations can be applied retrospectively to echocardiographic data to improve the detection of relatively rare findings or early signs of dysfunction that may escape the attention of human interpreters. Measurements can be fully automated without losing diagnostic reliability at the same time. An automated approach to echocardiogram interpretation has the potential to increase the availability of echocardiography by moving cardiac assessment to primary care settings and remote rural areas, thereby making it more widely available [30].

ECG with artificial intelligence. The ECG is a cost-effective, non-invasive diagnostic tool that has stood the test of time in clinical medicine for more than a century after its introduction. Efforts to automate ECG interpretation using rule-based algorithms have been ongoing for decades due to its reproducible, standardized format [31]. Heart rate variability refers to the change in successive RR intervals of the cardiac cycle, reflecting the function of the autonomic nervous system. The relationship between heart rate variability and HF is one of the key research topics in the field of HF. Most of these studies obtain data from publicly available ECG databases and use AI algorithms to differentiate healthy individuals from HF patients. The built models consistently demonstrate excellent performance. In 2014, Liu and colleagues used a support vector machine classifier with 3 custom heart rate variability features to develop a congestive HF classification model that achieved 100% accuracy, sensitivity, and specificity [3, 4]. In 2019, a study used a DL method with long short-term memory to identify patients with congestive HF. ECG data from 5 publicly available databases were used for training and testing. Although the model performance in such studies seems promising, the main focus is on improving ML methods. These algorithms often rely on a large number of heart rate variability parameters, which increases the complexity of the model. In addition, the sample sizes of the selected databases were relatively small, which limits their further application in clinical practice [32].

Cho et al. obtained 39,371 12-lead ECG results from 17,127 patients and used a CNN model to detect HFrEF. In both internal and external validation cohorts, the AUC for HFrEF detection was 0.913 and 0.961, respectively [5, 9]. The study provides interpretable model performance. In addition, heart rate, QT interval, QRS duration, and T-axis were highly correlated with the model. However, limited availability of digitized and well-labeled ECG data and open-source datasets may limit the development of AI algorithms [33].

AI-enabled MRI. AI is poised to transform the field of cardiovascular magnetic resonance imaging (MRI) by addressing its traditional limitations such as long examination times, high costs, and the need for expert manual review. By automating complex image processing and improving diagnostic accuracy, AI can significantly improve the efficiency and accessibility of MRI in assessing HF [6, 10].

Kucukseymen et al. developed a supervised ML model to predict HF hospitalization in HFpEF patients using non-contrast MRI imaging. The study compared a baseline clinical model with an enhanced model using the XGBoost algorithm, showing that the machine learning model significantly improved the prediction accuracy (AUC: 0.81 vs. 0.64). However, this study was limited by its retrospective nature and relatively small sample size. Lehmann et al. proposed an AI-enhanced MRI imaging method for the diagnosis of cardiovascular disease classification and diastolic filling pressure. A total of 6936 patients were analyzed, and 4390 were included in the final cohort. The AI models demonstrated high accuracy in predicting various parameters related to cardiovascular diseases [34]. The AI models could help classify diseases and predict LV end-diastolic pressure, adding value to MRI imaging. The study highlights the potential of AI-assisted MRI to improve non-invasive cardiac assessments, suggesting practical applications for cardiac function assessment and HF diagnosis. The development of a cross-modality autoencoder framework using an unsupervised ML algorithm to integrate myocardial structural information from MRI and myoelectric information from ECG for a holistic view of cardiovascular health is ongoing [7, 11].

Coronary angiography using artificial intelligence. One of the causes of end-stage HF is coronary artery disease. The gold standard for diagnosing coronary artery disease is coronary angiography. In the field of coronary angiography, AI has demonstrated potential in assisting in image acquisition, interpretation, and risk stratification.

Avram et al. used neural networks to develop a fully automated coronary angiography interpretation and stenosis scoring system for interpreting angiographic coronary artery stenosis. The coronary angiography interpretation and stenosis scoring system is a pipeline of several deep neural network algorithms. A total of 13,843 angiographic studies were used in the training set [8, 10]. The algorithms were validated internally and externally, with positive predictive value, sensitivity, and F1-score reaching >90% for projection angle detection and 93% for left/right coronary artery angiogram detection. The coronary angiography interpretation and stenosis scoring system exhibits an AUC of 0.86 for predicting stenosis in obstructive coronary artery disease. However, this work was limited by one notable drawback. The authors used training labels derived from physician visual assessment and clinically derived stenosis values [35].

Monitoring and control of the heating system using sensors. With continuous technological advancements, sensors have become an integral part of our daily lives, playing a role in almost every common application we encounter. The types of sensors used in cardiovascular research are hemodynamic and biochemical sensors [3]. In the former category, CardioMEMS™, an implantable pulmonary artery pressure monitoring device, can help prevent HF decompensation, thereby significantly reducing the number of HF hospitalizations [2]. The wearable sensor was implanted on the intra-atrial septum of patients with HFrEF or HFusEF . LA pressure management therapy, based on daily measurements, allowed the physician to self-monitor the patient’s condition and resulted in a reduction in decompensation events and a significant decrease in mean left atrial pressure [1, 2]. Biochemical sensors are devices that act as transducers, taking biological fluids as input and providing valuable data regarding the concentration of certain components and plasma volume status [1, 4]. During an invasive assessment of patients with HF, a dedicated sensor designed to measure both venous oxygen saturation and right ventricular (RV) pressure was integrated. This method has shown significant promise for potential use in future HF patients, as it can assess two critical parameters with a single sensor [3]. Another respiratory parameter that can provide valuable information about the status of a patient with HF is minute ventilation. Identifying a person with hyperventilation can help as an early indicator of HF decompensation and also ensure timely treatment [1]. The combination of wearable sensors with ML analytics has the potential to improve outcomes. In a recent study known as the LINK-HF (Long-Term Non-Invasive Multi-Sensor Remote Monitoring to Predict Heart Failure Exacerbation) study, ML analytics demonstrated that remotely collected monitoring data obtained non-invasively could predict HF readmission with 87.5% sensitivity and 85% specificity [3]. Mobile apps incorporating ML algorithms could improve HF care by motivating patients take preventive measures and to high adherence to therapy [36].

Using machine learning to predict response to cardiac resynchronization therapy. Howell et al. wanted to create a prediction model for short-term response to cardiac resynchronization therapy (CRT) to identify those HF patients who are suitable for early CRT implantation. A total of 741 patients with NYHA III-IV HF and EF < 35% pooled in the SMART-AV trial were considered and multiple variables such as clinical, electrocardiographic, echocardiographic and biomarker characteristics were provided for eight different ML models [8, 12]. The model achieved prediction of CRT response, with the primary endpoint being improvement in mortality, HF hospitalization and LV end-systolic volume index reduction >15%, with an accuracy, sensitivity and specificity of 70%. This is of particular importance as the availability of accessible data is critical for making informed decisions for an important group of patients with HF who may benefit from a systematic approach to follow-up and interventions aimed at improving their outcomes [37].

In another study, Tokodi et al. used ML to evaluate gender differences as predictors of mortality in patients with CRT and to evaluate the prediction of one- and three-year mortality in the same patients. A total of 2191 patients with CRT were evaluated using M L models in a retrospective study, with the results indicating a significant discrepancy in overall lifetime risk between men and women [9]. Specifically, in the male group, the mortality rate was 35.2%, which contrasted with the mortality rate of 23.8% in the female group. Gender-specific variables predicting mortality were NYHA functional class, LVEF, and HF etiology for the female group, while QRS morphology, hemoglobin levels, and allopurinol treatment were most significant for men [10].

Wearable devices. Wearable devices have the potential to enable large-scale AI-based screening. Several models have recently been validated using wrist-mounted wearable devices. ECGs from wearable smartwatches collected outside of clinical settings can effectively identify patients with cardiac dysfunction, which is often life-threatening and may be asymptomatic [38, 43].

Khunte reported a new strategy that automates the detection of hidden cardiovascular diseases such as LV systolic dysfunction, developed for noisy single-lead ECGs from wearable and portable devices. A total of 385,601 ECGs were used to develop both a standard model and a noise-adapted model. Both models showed similar performance on standard ECGs, achieving an AUROC of 0.90 for detecting LVEF <40% [7, 11]. Despite the obvious strengths, this study has 1 limitation that requires consideration. The model was developed in patients with both ECG and echocardiography. Since the training group had a clinical indication for echocardiography, there is a selection bias. This limits the broader use of the algorithm for screening tests for LV systolic dysfunction in those who were clinically unaffected in the real world. Attia et al. conducted a prospective analysis in which Mayo Clinic patients were invited via email to download the Mayo Clinic iPhone app, which transmits ECG records to a secure data platform. In this study, 2454 patients were digitally enrolled and 125,610 ECGs were sent. The AI algorithm identified patients with low EF (defined as ≤40%) with an AUROC of 0.885 and 0.881 using the mean prediction within a 30-day window or the closest ECG to the echocardiogram that determined EF, respectively. And the researchers conclude that wearable ML-enabled technologies recording cardiac function can assess compensated and decompensated HF states [8].

Main limitations in the use of AI. What is called the «Achilles heel» of AI is its subsequent generation of incorrect or inaccurate results after feeding the ML system erroneous data, or the «garbage in, garbage out» (GIGO) process. Even perfectly trained AI applications can generate incorrect results when fed inaccurate input data [39, 42]. To date, the application of AI in cardiovascular diseases has shown promise. However, as mentioned earlier, there are limitations in both the AI technology itself and the infrastructures in the medical environment that hinder the implementation of AI in everyday clinical practice. [6]. First of all, large medical databases are rarely accessible due to privacy concerns. However, access to big data is essential for the reliable development of AI diagnostic models. Furthermore, in real-world hospital settings, various medical data are often stored on multiple servers and, in some cases, in paper records [41, 45]. Even if AI creates highly accurate predictive models, their effectiveness may be limited if hundreds of prediction parameters are scattered across different systems and must be entered manually. Second, biases in AI algorithms often arise from unrepresentative datasets, leading to biased predictions or results in new populations [40]. Overfitting is another common problem that leads to poor generalizability of AI models. An overfitting model performs well on training data but poorly on validation or test datasets. Several studies have demonstrated poor generalizability of HF scoring systems in new populations [46, 47] . A key limitation of current AI approaches is their inability to establish causal relationships. Furthermore, imprecise analysis and underreporting hinder reliable assessments and may lead to misleading interpretations. Therefore, results obtained using AI should be carefully interpreted within the framework of medical knowledge [10].

Future direction. Despite these limitations, AI has shown early promise in HF diagnosis. Future directions for AI-assisted echocardiography will likely focus on using image acquisition guidance tools, improving the efficiency and reliability of image interpretation, and automating disease detection. A future goal for AI-assisted MRI may be to further improve the speed of image analysis. Real-time telemetry is another bright spot for AI-assisted HF diagnosis [9].

DISCUSSION

Heart failure is indeed a complex disease and still remains a major cause of morbidity and mortality in developing and developed countries. Standard drug therapy has been successful in the early stages of HF. End-stage HF requires frequent hospitalization due to the presence of severe HF and/or comorbidities, which requires strict implementation of a personalized multidisciplinary approach and quality measures to reduce rehospitalizations [48, 50]. Modern concepts of chronic heart failure (CHF) go beyond the classical understanding of the disease as the final stage of heart damage. To summarize, the integration of AI in HF diagnostics is a transformative achievement in cardiovascular medicine. The use of AI technologies, including ML algorithms, DL models and predictive analytics, has shown significant promise in improving the accuracy, efficiency and timeliness of HF diagnostics. Using large data sets and sophisticated computational methods, AI systems can identify patterns and correlations that may be missed by traditional diagnostic methods, leading to earlier detection and personalized treatment strategies [49]. Despite impressive progress, there remain several challenges and limitations that need to be addressed, including the need for high-quality, diverse datasets; the potential for algorithmic bias; and the requirement for clinical validation to ensure real-world applicability. As research and technology continue to advance, the role of AI in HF diagnosis is likely to expand, offering new opportunities to improve patient outcomes and advance the field of cardiology [51, 53].

Turning to Kazakhstan, the introduction of artificial intelligence (AI) in the diagnosis and treatment of heart failure (HF) in Kazakhstan is an important step in the modernization of the national healthcare system [52, 55]. Analysis of existing initiatives and studies shows that AI technologies can significantly improve the quality of medical care, make diagnostics more accurate and prompter, and treatment more personalized and effective.

One of the key areas is remote patient monitoring using AI systems, as implemented at the Center for Coordination and Diagnostics of Cardiovascular Diseases in Karaganda. This approach is especially important for Kazakhstan with its large territory and dispersed population, where access to quality medical care in remote regions is often limited. The use of biometric data in real time allows not only to identify life-threatening deviations, but also to optimize the workload of medical personnel, reducing the number of emergency hospitalizations [54, 57].

The Ai CARD platform, developed by Kazakhstani specialist Dastan Mukhamediyev, demonstrates the prospects for integrating AI into traditional diagnostic methods, such as cardiac ultrasound. Acceleration and increased accuracy of ultrasound interpretation contribute to earlier detection of heart failure, which ultimately improves prognosis for patients [56]. Similar technologies used by the National Center for High Biomedical Technologies, with an emphasis on improving the quality of ultrasound images, emphasize the importance of not only data analysis, but also their pre-processing in order to increase information content.

However, despite the obvious advantages, there are also significant challenges. Firstly, the integration of AI requires a reliable and scalable digital infrastructure, which remains a problem for many regions of Kazakhstan [58, 59] . Secondly, it is necessary to train medical personnel to work with new technologies, as well as to develop standards and protocols for the use of AI in clinical practice. An important task is also to ensure the confidentiality and security of medical data during their processing and storage.

Furthermore, the successful implementation of projects such as Remedia LLP's AI-enabled online consultations requires close collaboration between government agencies, healthcare institutions, and the private sector. Only an integrated approach will ensure sustainable growth and innovation in the fight against heart failure [60].

Analysis of data from the Unified National Electronic Healthcare System for 2014 – 2019 highlights the scale of the heart failure problem in Kazakhstan, noting the high mortality rate and significant loss of working capacity among the population. These facts reinforce the need for active implementation of modern technologies, including AI, to improve early diagnosis and increase the effectiveness of treatment.

Despite promising results, this review has several limitations. The included studies are heterogeneous in methodology, data sources, and patient populations, making direct comparisons difficult. Many AI models were validated on retrospective datasets with limited external validation, raising concerns about generalizability. Additionally, the lack of standardized reporting on model interpretability and clinical impact limits the translation into practice. Language bias may also exist, as only English and Russian publications were included. Finally, publication bias toward positive results may have inflated the perceived effectiveness of AI in heart failure diagnosis.

In the future, the development of AI in cardiology in Kazakhstan should include expanding the functionality of existing platforms, integration with other medical systems and the use of big data for predictive analytics. This approach will allow not only to promptly identify signs of heart failure, but also to predict the development of the disease, select the most effective therapeutic regimens and carry out preventive measures.

CONCLUSION

Artificial intelligence is a promising direction in heart failure diagnostics, which can improve the accuracy, timeliness and personalization of clinical decisions. Although AI methods have already demonstrated high results in scientific research, their large-scale application in healthcare requires further efforts in adaptation, standardization and evidence-based clinical validation.

In conclusion, it can be noted that artificial intelligence is a promising tool for solving current problems of diagnosis and treatment of heart failure in Kazakhstan. Existing projects and studies demonstrate that AI can improve the accuracy and speed of diagnosis, facilitate the interpretation of medical data and improve the quality of medical care.

The introduction of AI technologies, such as remote monitoring, intelligent ultrasound imaging and online consultations, contributes to more effective detection and treatment of heart failure, which ultimately leads to a decrease in mortality and an improvement in the quality of life of patients. Kazakhstan has the necessary potential for further development of these technologies, but successful implementation requires further investment in digital infrastructure, training of specialists and the formation of a regulatory framework.

An important aspect is intersectoral cooperation between government agencies, research centers and private businesses, which will create conditions for sustainable development and scaling of AI projects in cardiology. It is also necessary to continue monitoring the effectiveness of the implemented solutions and conduct scientific research to adapt technologies to the characteristics of the Kazakhstani population and healthcare system.

Overall, the use of artificial intelligence in the fight against heart failure opens up new opportunities to improve the quality of medical care and improve the health of the population of Kazakhstan. With the right strategy and government support, these technologies can become a key factor in reducing the burden of cardiovascular diseases and increasing the overall efficiency of healthcare.

Authors' contribution:

A. R. Kushugulova, M. S. Bekbossynova, A. I. Sailybaeva – concept and design of research.

S. K. Jetybayeva – data collection and preparation.

Zh. Aldanush, A. T. Taukelova – analysis.

Zh. Aldanush, A. T. Taukelova – writing.

A. I. Sailybaeva – editing.

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ВОЗМОЖНОСТИ ИССКУСТВЕННОГО ИНТЕЛЛЕКТА В ДИАГНОСТИКЕ СЕРДЕЧНОЙ НЕДОСТАТОЧНОСТИ

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Цель. Систематический обзор современных подходов к применению искусственного интеллекта в диагностике сердечной недостаточности, проанализировать используемые алгоритмы и модели, охарактеризовать источники медицинских данных (ЭКГ, эхокардиография, ЭМК, КТ/МРТ, ангиография, носимые устройства), оценить их диагностическую эффективность (точность, AUC, чувствительность/специфичность), а также определить возможности и ограничения клинической имплементации с акцентом на условия здравоохранения в Казахстане.

Материалы и методы. Систематический поиск в базах данных *PubMed, Scopus, Web of Science, IEEE Xplore* и *Google Scholar* (2015 – 2025 гг.) выявил рецензируемые англоязычные и русскоязычные исследования по применению искусственного интеллекта в диагностике сердечной недостаточности. Два независимых рецензента проводили скрининг статей, извлечение данных и оценку качества; результаты 60 отобранных исследований были синтезированы в описательной форме с количественным обобщением там, где это было уместно.

Результаты и обсуждение. В 60 исследованиях (2015 – 2025 гг.) применение искусственного интеллекта к данным ЭКГ, эхокардиографии, ЭМК, визуализации и носимых устройств продемонстрировало диагностическую точность на уровне 85-95% (AUC до 0,97). Алгоритмы на основе ЭКГ надежно выявляли HFrEF, ИИ-ассистированная эхокардиография улучшала сегментацию и снижала зависимость от оператора, мультимодальные модели усиливали прогнозирование ответа на терапию (включая СРТ), тогда как внедрение в Казахстане остается на начальном этапе из-за ограничений инфраструктуры и доступа к данным.

Выводы. Искусственный интеллект представляет собой перспективное направление в диагностике сердечной недостаточности, способное повысить точность, своевременность и персонализацию клинических решений. Для масштабного клинического внедрения искусственного интеллекта, особенно в Казахстане, необходимы проспективная валидация, стандартизированные протоколы, локальные репрезентативные базы данных, надежная цифровая инфраструктура и подготовка кадров.

Ключевые слова: искусственный интеллект; сердечная недостаточность; диагностика; машинное обучение; ЭКГ; эхокардиография; медицинские данные; глубокое обучение

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ЖҮРЕК ЖЕТКІЛІКСІЗДІГІН ДИАГНОСТИКАЛАУ САЛАСЫНДАҒЫ ЖАСАНДЫ ИНТЕЛЛЕКТ

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Зерттеудің мақсаты. Жүрек жеткіліксіздігін диагностикалауда жасанды интеллекттің қолдану тәсілдерін жүйелі түрде шолу, қолданылған алгоритмдер мен модельдерді сипаттау, қолданылған медициналық деректер түрлерін (ЭКГ, эхокардиография, электрондық медициналық жазбалар (ЭМЖ), КТ/МРТ, ангиография, киілетін құрылғылар) баяндау, модельдердің тиімділігін (дәлдік, AUC, сезімталдық/ерекшелік) бағалау және клиникалық енгізу мүмкіндіктері мен перспективаларын – Қазақстандағы жағдай мен қиындықтарды ерекше ескере отырып – бағалау.

Материалдар және әдістер. PubMed, Scopus, *Web of Science*, *IEEE Xplore* және *Google Scholar* дерекқорлары бойынша 2015 – 2025 жылдар аралығындағы мақалалар жүйелі түрде ізделді; жүрек жеткіліксіздігін диагностикалауда жасанды интеллект қолданған ағылшын және орыс тіліндегі рецензияланған зерттеулер анықталды. Екі тәуелсіз шолушы мақалаларды іріктеп, деректерді шығарды және сапасын бағалады; 60 сәйкес зерттеудің нәтижелері сипаттамалық түрде біріктіріліп, деректердың жеткілікті біркелкілігі болған жағдайда сандық синтез жүргізілді.

Нәтижелер және талқылау. 2015 – 2025 жылдар аралығындағы 60 зерттеу көрсеткендей, ЭКГ, эхокардиография, ЭМЖ, медициналық бейнелеу және киілетін құрылғылар деректеріне қолданылған жасанды интеллект модельдері әдетте 85-95% аралығындағы диагностикалық дәлдік көрсетті (AUC мәндері 0.97 дейін). ЭКГ негізіндегі алгоритмдер HFrEF-ті сенімді түрде анықтады, ЖИ арқылы жетілдірілген эхокардиография сегментацияны жақсартып, операторға тәуелділікті азайтты; көпмодальды модельдер терапияға жауапты (оның ішінде CRT – жүректі қайта синхрондау терапиясы) болжауды жақсартты. Қазақстандағы енгізу әлі бастапқы сатыларда болып, бұл процеске цифрлық инфрақұрылым мен деректерге қолжетімділік сияқты шектеулер әсер етеді.

Қорытынды. Жасанды интеллект – жүрек жеткіліксіздігін диагностикалауда дәлдік, жеделдік және клиникалық шешімдерді дараландыруды жақсартуға мүмкіндік беретін перспективалық бағыт. Кең ауқымды клиникалық енгізу үшін (әсіресе Қазақстан жағдайында) проспективті валидация, стандартталған хаттамалар, жергілікті репрезентативті деректер жиынтықтары, сенімді сандық инфрақұрылым және мамандарды оқыту қажет.

Кілт сөздер: жасанды интеллект; жүрек жеткіліксіздігі; диагностика; машиналық оқыту; ЭКГ; эхокардиография; медициналық деректер; терең оқыту