

Artificial Intelligence in Medical Diagnostics: Current Capabilities, Clinical Applications, and Limitations

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Article History	Abstract
Received: 28 th March 2026 Accepted: 26 th April, 2026	Lately, artificial intelligence is being used in many areas of medicine. It's viewed as a promising aid for specialists who handle tons of medical information and need to make diagnostic calls. AI's role in medical diagnostics grabs attention—timely, accurate diagnoses matter a lot for treatment choices and disease outlooks. This review article aims to explore how AI can be used in medical diagnostics today. It will look at its advantages, limitations, and future in clinical settings. Key focuses include how AI is used in medical image analysis, digital pathology, and processing clinical data—along with current machine learning and deep learning methods. There's a spotlight on diagnostic accuracy of algorithms. Plus, how they're interpreted, algorithmic bias, and the privacy and security of medical data. AI holds great potential to boost diagnostic processes. Still, for it to be used widely in clinics, we need more validation, standardization, and to tackle ethical and legal challenges. Remember—AI should be seen mainly as a tool to support a doctor's clinical reasoning, not replace it.
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Introduction:

One of the reasons for the active implementation of artificial intelligence (AI) in medicine is the rapid growth in the volume of medical information. The constant emergence of new scientific data, diagnostic methods, and treatment approaches increases the information burden on medical specialists. Additional factors include the doctor's limited time and the need to process a large amount of heterogeneous data. Under these conditions, AI is considered a tool capable of rapidly analyzing significant amounts of medical information and providing support to the specialist in making clinical decisions [1,2].

Artificial intelligence is a set of computational methods and models that allow computer systems to analyze data, identify patterns, and perform tasks related to specific intellectual functions. In modern medicine, machine and deep learning methods that can identify complex dependencies in large datasets have gained particular importance. Their application is being studied in various fields, including diagnosis, disease prognosis, clinical support for decision-making, and medical documentation processing [2,3].

One of the most actively developing areas of AI application is medical diagnostics. This is due to the fact that the timely detection of pathological changes is of direct importance for choosing further examination and treatment tactics. Modern AI systems are used to analyze medical images, including radiography, computed and magnetic resonance imaging, digital histological images, as well as for processing laboratory and electronic medical data [4-7].

At the same time, the high technical accuracy of the algorithm alone does not guarantee its effectiveness in real clinical practice. The results of AI's work may depend on the quality and representativeness of the initial data, the characteristics of the studied population, the conditions for obtaining medical information, and the method of external model validation. Therefore, assessing the diagnostic potential of AI should include not only an analysis of sensitivity and specificity indicators but also a study of safety, reproducibility, portability of results to independent patient groups, and the possibility of integrating technology into the clinical process [8,9].

Issues of medical information confidentiality, algorithmic bias, result interpretation, and the specialist's excessive trust in automated recommendations are also of particular importance [1,10-13]. The World Health Organization emphasizes the need to maintain human control over medical decisions and views

AI as a tool to support healthcare workers, rather than as an independent replacement for clinical thinking [1].

Thus, the development of AI opens up new opportunities for increasing the efficiency of the diagnostic process, but its clinical application requires simultaneous assessment of advantages, limitations, and potential risks. The purpose of this review is to analyze the modern capabilities of AI in medical diagnostics, its main clinical applications, advantages, limitations, and prospects for further implementation in medical practice.

However, the obtained results cannot always be directly translated into real clinical practice, as the effectiveness of algorithms may depend on the quality and representativeness of the data used, the characteristics of the studied population, and the conditions of their application [4,9]. For example, a systematic review and meta-analysis of AI application in digital pathology demonstrated high diagnostic efficacy indicators, yet 99% of the included studies had at least one area with a high or unclear risk of systematic error or applicability issues [5]. The authors also pointed out the heterogeneity of the research design and the insufficient transparency of some aspects of model development and validation [5].

Despite the significant advantages of using artificial intelligence in medical diagnostics, its use is accompanied by a number of potential risks and limitations. These include possible violations of privacy and leaks of medical information, algorithmic errors resulting from insufficient quality or representativeness of initial data, as well as incorrect interpretation of obtained results [1,9]. The risk of specialists trusting AI recommendations excessively is of particular importance, as a doctor may not sufficiently critically evaluate the algorithm's performance results [11,13]. Furthermore, algorithmic bias can lead to unequal efficiency of diagnostic systems for different patient groups [10]. Therefore, the use of AI in diagnostics should be viewed as a tool to support the clinical thinking of a physician, rather than as a substitute for it [1].

Despite the rapid development of artificial intelligence technologies and the increase in research in this field, there remains a need for a comprehensive assessment of its diagnostic capabilities, advantages, limitations, and clinical application prospects [4,8,9].

The purpose of this review is to analyze the modern capabilities of artificial intelligence in medical diagnostics, its clinical application, main advantages and limitations, as well as prospects for further implementation in clinical practice.

Main Section

Main artificial intelligence technologies in medical diagnostics.

Modern artificial intelligence technologies in medical diagnostics include machine and deep learning, artificial neural networks, natural language processing, and generative and multimodal models. Their application allows for the analysis of medical images, laboratory indicators, electronic medical records, and other clinical data. At the same time, the practical value of AI is determined not only by the technical characteristics of the model but also by the quality of the initial data, the possibility of external validation, and the safety of using the obtained results [1,8,9].

One of the main approaches is machine learning (ML, Machine Learning), a method where an algorithm identifies patterns based on previously obtained data and uses them to analyze new observations. In medical diagnostics, ML models can be trained on patient data with known clinical characteristics and established diagnoses, and subsequently applied to classify diseases, assess individual risk, and support diagnostic decisions. The effectiveness of such models largely depends on the quality and representativeness of the training data, as well as the algorithm's ability to maintain performance when analyzing patients who differ from the original research sample [3,9].

A more complex direction is deep learning (DL, Deep Learning), which is based on the use of multi-layered artificial neural networks. In the learning process, such models are capable of independently forming ideas about the features contained in the initial data and identifying complex relationships between them. Thanks to this, deep learning has become widespread in the analysis of medical images, including X-rays, computed tomography, and magnetic resonance imaging [3,4]. In diagnostics, DL is used to detect pathological changes, classify diseases, and segment anatomical structures [3,4].

Artificial neural networks (ANNs) are computational models consisting of interconnected elements organized into sequential layers. During training, network parameters are modified in such a way that errors are minimized when performing the assigned task. When information passes through successive layers, representations of varying complexity can be formed: from relatively simple features to more complex structures. This allows for the use of neural networks to analyze images and other types of medical data [3].

One of the most common types of deep neural networks is convolutional neural networks (CNN, Convolutional Neural Networks). They have become

widespread in image analysis due to their ability to sequentially identify local features of an image and combine them into more complex representations. In the early stages, relatively simple features can be determined, such as boundaries and contours, while in the later stages, more complex forms and structures can be identified. In medical diagnostics, CNNs are used to detect pathological areas, classify diseases, and segment organs and neoplasms. They are particularly actively used in the analysis of radiography, CT, MRI, ultrasound imaging, and digital histological preparations [4,5].

In addition to image analysis, AI is used to process medical text information. Natural Language Processing (NLP) includes methods that allow computer systems to analyze and structure text presented in a natural language. In medicine, NLP is used when processing electronic medical records, medical histories, specialist reports, and other clinical documentation [7]. Such systems can extract information from the text regarding symptoms, diagnoses, test results, and other patient characteristics, transforming unstructured information into data suitable for further analysis.

NLP is of particular importance when working with electronic medical records. Automated clinical text processing can be used to extract diagnostically significant information, classify patients, assess risk, and support clinical decision-making. A systematic review by Eguia et al. showed that NLP is already being used to extract clinical information and work with electronic medical records, yet most of the studied systems remained at the level of individual research solutions, highlighting the need for further clinical validation [7].

A separate direction of modern AI development is generative models capable of creating new textual, visual, or other content based on patterns mastered during learning. In medicine, they are studied to work with clinical documentation, form preliminary textual conclusions, interact with medical information, and support clinical decisions. At the same time, generative models can generate plausible but actually incorrect information. Therefore, information obtained through them should not be used without critical verification by a medical specialist [1,14].

A promising development of generative AI is multimodal models capable of processing several types of information simultaneously. In medical diagnostics, these can include images, text data, laboratory indicators, and physiological signals. Combining various modalities allows for considering a broader clinical context and potentially forming a more comprehensive assessment of the patient's condition [15,16].

Thus, modern AI technologies allow for the analysis of various types of medical information - from images to text and structured clinical data. However, the use of complex models does not eliminate the need to evaluate the quality of initial data, external validation, safety, and algorithm compliance with a specific clinical task. It is the combination of technical efficiency with clinical testing that determines the possibility of safe implementation of AI in diagnostic practice [1.8].

Application of artificial intelligence in digital pathology

Digital pathology is one of the promising areas for applying artificial intelligence in medical diagnostics. In a digital approach, histological specimens are scanned and converted into images of a whole-slide glass (WSI images), which can be analyzed using computer algorithms. This creates the opportunity to automate individual stages of processing large volumes of morphological information [5]. In digital pathology, AI algorithms are used to detect pathological areas, classify diseases, identify cellular and tissue structures, and quantify morphological features. Their use is particularly important in oncology, where diagnostic assessment may require the analysis of a large number of morphological characteristics. Automated analysis can help a specialist identify suspicious areas and perform a quantitative assessment of individual morphological parameters [5,17].

High rates of AI diagnostic effectiveness in digital pathology were demonstrated in a systematic review and meta-analysis by McGenity et al. It included 100 diagnostic studies that included over 152,000 images of entire object glass, with 48 studies included in the quantitative meta-analysis. The combined results showed an average sensitivity of AI of 96.3% and a specificity of 93.3% [5].

The results obtained indicate the high diagnostic potential of AI in analyzing digital histological images. However, accuracy indicators must be interpreted taking into account the quality of the evidence. In the same systematic review, 99% of the included studies identified at least one area of high or unclear risk of systematic error or a problem with the applicability of the results. Furthermore, the authors noted the heterogeneity of the research design and insufficient completeness in describing the formation of data sets, their division into training and validation samples, and initial performance indicators [5].

One of the key issues is the portability of algorithms between different medical institutions. Digital images may differ depending on the scanner used, the quality of material preparation, coloring methods, and other technical characteristics.

Therefore, a model that demonstrates high efficiency on data from one institution will not necessarily show similar results in another clinical setting. This emphasizes the need for independent external validation before the widespread implementation of the algorithm [5,9].

Digital pathology is of particular importance in oncology. AI can be used to detect tumor tissue, evaluate the morphological characteristics of neoplasms, and conduct quantitative analysis of individual components of the tumor microenvironment. The development of such technologies potentially expands the capabilities of traditional morphological analysis, but the clinical significance of such approaches must be confirmed by research conducted in real practice [17]. Aggarwal et al. emphasize that the further implementation of AI in digital pathology requires not only the improvement of algorithms but also the assessment of evidence quality, clinical utility, regulatory aspects, and the integration of technology into the existing diagnostic process [17].

Thus, artificial intelligence has significant potential in digital pathology and is capable of performing a range of tasks for detecting and classifying pathological changes with high diagnostic accuracy. However, the existing data do not yet allow for the consideration of most algorithms as independent substitutes for a specialist. At the current stage, it is most justified to use AI as a support tool for the pathomorphologist, where the final interpretation of results and clinical decision remains with the medical specialist [1,17].

Application of artificial intelligence in oncological diagnostics

Oncology is one of the most actively developing areas for applying artificial intelligence in diagnostics. This is due to the large volume of information that must be taken into account during patient examination: imaging results, morphological data, laboratory indicators, and clinical characteristics can be considered together. In practice, AI is most often used to search for suspicious changes in medical images and subsequently classify the identified formations.

The use of AI directly in the diagnostic process involving a physician is of particular interest. Zhao et al.'s systematic review and meta-analysis, which included 34 studies, evaluated changes in the diagnostic effectiveness of specialists when using AI to identify malignant neoplasms. In 23 studies, data suitable for quantitative analysis were obtained. When independently evaluating the images, the combined sensitivity and specificity indicators were 0.67 and 0.82, respectively. When AI was used as an additional tool, these indicators

increased to 0.79 and 0.87. At the same time, a risk of systematic error was identified in half of the included studies, so the results obtained require careful interpretation [18].

AI is used in the diagnosis of tumors of various localizations. The review by Wu et al. covered 158 systematic reviews and meta-analyses dedicated to cancer detection based on medical imaging data. The studies included tumors of the central nervous system, respiratory organs and digestive system, urinary system, breast, skin, and other organs. The obtained results generally demonstrated high diagnostic effectiveness of the algorithms, although the indicators differed significantly depending on the tumor type, imaging method, and the characteristics of the studied data [19].

A prominent example is the diagnosis of breast cancer based on magnetic resonance imaging data. In the systematic review and meta-analysis by Abdullah et al., 40 studies were analyzed, 21 of which were included in the quantitative analysis. For deep learning models, the combined AUC value was 0.90, sensitivity was 88%, and specificity was 90%. At the same time, the authors noted significant variability in results between studies and the dependence of model effectiveness on the volume of training data [20].

Thus, the greatest practical value of AI in oncological diagnostics lies not only in the automatic recognition of pathological changes. It is more promising to use it together with a specialist. The algorithm can draw the doctor's attention to the suspicious area, provide an additional assessment of the image, and thereby assist in making a diagnostic decision. At the same time, the final interpretation of the results must take into account the clinical picture and other examination data of the patient.

A significant obstacle to the widespread implementation of such systems remains the discrepancy between research results and the conditions of real clinical practice. Diagnostic effectiveness may be influenced by image quality, characteristics of the studied population, equipment used, and data preparation features. Furthermore, not all algorithms undergo independent external verification. Therefore, the high accuracy obtained within the framework of a separate study does not yet confirm the model's versatility [9,18-20].

Consequently, modern data indicate significant AI potential in oncological diagnostics, especially in the analysis of medical images. The most justified approach today is its use as an additional tool that works together with the physician. To transition from promising research results to daily clinical practice,

it is necessary to conduct external validation of algorithms, standardize assessment methods, and confirm their clinical benefits in real conditions.

AI in cardiological diagnostics

Cardiology is another field where artificial intelligence technologies are actively applied to analyze diagnostic data. The most studied areas are electrocardiography (ECG) and echocardiography. The use of AI allows for processing large amounts of information in a short period of time and can be a useful supplement to the standard assessment of research results by a physician. During ECG analysis, artificial intelligence algorithms can detect signs of various heart rhythm disorders, including arrhythmias and atrial fibrillation, as well as signs of ischemic changes and conduction disorders. A systematic review of modern research has shown a significant increase in the number of works dedicated to the application of AI for ECG interpretation, particularly for detecting atrial fibrillation, myocardial infarction, and heart failure [21]. Rapid automated ECG processing can shorten the time for preliminary assessment of the study and help the doctor focus on potentially significant changes [21].

The use of AI to analyze echocardiographic images is also of interest. Algorithms can recognize various heart structures, automatically determine their boundaries, and perform the necessary measurements. In addition, AI is used to assess heart function, including determining the left ventricular ejection fraction, as well as to identify signs of valvular diseases and other pathological changes. Automating individual stages of echocardiographic examination can make the assessment more standardized and reduce the specialist's routine workload [22].

A separate promising direction is the use of AI to predict cardiovascular diseases based on ECG. In this case, the algorithm analyzes not only clearly expressed pathological changes but also less noticeable features of the heart's electrical activity, which may be associated with an increased risk of disease development in the future. Thus, the potential value of AI lies not only in detecting already existing pathologies but also in identifying patients with an increased probability of future cardiovascular events [23].

Despite the promising nature of this approach, the results of the algorithms' work should not be considered an independent diagnosis. AI accuracy depends on the quality of electrocardiographic records and images, the characteristics of the training data, and the characteristics of the population under study. Furthermore, the algorithm can yield both false positive and false negative results. Therefore,

the final interpretation of the results must be carried out by the physician, taking into account clinical data and other examination methods of the patient.

Thus, the application of artificial intelligence in cardiology is gradually moving beyond the simple automatic interpretation of diagnostic studies. AI can be used to analyze ECGs, process echocardiographic images, and assess individual cardiovascular risk. At the current stage, it is most rational to use it as a support tool for the doctor, which helps to process information faster and draw the specialist's attention to potentially significant changes.

AI in ophthalmology.

Ophthalmology is one of the fields of medicine where artificial intelligence has found wide application due to the large amount of diagnostic data presented in the form of images. Algorithms are most actively used when analyzing eyeball photographs and optical coherence tomography (OCT) data. Such methods allow for the assessment of the condition of the retina and optic nerve, the identification of pathological changes, and the automated screening of a number of diseases.

One of the most studied areas is the identification of diabetic retinopathy. In this disease, microaneurysms, hemorrhages, exudates, and other changes may appear on the retina, which must be detected in time to prevent the progression of vision damage. AI can analyze eyeball photographs and classify images based on the presence and severity of pathological changes. In a systematic review and meta-analysis by Alqahtani et al., which included 18 studies, the combined sensitivity and specificity indicators of AI in diabetic retinopathy screening were 87.7% and 90.6%, respectively [24].

The practical value of automated screening is particularly noticeable when examining a large number of patients with diabetes mellitus. Preliminary analysis of images using AI can help identify patients who require a more detailed examination by an ophthalmologist. This potentially reduces the workload on specialists and increases the accessibility of screening programs. Currently, most approved AI systems for analyzing ophthalmological images are also specifically focused on detecting diabetic retinopathy. However, there are solutions designed to detect age-related macular degeneration, glaucoma, and other retinal pathologies [25].

Another important method is optical coherence tomography, which allows for the acquisition of layered images of the retina. Unlike conventional eye fundus photography, OCT provides information about the internal structure of tissues and allows for assessing the thickness of individual layers, the presence of fluid,

and other morphological changes. AI algorithms can be used to automatically segment images, identify pathological areas, and subsequently analyze the obtained data. The combination of eye fundus photographs and OCT is also considered a promising approach, as it allows for assessing the condition of the retina from different angles [25].

In addition to diabetic retinopathy, artificial intelligence is being studied in the diagnosis of age-related macular degeneration, glaucoma, and other retinal diseases. For example, in age-related macular degeneration, algorithms can analyze photographs of the eye and OCT to identify changes related to damage to the macular region. Existing studies demonstrate the high diagnostic accuracy of such models, but the results depend on the quality of the images, the characteristics of the study group of patients, and the specifics of the algorithm used [26].

Despite promising results, the application of AI in ophthalmology has several limitations. One of the problems remains the discrepancy between the data on which the model was trained and the images obtained in real clinical practice. The quality of the analysis may be influenced by the camera type, image resolution, imaging features, and the patient's characteristics. Furthermore, not all developed algorithms have sufficient external validation. Even among systems that have received regulatory approval, published evidence of their effectiveness is presented unevenly: in one of the 2025 reviews, 19% of identified systems lacked published data describing their diagnostic effectiveness [25].

Thus, artificial intelligence has significant potential for early detection of eye diseases and automation of ophthalmological screening. Its application is most actively being studied in the analysis of eye fundus images and OCT, primarily for the diagnosis of diabetic retinopathy, age-related macular degeneration, and glaucoma. At the same time, the results of the automated analysis must be considered in conjunction with clinical data and should not replace a full examination of the patient by an ophthalmologist.

AI in laboratory and clinical diagnostics

Laboratory and clinical diagnostics are another important area of application for artificial intelligence. Unlike medical images, where the primary source of information is visual material, in this case, algorithms can analyze numerical laboratory test results, functional test results, information from electronic medical documentation, and other clinical data. The use of AI allows for the simultaneous consideration of a large number of parameters and the identification of

relationships between them, which may be difficult to evaluate during the conventional analysis of individual indicators [27,28].

In laboratory diagnostics, artificial intelligence can be used at various stages of the laboratory process. The algorithms are capable of analyzing the results of biochemical, hematological, immunological, and other studies, identifying deviations from expected values, and determining combinations of indicators characteristic of certain pathological conditions. Furthermore, AI is considered a tool for automating quality control of laboratory research and identifying potential errors at individual stages of the laboratory process [27]. Thus, the use of AI in the laboratory can be aimed not only directly at diagnosing the disease but also at increasing the reliability and efficiency of the diagnostic process itself. The analysis of the set of laboratory indicators is of particular interest. A separate test result does not always allow for the unambiguous determination of the presence of the disease, as its significance must be interpreted taking into account other indicators and the clinical situation. Machine learning algorithms are capable of processing a large number of parameters simultaneously and forming diagnostic or prognostic models based on them. In modern research, such approaches are considered for identifying diseases, assessing their development risk, and predicting the further course of the pathological process [28].

Another direction is the application of AI to analyze electronic medical records. The electronic medical documentation contains information regarding the patient's complaints, medical history, laboratory and instrumental examination results, prescribed treatment, and previously established diagnoses. Combining these data allows for the construction of individualized diagnostic models. AI can be used to identify patients with an increased risk of certain diseases, assess the likelihood of a specific diagnosis, and support a doctor in choosing further examination tactics [27,28].

In the systematic review by Hunik et al. on AI-based diagnostic models and electronic medical records in primary care, out of 10,657 publications found, only 15 studies met the inclusion criteria. Most of the works were dedicated to predicting one chronic disease, with only two studies conducting external testing of models in primary care settings. Nine out of 15 studies revealed a high risk of systematic error, and the authors concluded that most existing models are not yet sufficiently prepared for direct implementation in clinical practice [29].

The obtained data are of great importance, as the high accuracy of the algorithm in the research sample does not yet mean its clinical effectiveness. When using

electronic medical records, it is necessary to consider missing data, differences in their registration methods, and the structure of medical documentation. Furthermore, the information used to train the model in one healthcare facility may differ significantly from the data in another facility. Such differences can reduce the accuracy of the algorithm when transferring it to a new clinical environment [29].

Artificial intelligence can also be used as a clinical decision-making support system. In this case, the algorithm analyzes available information about the patient and provides the doctor with an additional assessment of the probability of the disease, the risk of complications, or the need for a specific diagnostic study.

This approach allows for combining laboratory test results with other clinical characteristics of the patient, thereby transitioning from assessing individual indicators to a more comprehensive analysis of the patient's condition [28-29].

At the same time, the use of AI in laboratory and clinical diagnostics requires a careful approach to the results of the algorithms. Currently, the number of commercially available and validated AI systems for laboratory medicine remains limited. Among the obstacles to widespread implementation are the high cost of certain technologies, the need for manual verification of results, insufficient standardization, and the lack of unified approaches to evaluating the effectiveness of such systems [27]. Additional issues include the quality of initial data, the presence of missing values, algorithmic bias, and insufficient external validation [9,10,27].

Thus, artificial intelligence in laboratory and clinical diagnostics allows for a transition from analyzing individual research results to comprehensively processing a large amount of interconnected data. The most promising areas are the automated analysis of laboratory indicators, quality control, diagnostic forecasting, and processing of electronic medical records. However, most existing models still require additional external validation and evaluation in real clinical settings. Therefore, at the current stage, AI should primarily be viewed as a support tool for the physician, capable of increasing the efficiency of diagnostic information processing, but should not replace the clinical assessment of the patient [27-29].

Multimodal diagnostics using AI.

One of the most promising areas for the development of artificial intelligence in medical diagnostics is multimodal data analysis. In real clinical practice, a doctor

rarely relies solely on a single source of information. To establish a diagnosis, the patient's complaints and history, physical examination results, laboratory indicators, medical imaging data, and the conclusions of other specialists are taken into account simultaneously. Multimodal artificial intelligence systems are developed to combine these different types of information and analyze them together [30,31].

Unlike traditional algorithms that typically work with a single type of data, multimodal models are capable of processing several information modalities simultaneously. These may include medical images, electronic medical documentation text, laboratory indicators, physiological signals, and other clinical data. This approach allows for treating the disease not in isolation, but taking into account the patient's various characteristics [30,31].

Multimodal large language models (MLLMs) have been particularly developed in recent years. They combine the capabilities of natural language processing with visual information analysis. For example, the system can simultaneously account for chest X-rays, clinical information about the patient, and the diagnostic question posed by the doctor. Based on the combined information, the model can form a preliminary conclusion, draw attention to suspicious changes, or provide additional information to support the diagnostic decision [30].

One of the potential advantages of the multimodal approach is the ability to compare data that, individually, may have limited diagnostic value. For example, a pathological change detected on a CT scan can be evaluated simultaneously with the patient's age, symptoms, laboratory test results, and medical history. This allows for the consideration of the clinical context during image interpretation and potentially enhances the informativeness of the diagnostic process [30,31].

Multimodal AI is also considered a promising tool for generating preliminary medical conclusions. The system can analyze the image and associated clinical information, then generate a textual description of the identified changes. In radiology, such models are studied to automatically generate preliminary reports, answer questions based on medical images, and provide interactive support to the physician when interpreting research results [30].

The broader development of multimodal models is associated with the creation of medical foundation models—large, pre-trained models capable of adapting to various clinical tasks. Such models can be trained on large arrays of diverse

medical data and then used to solve several tasks, including diagnosis, prediction, and support for clinical decisions. Modern research considers them as one of the possible stages in the transition from highly specialized algorithms to more universal artificial intelligence systems in medicine [31].

Despite its high potential, multimodal analysis has several serious limitations. One of the main problems is the heterogeneity of medical data. Images, laboratory indicators, and text information have different structures, scales, and quality, so their correct combination requires special processing methods. Furthermore, training such models requires large volumes of qualitatively labeled multimodal data, which remains limited in medicine [30,31].

A separate problem is the errors of generative models, including the formation of plausible but actually incorrect information. When using multimodal AI in diagnostics, such an error can have clinical significance, especially if the conclusion formed by the system is perceived by the doctor as reliable without additional verification. Therefore, the results of the model's work must be evaluated by a specialist, taking into account the patient's initial data [14,30,31].

Another limitation is the insufficient transparency of the decision-making process. Even if the multimodal model forms the correct answer, it may be difficult for a doctor to determine which specific image features, laboratory indicators, or clinical data had the greatest impact on the outcome. This complicates assessing the validity of recommendations and limits the application of such systems in situations requiring a high degree of explainability [11,30].

Furthermore, multimodal models require significant computational resources, and their effectiveness may change when working with data that differ from those on which the training was conducted. Insufficient external validation, differences between medical institutions, and the characteristics of individual patient groups can lead to a decrease in the accuracy of algorithms when transferred to another clinical setting [9,30,31].

Thus, multimodal artificial intelligence represents one of the most promising areas for the development of medical diagnostics. Combining medical images, laboratory indicators, clinical information, and text data allows algorithms to approach the principles of integrated clinical thinking. However, modern multimodal systems are still predominantly at the stage of active research and clinical validation. Their further implementation requires improving data quality,

developing explainable AI methods, independently assessing diagnostic effectiveness, and ensuring control by a medical specialist.

Improving diagnostic accuracy and early detection of diseases

One of the main advantages of using artificial intelligence in medical diagnostics is its ability to increase the accuracy of detecting pathological changes and detect disease signs at earlier stages. This is especially important for conditions where timely diagnosis directly affects further prognosis and treatment effectiveness. Unlike the traditional approach where a doctor sequentially evaluates individual features, artificial intelligence algorithms are capable of analyzing a large number of parameters simultaneously and identifying complex relationships between them.

The most convincing results were obtained during the analysis of medical images. In various areas of diagnostics, deep learning algorithms demonstrate high sensitivity and specificity in detecting pathological changes. For example, in digital pathology, the combined results of systematic review and meta-analysis showed an AI sensitivity of 96.3% and a specificity of 93.3% when analyzing digital histological images. However, the authors simultaneously identified a high or unclear risk of systematic error or applicability issues in 99% of the included studies, emphasizing the need for careful interpretation of such indicators [6].

An important advantage of AI may be its ability to detect subtle changes that are difficult to recognize during initial visual assessment. When analyzing X-rays, computed tomography, and magnetic resonance imaging, algorithms can identify suspicious areas and draw the doctor's attention to them. This approach is especially important in the early stages of diseases, when pathological changes may be minor or exhibit non-specific signs. In oncology, this can facilitate the earlier detection of tumor changes, and in radiology, the detection of small foci and other pathological findings [4,11,12].

The potential benefits of AI are not limited to detecting a disease that has already formed. When analyzing a set of clinical, laboratory, and instrumental data, algorithms can be used to assess the individual risk of developing certain pathological conditions. In this case, the model identifies a combination of signs that may be associated with the subsequent occurrence of the disease, even if there are no pronounced clinical manifestations at the time of the examination.

This creates prerequisites for moving from diagnosing already existing pathologies to more early identification of patients with increased risk [22,32]. However, the high diagnostic accuracy of the algorithm should not be considered an absolute advantage over the doctor. Research results significantly depend on the characteristics of the sample used, data quality, and validation methodology. Furthermore, the indicators obtained under experimental conditions are not always reproduced when using the model in real clinical practice. External validation remains a particularly important issue, as the algorithm can demonstrate high accuracy on data similar to a training sample, but performs worse when analyzing patients from another population or medical institution [33,34].

This is well demonstrated by research on generative artificial intelligence. In a systematic review and meta-analysis by Takita et al., which included 83 studies, the overall diagnostic accuracy of the generative models was 52.1%. When compared with doctors, there were no statistically significant differences in overall diagnostic effectiveness, but generative AI showed lower results compared to expert doctors. The authors emphasize that modern models possess significant diagnostic potential, but have not yet reached the level of reliability necessary for the independent replacement of specialists [25].

Thus, the primary value of artificial intelligence lies not only in obtaining high sensitivity and specificity indicators but also in the ability to supplement a doctor's work with an additional source of diagnostic information. The algorithm is capable of systematically analyzing large volumes of data, identifying potentially pathological signs, and helping the specialist pay attention to changes that might be missed during routine assessment. At the same time, the final diagnostic decision must be made taking into account the clinical presentation, results of other studies, and the professional assessment of the physician [1].

Consequently, artificial intelligence has significant potential for increasing diagnostic accuracy and early detection of diseases. However, the clinical effectiveness of such systems should be evaluated not only by the algorithm's accuracy indicators but also by its ability to improve real diagnostic results for patients. This requires independent external validation, prospective studies, and an assessment of AI effectiveness directly within clinical practice [33,34].

Reducing the workload on medical specialists and increasing diagnostic efficiency

One of the potential advantages of artificial intelligence is the ability to reduce the volume of routine work for medical specialists and increase the efficiency of the diagnostic process. The increasing number of patients and the increase in the volume of medical information lead to a significant burden on doctors, especially in areas related to processing a large number of diagnostic studies. Under these conditions, AI can be used to automate individual work stages, perform preliminary data analysis, and distribute diagnostic studies by priority level [4,27].

Such possibilities are most actively studied in radiology. Artificial intelligence algorithms can automatically analyze images, identify suspicious changes, and highlight studies that require faster medical attention. For example, if there is a suspicion of intracranial hemorrhage, stroke, or pulmonary embolism, the algorithm can be used to change the order of examinations in the work list. As a result, potentially dangerous cases may be presented to a specialist before less urgent examinations [9,26].

The effectiveness of such approaches was examined in a systematic review by Momin et al., which included 38 studies from 20 publications and more than 138,000 medical images. Following the implementation of deep learning algorithms, the median time for preparing radiological reports was reduced in various clinical scenarios. The most pronounced contraction was observed in chest diseases, stroke, and pulmonary embolism [26]. These results indicate the possibility of using AI not only directly for diagnostics but also for optimizing workflow organization.

Another direction is the automation of repetitive stages in processing diagnostic information. Algorithms can perform preliminary image segmentation, perform quantitative measurements, identify pathological areas, and generate preliminary analysis results. This allows for a reduction in the number of similar operations that were previously performed by a specialist manually. This approach can be particularly important in digital pathology, radiology, and ophthalmology, where a doctor must regularly analyze a large number of images [4,6,18].

However, the impact of AI on workload is not always unambiguously positive. In a systematic review and meta-analysis by Wenderott et al., which included 48 studies, 33 works evaluated changes in diagnostic task execution time, and 67%

of them reported its reduction following the implementation of AI. At the same time, three meta-analyses of individual study groups did not reveal a statistically significant overall reduction in time. The authors also noted significant heterogeneity in the research and a lack of data on the actual change in specialists' workload [27].

One reason for such ambiguity is the way AI is integrated into the clinical workflow. If the algorithm is used as an additional source of information after the usual analysis of the study, the doctor must independently evaluate both the initial data and the result of the AI's work. In some cases, this may not reduce working time, but rather create an additional information burden. It may be more effective to use AI directly during the analysis process, for example, to automatically highlight suspicious areas or prioritize research [26,27].

Furthermore, the automation of individual tasks does not mean the complete release of the physician from the corresponding work. Even if the algorithm is capable of performing a preliminary analysis, the specialist must monitor the result, evaluate potential errors, and compare it with clinical information. Therefore, it is more correct to speak not of replacing a specialist, but of redistributing their working time from routine operations to tasks requiring clinical thinking and decision-making [1].

The possibility of increasing the accessibility of diagnostic care is also of great importance. If there is a shortage of medical specialists, AI can perform a preliminary analysis of a large number of studies and help identify patients who require a faster or more in-depth examination. However, the effectiveness of this approach depends on the quality of the algorithm and the organization of the workflow. Modern research emphasizes that it is not enough to demonstrate the technical accuracy of the system - it is also necessary to prove that its implementation truly improves the clinical process in real conditions [26,27].

Thus, artificial intelligence is capable of increasing the effectiveness of medical diagnostics by automating routine operations, preliminary data analysis, and research prioritization. The most convincing data have been obtained in radiology, but the research results remain heterogeneous. Therefore, the clinical effectiveness of AI should be evaluated not only by reducing analysis time but also by its impact on the overall organization of work, diagnostic quality, and patient safety. The optimal approach is to integrate AI into the workflow in such a way that the technology reduces the doctor's routine workload, while retaining

control over the specialist's interpretation of results and final clinical decision-making [1,27].

AI as a tool for supporting clinical decisions.

One of the most important areas for applying artificial intelligence in medicine is supporting clinical decision-making. In this case, AI is not considered an independent diagnostic tool, but is used together with a physician to analyze medical information, assess disease probability, and select further diagnostic tactics. This approach allows for combining the algorithm's computational capabilities with the specialist's clinical experience [1,2].

During the diagnostic process, the doctor must account for a large amount of heterogeneous information: patient complaints, medical history, physical examination results, laboratory indicators, imaging data, and previous research results. At the same time, some information may be incomplete or have varying diagnostic significance. Artificial intelligence is capable of systematizing this data and identifying patterns that may be less obvious when sequentially evaluating individual indicators. This makes AI a potentially useful tool for forming a differential diagnostic series and assessing the risk of certain diseases [5,22].

A comparison of the doctor's independent work with the collaborative work of the doctor and AI is of particular interest. Modern research shows that the use of AI does not necessarily lead to a specialist's replacement, but it can change the quality of their decisions. In a systematic review and meta-analysis of studies on human interaction and large language models, diagnostic accuracy when a doctor and AI work together showed a tendency to improve compared to a doctor's work without AI. Specifically, when analyzing the five most likely diagnoses, the relative diagnostic accuracy of collaborative work was 1.42 compared to doctors working independently. However, the authors emphasize the significant heterogeneity of the studies and the need for further verification of these results in real clinical conditions [28].

Additional data were obtained in a study dedicated to the impact of AI on doctors' clinical decision-making when assessing patients with chest pain. After receiving the recommendations formulated by GPT-4, the accuracy of doctors' clinical decisions increased from 47% to 65% in one group of patients and from 63% to 80% in another. At the same time, the study did not reveal an increase in differences in decision accuracy between the represented demographic groups [29]. These results demonstrate the potential for using AI not only for automatic

information processing but also directly as an additional source of recommendations for a physician.

However, the effectiveness of such interaction depends on how the specialist utilizes the algorithm's recommendations. If a doctor critically evaluates an AI result and compares it with clinical data, the technology can complement professional thinking. On the contrary, the uncritical acceptance of algorithm recommendations can lead to an erroneous decision. This is especially true for generative models, which can generate convincing but actually incorrect answers [3,38].

The problem of excessive trust in an algorithm has been named automation bias. In such a situation, the specialist may attach more importance to the result of the automated system than to their own clinical analysis. The opposite problem is also possible: a doctor may ignore useful AI recommendations due to insufficient trust in the technology. Therefore, effective interaction between humans and AI requires not only a technically accurate model but also the correct organization of its use in clinical practice [36-38].

The explainability of the results is also an important factor. To make a clinical decision, it is desirable for the doctor to understand on the basis of which data the system has formed the recommendation. If the algorithm only provides the final result without being able to evaluate its validity, it is more difficult for the specialist to determine how the conclusion corresponds to the specific clinical situation. Therefore, the development of explainable artificial intelligence is considered one of the important conditions for the safe implementation of clinical decision support systems [36,37].

At the same time, modern data does not allow for the claim that the joint work of a doctor and AI always improves diagnosis. A meta-analysis by Takita et al. showed that generative models were generally inferior to expert physicians in diagnostic accuracy, despite comparable results with physicians without specialization in specific tasks [25]. Additionally, a significant portion of generative AI studies had a high risk of systematic error. This emphasizes the need to consider the results of such systems as additional information rather than a final clinical conclusion [25].

Thus, the most promising model for applying artificial intelligence in clinical diagnostics is not replacing a doctor, but the interaction between a specialist and an algorithm. AI can perform functions such as processing and structuring

information, identifying potentially significant features, assessing risk, and forming additional diagnostic hypotheses. The doctor, in turn, evaluates the results obtained, taking into account the clinical picture, the patient's individual characteristics, and other diagnostic data. This approach allows for the utilization of artificial intelligence advantages while maintaining professional control and the responsibility of the medical professional [1].

AI's impact on accessibility and personalization of medical diagnostics

One of the promising areas for applying artificial intelligence is increasing the accessibility of diagnostic assistance. This may be particularly relevant for regions where there is a shortage of medical specialists or limited opportunities for conducting specialized research. The use of AI allows for the automation of individual stages in analyzing diagnostic information and potentially expands the possibilities for primary examination of patients [30,31].

The most obvious prospects are related to primary health care and remote formats of medical services. Algorithms can be used to pre-assess symptoms, analyze medical images and laboratory indicators, and identify patients who require specialist consultation. In this case, AI does not replace a full-fledged medical examination, but helps determine the priority of further diagnostic care. A modern review of AI application in primary healthcare has shown that the most frequently studied areas are early intervention and decision-making support, management of chronic diseases, and the organization of medical care [30].

Increasing the accessibility of diagnostics can be of particular importance in rural and remote regions. In the absence of a specialist on-site, the preliminary analysis of diagnostic data using AI can potentially be performed remotely, after which the results are transmitted to the physician for final assessment. This approach is particularly promising for image analysis, as digital X-rays, eyeball photographs, and other studies can be transmitted between medical institutions without the need for a specialist's physical presence [4,18,30].

At the same time, the impact of AI on the accessibility of medical care should not be assessed positively. Implementing such technologies requires appropriate digital infrastructure, access to modern equipment, stable internet connectivity, and trained specialists. If these conditions are absent, the use of AI may, on the contrary, increase the differences between medical institutions and population groups. Therefore, increasing accessibility through AI should be considered in the context of the broader issue of digital inequality [31].

Another important advantage of AI is the ability to personalize the diagnostic process. The traditional diagnostic approach in many cases is based on general clinical criteria, while algorithms are capable of simultaneously accounting for the patient's individual characteristics. Depending on the specific task, these may include age, gender, medical history, laboratory findings, imaging results, genetic data, and other characteristics [32].

Machine learning allows for the analysis of combinations of various factors and the formation of an individual assessment of the probability of disease or adverse outcome. This approach is especially important for patients with several risk factors, when the value of a single indicator may be insufficient for an accurate assessment of the condition. In a meta-analysis by Daemi et al., which included 17 studies dedicated to AI models for predicting diagnostic indicators, the combined area under the ROC curve was 0.9025. However, significant heterogeneity was observed between the studies ($I^2 = 91.01\%$), which limits the possibility of directly transferring the obtained results to various clinical conditions [32].

Personalization can be particularly significant when assessing the risk of developing diseases. Instead of determining only the presence or absence of a pathological condition, the algorithm can calculate the individual probability of its occurrence or progression. This creates opportunities for earlier examination of patients in high-risk groups and a more rational choice of subsequent diagnostic measures [22,32].

Thus, artificial intelligence is potentially capable of simultaneously expanding access to diagnostic assistance and making it more personalized. Its application can be particularly useful in primary healthcare, remote diagnostics, and conditions with a limited number of specialists. However, the realization of these advantages depends on the availability of digital infrastructure, data quality, and equal access to technologies. Furthermore, individualized prognoses should undergo clinical validation and be used as an additional tool rather than the sole basis for medical decision-making [1,32].

Consequently, the impact of AI on accessibility and personalization of diagnostics has significant potential, but is not an automatic result of technology implementation. To achieve real clinical benefit, it is necessary to ensure the availability of appropriate infrastructure, training medical workers, quality control of algorithms, and evaluation of their effectiveness in various patient

groups. Only when these conditions are met can AI facilitate more accessible and personalized diagnostic assistance.

Limitations and risks of using AI in medical diagnostics.

Data quality, algorithmic bias, and external validation

One of the main limitations of applying artificial intelligence in medical diagnostics is the dependence of algorithm quality on the data used for its training and evaluation. Even a high-precision model may show unstable results if the training sample is not sufficiently representative, contains errors, or differs significantly from the data the algorithm encounters in real clinical practice. Therefore, the quality and structure of initial data are among the key factors determining the reliability of the diagnostic system [33].

A particular problem is the limited representativeness of medical data sets. In individual studies, data from patients from the same medical institution, region, or specific age group predominate. Additionally, patients with various clinical characteristics may be insufficiently represented. As a result, the algorithm is capable of working well in the initial sample, but showing lower efficiency when applied to another population. Such a decrease in efficiency may be related to differences in disease prevalence, patient characteristics, equipment used, and the specifics of medical care organization [33,34].

External validation plays an important role, where the model's effectiveness is verified on an independent data set that differs from the original sample. It allows for an assessment of how well the algorithm is capable of generalizing the obtained patterns to new clinical conditions. A systematic review of externally validated AI models for brain emergency CT analysis revealed that such studies are still limited: out of 5,636 identified publications, only six studies met the inclusion criteria. At the same time, the authors noted significant methodological and clinical heterogeneity between the works [9].

The problem of model portability is also related to the so-called data distribution shift (dataset shift). The data obtained after the system's implementation may differ from the data it was trained on. This may occur due to the use of other medical equipment, changes in examination protocols, data registration features, or changes in patient characteristics. A study conducted on 13 medical datasets, including X-ray and CT images, ECG, medical texts, and other data, showed that model performance could be overestimated by an average of up to 20% due to

the use of hidden patterns related not to the disease, but to the specifics of obtaining data [34].

A separate problem is algorithmic bias. It occurs when the algorithm demonstrates varying effectiveness for specific patient groups. The reason may be the insufficient representation of certain groups in the training sample, historical differences in medical care provision, or the specific characteristics of the data itself. Systematic reviews show that such issues can affect various demographic groups and potentially exacerbate the already existing inequality in healthcare provision [35].

Thus, the high accuracy obtained during initial training or internal validation of the model does not yet guarantee its equal effectiveness for all patients and in all medical institutions. For safe clinical application, it is necessary to conduct independent external validation, evaluate the algorithm's performance in various patient groups, and regularly monitor its effectiveness after implementation. It is also important to provide a transparent description of the characteristics of training data and results across individual clinical and demographic subgroups [33-35].

Consequently, the reliability of medical artificial intelligence is determined not only by the complexity of the algorithm used, but also by data quality, sample representativeness, and the model's ability to maintain effectiveness despite changing clinical conditions. Solving these problems is a necessary condition for moving from promising experimental results to the safe and fair use of AI in medical diagnostics.

AI errors, explainability, and the role of the doctor.

Despite its high diagnostic accuracy, artificial intelligence does not rule out the possibility of errors. Algorithms can generate both false positive and false negative results, especially when working with data that differs from those used in model training. In clinical practice, this is of particular importance, as an error in the algorithm can lead to both additional unnecessary examinations and the omission of a potentially dangerous disease. Therefore, even high sensitivity or specificity of the model does not exclude the need for its results to be monitored by a medical specialist [1,33,34].

A separate problem is the insufficient explainability of solutions for some artificial intelligence systems. Modern deep learning models often have a complex architecture where it is difficult for a physician to determine which features of the initial data had the greatest impact on the final result. Such systems

are commonly characterized as "black boxes." Insufficient transparency can make it difficult to assess the correctness of the recommendation and reduce the possibility of identifying an algorithmic error before it affects the clinical decision [36].

In this regard, the field of Explainable Artificial Intelligence (XAI) is actively developing. Its task is to provide additional information about how the model arrived at a specific result. To do this, methods can be used that allow for determining the relative contribution of individual features to the prognosis, visualizing image areas that influenced the algorithm's decision, or presenting the most significant patient characteristics. Such approaches potentially increase system transparency and facilitate the physician's interaction with AI [36,37].

However, the presence of an explanation alone does not guarantee a correct clinical decision. The explanation must be clear and truly useful to the specialist, rather than merely creating the impression of model transparency. A systematic review of XAI studies showed that explainability can influence doctors' trust in AI in both positive and negative ways. An overly convincing explanation can increase trust even when the algorithm's result is incorrect, while an unclear or insufficient explanation can lead to unjustified distrust of the system [37].

This is related to the problem of excessive trust in automated recommendations, known as automation bias. It arises in a situation where a specialist is inclined to accept a system recommendation without sufficient independent verification. In diagnostics, this can lead to the physician not noticing the algorithm's error or attaching greater importance to its conclusion than to their own clinical assessment. A modern systematic review of the application of generative AI in healthcare revealed reports of automation bias in 10 out of 29 included studies, as well as concerns regarding the gradual decline of specialists' diagnostic skills [38].

The opposite situation is also possible. A doctor may not trust the algorithm enough, even in cases where their recommendation is well-founded. This phenomenon may reduce the potential benefits of AI and lead to the ignorance of additional diagnostic information. Therefore, for the safe application of the technology, it is necessary to form not maximum trust in AI, but so-called justified trust, whereby the specialist understands the system's capabilities and limitations and is able to independently evaluate its outcome [36,37].

The problem becomes particularly significant when using generative AI. Such models are capable of forming coherent and convincing answers, which may

contain factual errors or information that is absent from the source data. In medical diagnostics, such errors require a particularly careful approach, as a seemingly convincing result can create a false sense of reliability. Therefore, the information obtained from the generative model must be verified against the initial medical data and evaluated by a specialist [3,38].

An important problem is the potential impact of constant AI use on a doctor's professional skills. If a portion of diagnostic tasks is performed automatically for a long time, the specialist may less frequently conduct the corresponding analysis independently. In the long term, this may lead to a decrease in confidence in one's own diagnostic skills and increased dependence on automated systems. At the same time, existing research does not allow for such an effect to be considered inevitable: if the work is properly organized, AI can, on the contrary, be used as an additional tool for training and increasing the effectiveness of the doctor [38]. Thus, the safety of applying artificial intelligence is determined not only by the accuracy of the algorithm but also by the nature of the interaction between the system and the medical specialist. The optimal model is the human-in-the-loop model, where AI performs analysis and generates additional information, while the doctor retains the ability to critically evaluate the result and make a final clinical decision. This requires clear interfaces, adequate explainability of algorithms, training of medical workers, and constant monitoring of the system's performance quality [1,36-38].

Therefore, artificial intelligence should not be viewed as an autonomous source for final diagnosis. Its task is to support clinical thinking, not to replace it. Maintaining the leading role of the doctor allows for the use of AI computational capabilities while simultaneously reducing the risk of errors related to automation, insufficient explanation, and excessive trust in algorithmic recommendations [1].

The use of artificial intelligence in medical diagnostics involves not only technical but also ethical and legal issues. Training and operation of diagnostic algorithms require a large amount of medical information, which may include personal and potentially sensitive patient data. Therefore, ensuring the confidentiality and security of such information is one of the primary conditions for the safe implementation of AI in clinical practice [1].

A particular problem is the processing of electronic medical records, laboratory test results, medical imagery, and other data that may be associated with a specific

patient. Before using such data, it is necessary to ensure appropriate protection of personal information, determine the purposes of its processing, and restrict access to it. The World Health Organization emphasizes that the application of AI in healthcare must be carried out in compliance with human rights to privacy and autonomy, and the use of medical data must comply with existing information protection requirements [1].

An additional risk is related to cybersecurity. Medical AI systems can become targets of unauthorized access, data modification, or other cyberattacks. Such threats can potentially affect not only patient confidentiality but also the reliability of diagnostic results. Therefore, the security of AI systems must be considered throughout their entire use period, including development, implementation, updating, and subsequent monitoring [39].

From an ethical perspective, preserving patient autonomy and the leading role of the medical professional is an important issue. The use of AI should not result in transferring the final medical decision to an automated system. The patient must be aware if artificial intelligence technology is being used in the diagnostic process, especially when its results may influence further clinical management. The WHO considers maintaining human control, transparency, accountability, and fairness to be key principles for the use of AI in healthcare [1,39].

A separate issue is liability for incorrect decisions. If the algorithm provides an incorrect diagnostic recommendation, a question arises regarding the allocation of liability among the system developer, the medical organization, and the physician who used the technology. To date, a universal model for allocating such liability has not yet been established, which creates additional challenges for implementing AI in clinical practice [1,39].

Regulatory requirements are also becoming increasingly important as AI systems become more widespread. For medical algorithms, it is necessary to evaluate not only their technical characteristics but also their safety, effectiveness, intended purpose, and the system's behavior after implementation. The WHO recommends considering the life cycle of AI systems, conducting external validation, ensuring transparency in development, and subsequently monitoring their performance [39].

Regulatory approaches continue to develop in individual countries. For example, the U.S. Food and Drug Administration (FDA) published a draft of guidelines for AI-based medical device developers in 2025, providing for the consideration of issues regarding the development, documentation, maintenance, and monitoring

of such systems throughout their entire life cycle. In 2026, the FDA also published the final guidance on Clinical Decision Support Software, clarifying the regulatory approach to clinical decision support software [39,40].

Thus, the widespread implementation of artificial intelligence in medical diagnostics requires not only proving its diagnostic effectiveness but also creating a system for data protection, cybersecurity, ethical control, and regulatory oversight. These measures must ensure patient safety, transparency in technology use, and the preservation of medical specialist's responsibility for the final clinical decision [1,39,40].

In general, modern approaches to AI regulation are gradually moving from evaluating only the final product to controlling the entire life cycle of the technology. This approach involves evaluating the algorithm before its implementation, monitoring efficiency after use, monitoring updates, and identifying potential new risks. This is especially important for medical systems capable of changing their characteristics after updating or training on new data. Therefore, the further development of AI in diagnostics must be accompanied by the constant improvement of regulatory and ethical mechanisms for its application [39,40].

Prospects for developing artificial intelligence in medical diagnostics

The further development of artificial intelligence in medical diagnostics is linked to the transition from highly specialized algorithms designed to solve specific diagnostic tasks to more universal systems capable of working with various types of medical information simultaneously. Multimodal and generative models, which can combine medical images, text data, laboratory indicators, and information from electronic medical records, are of particular importance in this regard. This approach potentially allows for a more comprehensive assessment of the patient's condition and takes into account the clinical context when forming diagnostic recommendations [23,24].

The further development of personalized diagnostics remains a promising direction. As medical data accumulates, AI can use individual patient characteristics to more accurately assess disease probability, predict its development, and select the optimal sequence of diagnostic studies. In the future, combining clinical, laboratory, imaging, and molecular genetic data can facilitate the transition from a predominantly standardized approach to a more individualized diagnostic strategy [32].

An important condition for further development is the transition from the experimental application of AI to its controlled integration into daily clinical practice. To do this, it is not enough to demonstrate the high accuracy of the algorithm in a retrospective study. It is necessary to confirm its effectiveness in prospective studies and various medical institutions, evaluate the technology's impact on clinical outcomes and work processes, and determine situations where the use of AI truly benefits both the patient and the physician [4,10].

In the future, significant attention will be paid to creating systems capable of adapting to changes in medical data and their application conditions. At the same time, updating algorithms must be accompanied by monitoring their effectiveness and safety, as changes in training data or software can potentially affect diagnostic results. Therefore, the development of post-marketing monitoring systems and the evaluation of algorithms after their implementation will be of great importance [39,40].

The prospects for applying AI are also linked to expanding access to diagnostic assistance. Automated analysis of medical images and clinical data can potentially be used in medical institutions where access to specialized specialists is limited. However, such development is only possible if there is the necessary digital infrastructure, trained personnel, and quality control mechanisms. Otherwise, technological differences between medical institutions may, on the contrary, contribute to an increase in digital inequality [30,31].

Thus, the further development of artificial intelligence in medical diagnostics will likely be linked to the creation of more versatile multimodal models, the expansion of personalized risk assessment capabilities, and the gradual integration of AI into clinical work processes. At the same time, the key condition for its successful implementation will remain not only the improvement of algorithms but also ensuring their clinical effectiveness, safety, transparency, and compliance with regulatory requirements. The most promising model is one where AI performs the functions of an intelligent assistant to a doctor, while the final interpretation of diagnostic information and clinical decision-making remains with the medical specialist [1,23,24,39,40].

Conclusion

Artificial intelligence is currently one of the most promising areas for the development of medical diagnostics. Modern machine and deep learning algorithms are capable of analyzing large volumes of medical information,

including radiological research results, digital histological images, ophthalmological data, laboratory indicators, and electronic medical records. This creates opportunities for automating specific diagnostic tasks, identifying pathological changes, and increasing the efficiency of medical information processing.

The most convincing results of AI application have been obtained in medical image analysis, particularly in radiology, digital pathology, and ophthalmology. The algorithms demonstrate high diagnostic accuracy when solving a number of specific tasks and can facilitate the earlier detection of pathological changes. Furthermore, AI is capable of reducing the routine workload of medical professionals, prioritizing research, and providing additional information when making clinical decisions.

At the same time, the results of the conducted research show that high technical accuracy of the algorithm is not a sufficient condition for its safe implementation into clinical practice. The effectiveness of AI depends on the quality and representativeness of the initial data, the characteristics of the studied population, the equipment used, and the specific characteristics of the specific medical institution. Insufficient external validation, algorithmic bias, the risk of false results, limited explainability, and the possibility of a doctor's excessive trust in the system's recommendations remain significant issues.

A promising direction for further development is multimodal and generative models capable of combining various types of medical information. Their further improvement can contribute to the development of more comprehensive and personalized diagnostics. However, the widespread application of such technologies requires not only the improvement of algorithms but also the conduct of prospective studies, independent external validation, assessment of clinical efficacy, and constant safety monitoring.

Thus, at the current stage, it is advisable to consider artificial intelligence primarily as a tool for supporting a medical specialist rather than as a substitute for a doctor. The safest and most promising model involves human-algorithm interaction, where AI analyzes large datasets, identifies potentially significant signs, and provides additional diagnostic information, while the final interpretation of results and clinical decision-making remains with the physician. Further implementation of AI must be carried out based on the principles of evidence, transparency, medical data protection, fairness, and human control,

which is a necessary condition for obtaining real clinical benefits from this technology.

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