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Use of intelligent algorithms in virtual healthcare computer systems: From diagnosis to personalised treatment

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Abstract. The study aimed to theoretically substantiate approaches to the effective implementation of intelligent algorithms in virtual medicine. The methodology was based on theoretical, analytical, and normative-prognostic analysis of the effectiveness and development of intelligent technologies in digital healthcare. The study established that artificial intelligence (AI) is transforming approaches to the collection, analysis and use of medical data. Virtual medicine uses machine learning for diagnosis, prediction and personalised treatment, increasing the accuracy of decisions and reducing the burden on doctors. Machine learning methods are effective for processing electronic medical records and laboratory data, while deep learning forms the basis of virtual medicine by automating the analysis of large amounts of information. Generative models create synthetic medical data and clinical scenarios, supporting the development of personalised medicine and the concept of "digital twins". Multimodal systems combine different types of data, providing a comprehensive analysis of the patient's condition and more accurate clinical predictions. The benefits of AI implementation included an 18-25% increase in diagnostic accuracy, a 20-30% reduction in working hours among doctors, expanded access to medicine in remote regions, and lower healthcare costs. The main risks are issues of data security, explainability, ethics, bias, and doctor trust, which necessitate transparency, control, and legal regulation. The European Union has specific legislation that sets requirements for the safety and transparency of medical AI systems, while Ukraine's regulatory framework is still in the process of being developed. To improve virtual medicine, it is advisable to implement explainable AI, integrate Large Language Models with data protection, apply federated learning, generative simulations and blockchain following ethical and legal standards. The results of the study can be used by specialists when making decisions on the selection and application of intelligent algorithms in medical institutions, research centres, and the IT sphere of healthcare

Keywords: multimodal medical data analytics; digital monitoring; generative models for simulations; explainability of clinical decisions; telemedicine; security and privacy of medical data

Introduction

The rapid development of information technology and the growth of digital medical data volumes necessitate the introduction of intelligent algorithms into healthcare computer systems. The medicine of the 21st century increasingly requires effective tools capable of analysing large amounts of clinical, genomic and behavioural information, identifying hidden patterns and providing personalised recommendations. In this context, the integration of Machine Learning (ML) and Deep Learning (DL) methods into virtual medical systems forms the basis of a new stage of digital transformation in the industry, covering diagnosis, prognosis, treatment and real-time patient monitoring.

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Intelligent algorithms are considered the basis of clinical diagnostics, which can be used for the analysis of large arrays of clinical data, the identification of latent patterns, and the optimisation of the physician's decision-making process. S. Mizna *et al.* (2025) proved that the use of ML models in clinical decision support systems significantly reduces the number of diagnostic errors. The study demonstrated that a combination of structured and unstructured medical data increases the accuracy of automated systems by more than 20%, indicating the basic effectiveness of artificial intelligence (AI) in virtual medicine. S.R. Abbas *et al.* (2025) demonstrated that smart healthcare systems based on deep neural networks effectively use biomedical signals and visual data for early detection of pathological changes. This confirmed that AI algorithms can not only improve diagnostic accuracy but also support doctors in making decisions in complex clinical scenarios.

A significant portion of studies is devoted to the personalisation of treatment, where intelligent systems adapt therapeutic decisions to the individual characteristics of the patient. X. Guo & Y. Li (2024) demonstrated that health information systems form the basis for integrating heterogeneous data, from medical records to genetic profiles, which creates opportunities for predicting the course of diseases. Similar conclusions were made by H.B. Clark *et al.* (2024), emphasising the need to create hybrid models that combine statistical methods and deep neural networks to predict treatment outcomes. This has laid the groundwork for the development of personalised medicine, where AI algorithms act not as an auxiliary tool but as an active element in clinical decision-making, facilitating the transition from universal therapeutic approaches to individually tailored treatment strategies.

The issues of security and ethics in the use of AI in medicine remain central. M.M. Khan *et al.* (2025) determined that the lack of transparent data management policies threatens trust in AI decisions. The authors formulated a list of technical and organisational measures necessary to create a safe environment for the use of AI tools in clinics, which laid the foundation for the concept of "trusted AI in healthcare". Explainable AI is also one of the critical areas of development for medical AI. R. Alkhanbouli *et al.* (2025) systematised approaches to building transparent AI models in medicine and showed that the use of Explainable AI reduces the risk of misinterpretation of results by doctors. The study proved that explainable algorithms increase the trust and clinical acceptability of systems, forming the theoretical basis for their implementation in healthcare.

Ukrainian researchers are also contributing to the scientific discourse on the implementation of intelligent technologies in healthcare. O. Boychenko & T. Bubliy (2024) highlighted the potential of using AI algorithms to optimise diagnostic processes in the national healthcare system, while emphasising the limitations associated with the lack of high-quality medical databases and standardised information processing protocols. V.O. Korotka & V.A. Mokrynskyi (2024) highlighted the technical and organisational barriers to the digitalisation of Ukrainian medicine, in particular the shortage of qualified personnel capable of interpreting the results generated by DL algorithms. N. Sofilkanych *et al.* (2023) determined that the Ukrainian medical sector is only beginning to systematically implement intelligent solutions, but the prospects for their application (from personalised therapy to telemedicine services) are significant and strategic for the country. The overall contribution of Ukrainian researchers lies in creating a conceptual framework for the development of national digital medicine, which combines the technical, organisational and managerial aspects of AI implementation. This facilitates the adaptation of global approaches to the local context and lays the foundation for further interdisciplinary research in the field of virtual healthcare.

Despite the availability of scientific publications, several unresolved issues remain. Most studies emphasise technical aspects, neglecting issues of clinical validation, explainability of decisions, and user trust. There are no uniform standards for integrating intelligent algorithms into virtual healthcare systems that can ensure the compatibility of different platforms and the protection of confidential data. The mechanisms of personalising treatment based on a comprehensive analysis of multimodal medical data (images, texts, biosignals, genomic profiles) remain insufficiently studied. Therefore, the study aimed to provide a theoretical justification for the use of AI to improve the analytical, diagnostic, and prognostic capabilities of virtual healthcare systems. To achieve this goal, the following tasks were set: to analyse approaches to the application of AI in diagnosis and treatment, to identify the advantages and risks of using intelligent algorithms to assess the potential of personalised treatment models, and to formulate recommendations for the safe integration of AI technologies into virtual healthcare systems, in particular in Ukraine.

Materials and Methods

The study was analytical and theoretical in nature and was based on the systematisation, generalisation and critical analysis of scientific sources covering the application of AI in virtual medicine. The source base consisted of 27 scientific publications from 2022 indexed in the Scopus and Web of Science databases, an analytical report by the European Commission (2024), the Artificial Intelligence Act (2024) and data from the Ministry of Digital Transformation of Ukraine (2023) in the field of regulation, which define the principles of security, transparency and certification of medical AI systems. The sources were selected based on criteria of scientific reliability, relevance and representativeness for modern trends in AI development in medicine as of 2025. The research procedure involved the phased application of theoretical methods – analysis and comparison of ML concepts, DL, generative AI and multimodal architectures, summarising the results of practical AI implementations in clinical practice, comparative analysis of legal regulation in the EU and Ukraine, analytical synthesis of conclusions with the definition of strategic directions for the development of intelligent medicine.

Using methods of theoretical generalisation and comparative analysis, based on data from scientific sources, intellectual technologies in the field of virtual medicine were analysed: ML (Support Vector Machine (SVM) and Decision Trees models), DL (Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM) and Transformers), generative AI (Generative Adversarial Networks (GAN), Diffusion Models, Large Language Models (LLM) (in particular Generative Pre-trained Transformer (GPT), Medical Patient Language Model (Med-PaLM), Bidirectional Encoder Representations from Transformers for Biomedical Text Mining (BioBERT)) and multimodal architectures. The selection of these algorithms was based on the principle of representativeness in terms of key AI areas and their practical significance for medicine: ML for interpreted processing of structured data, DL for high-precision analysis of images, signals and texts, generative AI for synthesising medical data, and multimodal systems for integrating different types of information into a single clinical context. To evaluate the effectiveness of each area, a five-point rating scale was used based on the criteria of interpretability, accuracy, data requirements, flexibility, and practical applicability in medicine, which reflect the key requirements for AI algorithms in a clinical environment: clarity of results, reliability of predictions, resource efficiency, adaptability to different types of data, and real usefulness for medical decisions. The task of this stage was to systematically summarise the capabilities of different classes of intelligent algorithms for improving the efficiency, accuracy and adaptability of virtual medicine to create a theoretical basis for developing a generalised model for their implementation in digital medical systems.

To analyse practical areas of AI application, a classification method was used to identify key areas for integrating intelligent algorithms into medical practice: intelligent diagnostics, patient monitoring, personalised treatment, and telemedicine with clinical decision support systems. The selection of these areas is justified by their systemic importance in the structure of medical care: intelligent diagnostics determines the accuracy of clinical decisions, monitoring ensures timely response, personalised treatment increases the effectiveness of therapy, and telemedicine expands the availability of services. The goal of this stage was to create an analytical framework describing the real directions of AI integration into medical practice. The effectiveness of AI in virtual medicine was assessed according to three groups of indicators: clinical results (diagnostic accuracy, data processing speed), economic effects (cost reduction, productivity improvement), and social consequences (improved accessibility of medical services). The selection of areas was based on criteria of practical significance, measurability of effects, and socio-economic effectiveness. The task of this stage was not only to quantitatively and qualitatively assess the effectiveness of the application of intelligent technologies in key processes of virtual medicine, but also to justify their socio-economic feasibility as a basis for further optimisation of implementation models in healthcare systems.

Critical analysis and a comparative-normative approach were used to identify ethical, safety, and legal risks and barriers to the implementation of intelligent systems in medical practice. The EU regulatory framework was compared based on the provisions of the European Commission (2024) and the Artificial Intelligence Act (2024), which define the principles of safety, transparency and certification of medical AI systems, and Ukraine's Ministry of Digital Transformation of Ukraine (2023) document, which outlines the stages of forming a national regulatory system in the field of AI. This helped to identify and classify the main barriers to the safe integration of intelligent systems into clinical practice, as well as to define directions for improving the ethical, legal, and security mechanisms governing their use.

Results and Discussion

Technological and applied aspects of using intelligent algorithms in virtual medicine

Intelligent technologies have changed the way medical data is collected and analysed. Virtual medicine, including telemedicine and remote monitoring, uses ML and DL methods to automate diagnosis and prognosis. Algorithms process large amounts of information, identifying patterns, forming risk profiles, and proposing personalised treatment plans. This increases diagnostic accuracy and reduces the burden on medical staff, optimising clinical decision-making. AI methods – ML, DL, generative AI, and multimodal architectures – differ in their data processing principles, interpretability, accuracy, and clinical application capabilities. A comparative overview of these technologies is presented in Table 1.

Table 1. Comparative evaluation of AI methods in virtual medicine

Direction	Key algorithms	Data types/ processing	Main areas of medical application	Benefits	Limitations/ challenges
ML	SVM, Random Forest, K-Nearest Neighbours, Decision Trees	Tabular, laboratory, clinical data	Classification, risk prediction, personalised medicine	High transparency, ease of learning, stability with small samples	Limited accuracy on complex, unlabelled data, poor scalability
DL	CNN, RNN, LSTM, Transformers	Medical images, time series, signals (EEG, ECG)	Computer diagnostics, analysis of visual and biomedical signals	High accuracy, automatic feature extraction, noise resistance	Low interpretability, need for large amounts of data, risk of overfitting

Table 1. Continued

Direction	Key algorithms	Data types/ processing	Main areas of medical application	Benefits	Limitations/ challenges
Generative AI	GAN, Diffusion Models, LLM (GPT, MedPaLM, BioBERT)	Text, synthetic and multimodal data	Data generation, telemedicine, clinical forecasting, and reporting	Flexibility, ability to create synthetic samples, support for clinical decisions	Ethical risks, complexity of validation, and high energy consumption
Multimodal architectures	HAIM, DRAGONET, MOICVAE	Integration of visual, textual, genomic, and tabular data	Comprehensive diagnostics, personalised treatment, digital biomarkers	Highest accuracy and completeness of data, improved consistency of results	High resource requirements, complex interpretation

Note: HAIM (H – human, A – algorithm, I – information, M – machine), MOICVAE – multi-omics informed conditional variational autoencoder
Source: compiled by the authors based on L. Soenksen *et al.* (2022), M. Cascella *et al.* (2023), W. Abbaoui et al. (2024), H. Nilius *et al.* (2024), J. Pool *et al*. (2024), S. Thapa *et al*. (2024)

ML remains the basic tool for processing structured medical data, such as electronic health records (EHR), laboratory indicators, or disease progression statistics. SVM, Random Forest, K-Nearest Neighbours, and Decision Trees algorithms provide high explainability of decisions and accuracy with small samples. They are used to classify tumour types, assess the risk of hospitalisation, predict complications, etc. The main advantage of ML is interpretability and low computational complexity, but its effectiveness decreases in cases of unstructured data. DL has become the core of virtual medicine due to its ability to automatically identify patterns in large data sets. CNN, RNN, LSTM, and Transformer architectures achieve high accuracy in the analysis of medical images, time series, and clinical texts. CNNs enable the recognition of pathologies in computed tomography, magnetic resonance imaging, and X-rays, while RNNs and LSTMs work effectively with physiological signals (ECG, EEG). Transformers form the basis of intelligent clinical assistants, triage systems, and decision support. The high accuracy of DL is combined with low interpretability and high requirements for data quality and computing resources.

Generative architectures (GAN, Diffusion Models, LLM) create a new level of adaptability and personalisation. GANs are used to create synthetic medical images, expand datasets, and simulate clinical scenarios, while LLMs (GPT, MedPaLM, BioBERT) are used to process clinical texts, form conclusions, and interact with doctors and patients. They increase the accuracy of predictions and can be used for the creation of digital twins of patients, but require mechanisms for ethical monitoring and validation of results. ML provides transparency and speed of analysis, DL provides the highest accuracy and generalisation ability, and generative AI provides flexibility and innovation in personalised medicine. Their comprehensive combination creates the basis for the formation of an adaptive, explainable, and secure virtual medical ecosystem. Additionally, Table 2 presents an assessment of AI methods according to key performance criteria.

Table 2. Systematic assessment of AI applications in virtual healthcare

Method	Interpretability	Accuracy	Data requirements	Flexibility	Use in medicine
ML	5	3	2	3	4
DL	2	5	5	4	5
Generative AI	2	4	5	5	3
Multimodal architectures	3	5	5	4	5

Source: compiled by the authors based on L. Soenksen *et al.* (2022), M. Cascella *et al.* (2023), W. Abbaoui *et al*. (2024), H. Nilius *et al*. (2024), J. Pool *et al*. (2024), S. Thapa *et al*. (2024)

ML maintains the highest interpretability and stability on small samples, but is inferior to DL systems in terms of accuracy. The latter demonstrate the best results in visual diagnostics and signal analysis, but are highly dependent on data volume and resources. Generative models provide flexibility and the ability to create synthetic medical data, but require proven validation mechanisms and ethical controls. Multimodal architectures combine the advantages of all approaches – high accuracy, generalisation ability, and practical applicability, forming the basis for integrated virtual medicine systems. The differences between the approaches indicate the need for the comprehensive use of different technologies within a single healthcare system.

As of 2025, one of the areas of development of intelligent technologies in medicine is multimodal systems that combine different types of data (visual, textual, signal), as well as demographic and behavioural characteristics of the patient. Such systems can be used to create comprehensive clinical profiles that provide a more accurate determination of health status, improve the quality of diagnosis and the effectiveness of personalised treatment. Thanks to their ability to integrate heterogeneous sources of information, multimodal architectures are becoming the basis of a new paradigm of analytics in virtual healthcare. A key component of such systems is the cross-modal attention mechanism, which can be used in the model to coordinate information between different modalities, including images, numerical data, and medical report texts. This means that the system can simultaneously analyse magnetic resonance imaging results, laboratory indicators, electrocardiograms and clinical records to form an integrated assessment of the patient's condition. Such approaches provide synergy between different data sources, which increases the accuracy of clinical predictions and can be used for the identification of complex inter-system patterns (Abbaoui *et al.*, 2024; Nilius *et al.*, 2024).

The combination of medical imaging results, laboratory tests and text-based medical records can be used for effective prediction of the risks of recurrent stroke, complications from diabetes mellitus or other chronic diseases. Thanks to these technologies, virtual healthcare systems are gradually transforming into intelligent clinical assistants capable of analysing large amounts of diverse information in real time. This approach can be used to create dynamic, context-sensitive medical platforms that support clinical decision-making and promote the development of fully-fledged personalised medicine (Abbaoui *et al.*, 2024). Table 3 summarises the practical applications of ML and DL technologies in various components of digital healthcare.

Table 3. The use of intelligent algorithms in virtual healthcare systems

Direction	Characteristic	Implementation
Intelligent diagnostics based on deep learning	CNN, ViT, U-Net for medical image analysis (X-ray, computed tomography, magnetic resonance imaging, ultrasound), multimodal systems improve diagnostic accuracy and reliability	HAIM framework – image and text integration, diagnostic accuracy +6-33%, cGAN – synthetic data for oncology cases, image quality improvement, U-HPNet, GP-GAN – progression prediction for nodes and glioblastoma
Patient monitoring and digital biomarkers	RNN, LSTM, and Transformers algorithms for time series analysis; AI systems create digital biomarkers for predicting chronic diseases	GluGAN – glucose data generation, monitoring accuracy +15%, ML models integrate genomic and mass spectrometry data for patient phenotyping, use of wearables for early detection of complications
Personalised treatment and recommendation systems	Personalisation of therapy based on EHR, genomic and behavioural data, and the generation of digital twins	MOICVAE – drug sensitivity prediction in cancer (GDSC, CCLE), DRAGONET – generation of new drug candidates, generative AI for synthesising personalised treatment scenarios
Telemedicine and clinical decision support systems	LLM (ChatGPT, MedPaLM) for text analysis, consultations and report generation, hybrid models for decision support	ChatGPT, MedPaLM – asynchronous consultations and automatic reports, cGAN + Random Forest – forecasting the volume of teleconsultations, NLP assistants for reminders and medication planning

Note: U-HPNet – U-Net-based hierarchical prediction network; GP-GAN – generative prediction generative adversarial network; GDSC – genomics of drug sensitivity in cancer; CCLE – cancer cell line encyclopedia

Source: compiled by the authors based on L. Soenksen *et al.* (2022), M. Cascella *et al*. (2023), W. Abbaoui *et al*. (2024), I. Ghebrehiwet *et al*. (2024), H. Nilius *et al*. (2024), J. Pool *et al*. (2024), S. Thapa *et al.* (2024), E. Kumah (2025)

The application of intelligent algorithms in virtual medicine covers diagnostics, monitoring, personalisation of treatment and telemedicine. In particular, the HAIM framework (a conceptual approach used to integrate and manage various technologies and processes in medical and technological systems: H – human, A – algorithm, I – information, M – machine) has demonstrated a 6-33% increase in the accuracy of chest pathology diagnosis by integrating images, text, and time series (Ministry of Digital Transformation of Ukraine, 2023). cGAN (Conditional Generative Adversarial Network) architectures are successfully used to generate synthetic medical images in telemedicine for oncology, which improves the quality of data from portable devices. In the field of monitoring, the GluGAN model (a specific variation of GAN used to create or generate data with certain characteristics related to glucose in the body, particularly for medical applications) can be used to create synthetic glucose profiles, improving the accuracy of predictions in patients with type 1 diabetes. For personalised therapy, MOICVAE predicts drug sensitivity based on genomic data, while DRAGONET generates new candidates for the treatment of cancer and neurodegenerative diseases. In telemedicine services, ChatGPT and MedPaLM are used to automate consultations and generate reports, reducing patient service time. These results demonstrate the practical effectiveness of integrating AI into various stages of the medical process, from data collection to clinical decision support.

In practice, intelligent algorithms are effectively integrated into the functioning of virtual clinics and medical platforms. Virtual clinics Babylon Health and Ada Health use AI models for initial patient triage, automated symptom collection, and recommendations for further action (Cascella *et al.*, 2023). CardioAI and KardiaMobile systems use AI algorithms to analyse heart signals, detect arrhythmias, and monitor the cardiovascular system in real time (Thapa *et al.*, 2024). These examples demonstrate that virtual medicine has moved from experimentation to real-world clinical solutions, shaping accurate and safe digital medicine where AI becomes a "partner to the doctor" rather than a replacement.

Along with the development of clinical support systems, AI is becoming increasingly central in assisting patients before consulting a doctor. Virtual assistants and mobile applications with ML elements can be used to independently monitor basic physiological parameters such as body weight, blood pressure, heart rate, glucose levels, mood, and sleep quality. By analysing the dynamics of these indicators, the system can detect early signs of abnormalities and generate personalised recommendations: to continue collecting additional data (for example, using smart sensors or home devices) or to consult a doctor of a specific profile if the identified trends are persistent. This approach creates conditions for preventive medicine, where AI not only supports doctors but also actively helps people stay healthy. In addition, Table 4 presents the key benefits of implementing AI technologies in a virtual healthcare system.

Table 4. Practical advantages of using AI in virtual medicine

Benefits	Description	Use
Improvement of diagnostic accuracy	Deep neural networks (CNN, Transformers) exceed the accuracy of doctors in image analysis, multimodal models combine visual, laboratory and text data (+18-25% to accuracy)	ADS-GAN – synthetic EHR data without loss of quality; MixEHR-G – 1,515 phenotypes from 1.3 million patients, HAIM – integration of different types of data, exceeding unimodal models
Optimisation of time and workload for doctors	AI automates routine tasks (image analysis, reports), reducing time and workload by 20-30%, while CDSS provides real-time guidance to doctors	cGAN – imputation of gaps in EHR, stable performance on MIMIC-III, ChatGPT – automation of dental consultations, reduction in assessment time
Expansion of access to quality healthcare	Telemedicine platforms, chatbots, and LLMs provide consultations in remote regions, language translation, and asynchronous patient support	cGAN – data generation for haematological research (≈ 7,000 samples), LLM – multilingual triage and communication with patients, CareCall bot – support for patients in remote locations
Reduction in the cost of medical care	Automated documentation, fewer readmissions and physical resources (10-15% savings)	Graph-GAN – synthetic EHRs with performance similar to supervised learning (10% labels), generative AI – reduction in data annotation costs

Note: ADS-GAN – adversarial domain-specific generative adversarial network; MixEHR-G – mixed-type electronic health records generative model; MIMIC-III – medical information mart for intensive care; CDSS – clinical decision support system
Source: compiled by the authors based on R. Shinde *et al.* (2022), L. Soenksen *et al*. (2022), M. Cascella *et al*. (2023), W. Abbaoui *et al*. (2024), I. Ghebrehiwet *et al.* (2024), H. Nilius *et al*. (2024), J. Pool *et al*. (2024), S. Thapa *et al.* (2024), E. Kumah (2025)

The practical benefits of AI in virtual medicine include increased accuracy, efficiency, accessibility, and cost-effectiveness of medical processes. In particular, deep neural networks (CNN, Transformers) exceed the average accuracy of radiologists, providing up to a 25% increase thanks to multimodal data integration (Soenksen *et al.*, 2022; Abbaoui *et al.*, 2024; Nilius *et al.*, 2024). cGAN and Graph-GAN models demonstrate effectiveness in generating synthetic medical records, which can be used to train models without disclosing personal data (Pool *et al.*, 2024; Kumah, 2025). ChatGPT and LLM platforms are used in telemedicine for automated consultations and linguistic adaptation, facilitating access to care in remote regions. The integration of AI tools into virtual medicine not only improves diagnostic accuracy but also contributes to the creation of a more efficient, inclusive, and economically sustainable healthcare system.

AI significantly improves the efficiency and accuracy of virtual medicine, optimises the workflow of medical staff, and expands access to quality services. At the same time, despite the advantages, the introduction of intelligent systems is accompanied by several challenges related to ethics, security, and legal regulation. AI systems make decisions that can directly affect human life and health, so issues of transparency, security, and accountability are relevant. Deep learning models function as "black boxes" and demonstrate high accuracy, but it is not always clear why a model makes a particular decision (van Kolfschooten & van Oirschot, 2024). This creates risks for medical practice, where every recommendation must be justified and reproducible.

The use of ML and DL models significantly improves diagnostic accuracy, analysis speed, and the effectiveness of early detection of pathologies. The integration of CNN, LSTM, and Transformers into virtual medicine systems can not only classify images but also generate predictive models of disease progression. This correlates with the conclusions of H. Sadr *et al.* (2025) that deep neural networks demonstrate a level of diagnostic accuracy comparable to or higher than that of expert radiologists, particularly in the analysis of medical images. The study emphasised the importance of hybrid architectures capable of combining different data modalities (EHR, images, time series) to achieve high generalisation ability. This confirmed the leading role of AI as a tool for improving the accuracy, speed and reliability of clinical diagnosis.

M. Khalifa & M. Albadawy (2024) demonstrated that DL algorithms, particularly CNN, U-Net, and ViT, significantly improve diagnostic accuracy by enabling automatic tissue segmentation and pathology detection with minimal human intervention. Multimodal models that combine medical imaging data, laboratory tests, and clinical records provide a more objective basis for decision-making and reduce the probability of errors in radiological practice. The results of this study support these conclusions: the introduction of DL algorithms into virtual medicine has improved the reliability of image analysis and reduced the time required to make a diagnosis. AI is a key factor in improving the accuracy, speed, and reliability of clinical diagnostics.

The results of the study showed that the use of intelligent algorithms in monitoring systems can be used for the detection of deviations in physiological indicators and the prediction of the development of complications in real time. The use of RNN, LSTM, and Transformer architectures facilitates accurate time series analysis and the formation of digital biomarkers for chronic diseases. This was consistent with the study by S. Shajari *et al.* (2023), demonstrating that wearable sensors integrated with AI provide continuous monitoring of patient status and improve the accuracy of pathology detection. The combination of signals from wearable devices and intelligent algorithms creates a new model of digital health that prioritises prevention and early intervention, indicating the feasibility of using AI to create personalised dynamic health monitoring systems.

R.A. El Arab & O.A. Al Moosa (2025) have shown that the use of AI in medical practice can reduce overall service costs through automation, reduction of repeat hospitalisations, and resource optimisation. The study cited data on cost reductions in various AI application scenarios, from diagnostics to administrative services, demonstrating the positive budgetary impact of implementing intelligent systems. This was consistent with the presented study, which determined that the implementation of AI systems led to a significant reduction in costs, more efficient use of resources, and increased profitability of virtual medical services. AI not only improves clinical outcomes but also has a real economic impact that supports the sustainability of innovation in healthcare.

C.A. Gomez-Cabello *et al*. (2024) demonstrated that AI-based CDSS are being implemented in primary care, improving the quality of consultations and reducing the workload on doctors. The use of LLM, NLP methods, and ML algorithms automates the processes of triage, interpretation of examination results, and formulation of clinical recommendations, significantly reducing the cognitive load on doctors. In addition, the study noted that AI-CDSSs help improve interaction between patients and medical staff through adaptive interfaces and personalised information delivery, improving the quality of communication in telemedicine services. This approach was consistent with the results of the study: the integration of AI into telemedicine platforms and CDSS accelerated decision-making, reduced the burden on medical staff, and improved the accessibility of medical services. Thus, AI is transforming the virtual medicine system, ensuring higher diagnostic accuracy, faster clinical decisions, and cost-effective medical processes. The integration forms the basis of a human-centred, adaptive, and sustainable digital healthcare ecosystem of the new generation.

Regulatory and ethical aspects and prospects for the implementation of AI in virtual medicine

The issue of security in virtual medicine encompasses the protection of confidential medical data and the resilience of algorithms to external attacks. DL models can be vulnerable to adversarial attacks (deliberate changes in input data), leading to false diagnostic conclusions. In a medical context, such errors can have critical consequences, including misclassification of pathologies or incorrect clinical recommendations (Nilius *et al.*, 2024). Protecting patient privacy is the ethical foundation of digital medicine. Medical information belongs to the category of the most sensitive personal data, so its automated processing by artificial systems creates a potential threat of leakage, manipulation, or unauthorised access. Scenarios in which data is transferred via cloud services and integrated between several medical institutions or departmental information systems require critical attention (Abbaoui *et al.*, 2024).

Another significant ethical issue is the bias of training samples. When models are trained on unrepresentative data that predominantly covers patients of a certain gender, age or ethnic group, there is a risk of reproducing social inequalities. Such systems may demonstrate reduced accuracy or even generate discriminatory recommendations for other categories of patients, calling into question their fairness and reliability (Pool *et al.*, 2024). In addition, the principle of explainability is a prerequisite for the ethical use of AI models in clinical practice. The doctor must be able to justify the logic of the system's actions to the patient and explain the basis for the prognosis or recommendation. Despite significant progress in the development of Explainable AI methods, their reliability and reproducibility in real clinical settings remain limited.

The insufficient level of trust that doctors have in automated systems is also a significant barrier. Despite high accuracy rates in studies, clinicians tend to doubt the reliability of such solutions in real-life practice. The main reasons are the complexity of the models, the lack of explainability of the results, and the lack of standardised protocols for integrating AI into clinical processes. Trust in intelligent technologies is only formed when the system is transparent, validated, and provides a clear explanation of its decisions. At the same time, excessive reliance on algorithms is also dangerous: doctors should view AI as an assistant, not the final authority (Kumah, 2025). Therefore, modern 21st-century AI ethics emphasise the need to preserve the leading role of doctors in clinical decision-making, with automated systems performing a supporting function aimed at improving the quality and safety of medical care.

In the context of the growing role of patients as active participants in the healthcare process, it is advisable to consider the ethical and legal aspects of independent use of AI tools. Algorithms that provide advice or recommendations based on the user's personal data must be transparent in the logic of their conclusions and not create a false sense of "self-diagnosis". The collection of basic indicators (weight, blood pressure, mood, pulse, etc.) is only an auxiliary step that should guide a person to consciously seek professional help, rather than replace a doctor's consultation. Therefore, legal norms and standards for AI systems should cover not only clinical applications but also user scenarios for preliminary monitoring, ensuring a balance between convenience, safety, and responsibility.

One of the critical challenges of digital transformation in medicine remains the legal regulation of AI systems in clinical practice. Despite the rapid development of technology, regulatory mechanisms remain fragmented, especially in the area of safety and responsibility for medical decisions made with the participation of AI. At the EU level, a comprehensive regulatory framework has been developed that combines political and legal instruments. The European Commission (2024) document identifies five strategic areas for the development of digital medicine:

the safe integration of AI into clinical processes, including certification and risk assessment mechanisms; building trust in algorithms through transparency, explainability and controllability, creation of a European Health Data Space for the exchange of clinically relevant data sets between Member States, ethical and human-centred implementation of AI that guarantees the priority of human oversight, support for open data standards and interoperability in healthcare systems.

The document also defines ethical principles for the use of AI in medicine, such as patient safety as a key priority, explainability and transparency of algorithmic decisions, human oversight and final decision by a doctor, non-discrimination and prevention of algorithmic bias, and protection of personal data following the General Data Protection Regulation (2016). These principles are enshrined in the Artificial Intelligence Act (2024), which is the first EU legislation to systematically regulate AI. The AI Act classifies medical systems as high-risk and defines three groups of mandatory safety requirements: pre-deployment requirements (mandatory testing of the model for reliability and stability of results, verification of training data, assessment of potential harm to the patient), operational requirements (documentation of decision-making logic, traceability logs, continuous performance monitoring) and post-marketing surveillance (control of developers and operators after implementation, mandatory incident reporting, security system audits). In addition, the AI Act establishes the legal liability of developers and suppliers if it is proven that harm to the patient was caused by an algorithmic failure or non-compliance with data quality requirements. The European model combines ethical principles with specific technical and legal standards, ensuring transparency, traceability and human control at all stages of the AI system lifecycle.

In Ukraine, legal regulation is still in the early stages of development. The document "Roadmap for the Regulation of Artificial Intelligence in Ukraine" by the Ministry of Digital Transformation of Ukraine (2023) envisages the development of the Law of Ukraine "On Artificial Intelligence" and the harmonisation of approaches with the AI Act. The document defines the directions for development: introduction of risk classification for AI systems, development of safety and ethics assessment standards, creation of a national certification system for AI products, and establishment of the legal status of system developers and operators. At the same time, the Ukrainian strategy is conceptual in nature, as it does not contain definitions of the terms "medical algorithm", "clinical decision support system", or "automated recommendation". In contrast to the AI Act, it lacks specific requirements for testing, auditing, and liability in the healthcare sector. The Ukrainian approach is limited to emphasis on the future introduction of European standards, but without a practical mechanism for their implementation.

The European legal framework is characterised by a high level of specificity (requirements, classifications, security procedures), while the Ukrainian one is characterised by declarativeness and a lack of implementation tools. Both documents share a common value base of ethics, transparency and human-centredness, but differ in their level of detail and legal force. A comparison shows that the EU has already formed a multi-level regulatory model, where political strategy determines directions and principles, and the AI Act provides legal implementation. Ukraine is only approaching this system, maintaining its declared goals of harmonisation, but without legal mechanisms for security and accountability. To ensure the ethical implementation of AI in medicine, Ukraine needs to implement risk classification based on the AI Act model, introduce requirements for testing and auditing medical algorithms, legislate the principle of explainability and human control, and create a state body to oversee the safety of medical AI systems. The modern stage of AI evolution in virtual medicine is characterised by a transition from local, highly specialised solutions to complex, integrated and explainable systems that cover the entire clinical decision-making cycle, from data collection to the formation of diagnostic and therapeutic conclusions. Table 5 shows the promising areas of development for intelligent technologies.

Table 5. Conceptual directions for the formation of an intellectual healthcare system

Development area	Primary goal	Key technologies/examples	Challenges/trends
Explainable AI	Development of models capable of justifying decisions to increase the trust of doctors	Grad-CAM, LIME, SHAP for result interpretation; AI for phenotyping and in silico libraries	Balance between accuracy and interpretability; addressing the "black box"; ethical integration into clinical systems
Integration of LLM	Use of LLM for analysis, triage, and communication with patients	GPT-4/5, MedPaLM 2, BioMedLM; Retrieval-Augmented Generation (RAG); telemedicine, telepsychiatry	Control of bias; language localisation; responsible use and audit
Unification and standardisation of data	Ensuring interoperability and security of medical data	Federative learning; blockchain registries; multimodal integration (text, images, time series)	Unification of formats; personal data protection; elimination of "data silos"
Generative models and simulations	Creation of synthetic data and virtual scenarios for training and diagnostics	GAN, diffusion models, LLM-simulations; virtual patients and training	Data confidentiality; quality of synthetic samples; interpretability of models

Table 5. Continued

Development area	Primary goal	Key technologies/examples	Challenges/trends
Security and blockchain technologies	Protection of medical data and access control	Blockchain architectures for HER; AI audit and cyber resilience	Adversarial attacks; blockchain scalability; domain-specific decisions
Ethical and legal regulation	Provision of responsible use of AI in medicine	Regulation (EU) 2024/1689 (AI Act) Roadmap of AI regulation in Ukraine WHO, OECD, G7 standards	Certification of medical AI systems Harmonisation with the AI Act before 2027 Protection of patient rights and privacy

Note: Grad-CAM – Gradient-weighted Class Activation Mapping; LIME – Local Interpretable Model-agnostic Explanations; SHAP – Shapley Additive exPlanations

Source: compiled by the authors

The development of an intelligent healthcare system requires a combination of technological innovations with ethical and legal principles. The integration of Explainable AI changes the logic of diagnosis: doctors transition from "blind" use of the model to conscious interaction, forming the basis of responsible medical decision-making, where the algorithm enhances rather than replaces the specialist. LLMs expand the capabilities of telemedicine by providing personalised communication with patients and multilingual support, but require ethical control to prevent biased or erroneous conclusions.

Data standardisation through federated learning and blockchain paves the way for the creation of global clinical networks without compromising confidentiality, which will contribute to the formation of the European Health Data Space and its integration with Ukrainian systems. Generative models can be used to create digital twins of patients and virtual training, improving the quality of medical training without risk to patients. In the field of security and legal regulation, the key areas are the implementation of blockchain solutions for data protection and the harmonisation of legislation with the AI Act (2024/1689). Ukraine is gradually adapting the principles of certification, audit and transparency within the framework of the "Roadmap for AI Regulation". The further development of intelligent medicine requires a balanced combination of technological innovation, ethical responsibility and regulatory consistency. The identified conceptual directions, from explainable AI to the integration of blockchain and LLM, form the basis of a human-centred, safe and sustainable digital healthcare ecosystem.

The results of the study showed that the key barriers to the implementation of AI in medicine remain issues of ethical oversight, safety, and legal liability, which determine the level of trust in intelligent systems in virtual medicine. C. Mennella *et al.* (2024) analysed more than 150 studies and concluded that the main challenges for digital medicine are the lack of clear regulatory mechanisms, transparent model verification protocols and certification of medical AI systems. The study emphasised the need to create a regulatory framework that balances technological innovation with the ethical principles of patient autonomy, fairness, and privacy. These findings echo the conclusions of this study, which also emphasises the need to develop legal and ethical standards to minimise the risks of clinical AI applications. Both approaches confirm that without a reliable regulatory environment, the introduction of intelligent technologies into virtual medicine cannot be considered safe or ethically justified.

L. Tang *et al.* (2023) analysed the ethical aspects of the use of medical AI systems in a systematic review of empirical studies and determined that the main risks remain data bias, lack of model explainability, and uneven representation of socio-demographic groups in training samples. Such limitations lead to the reproduction of social inequalities in clinical recommendations and reduce user confidence in AI solutions. The results of this study are consistent with these findings, as they also found that the effectiveness of medical AI systems is determined not only by their level of accuracy, but also by their socio-ethical characteristics. Therefore, the elimination of algorithmic bias and the implementation of ethical standards are necessary conditions for the legitimate and safe use of AI in digital medicine.

In addition, Y. Ning *et al.* (2024) conducted a large-scale scoping review on the ethical challenges of using generative AI in medicine and developed an "Ethics checklist", a comprehensive system for assessing the risks of transparency, reliability, and accountability. The authors found that generative models, although they have significant potential for clinical decision support, can produce false or inaccurate conclusions, posing a danger to patients, particularly in the problem of determining responsibility for AI system errors between developers, medical institutions, and physician users. This correlates with the results of the current study on the risks of losing control over autonomous models and the need to regulate their clinical use. The opacity of generative AI can lead to ethical and legal conflicts in digital medicine; therefore, it is advisable to create audit, ethical monitoring and validation systems that will ensure the safe and accountable use of these technologies.

The results of the study indicated that explainability and user trust are key prerequisites for the successful implementation of AI in clinical practice. This was consistent with the study by K. Rasheed *et al.* (2022), stating that the development of Explainable AI is the only way to overcome the "black box" effect in deep neural networks. The study systematised model interpretation methods (LIME, SHAP, Grad-CAM) and showed how they help doctors verify the system's predictions. Without explainability, AI solutions cannot be acceptable in a medical context where clinical responsibility depends on transparency. The development of Explainable AI is not only a technical but also an ethical imperative for digital medicine.

The study by A. Bathula *et al.* (2024) presented the concept of the "triangle of the future", based on the interaction of blockchain, AI, and digital medicine. The combination of these technologies provides decentralised storage of medical data, transparent auditing of user actions, and increased cyber resilience of medical systems. The study substantiated the role of blockchain as a trust tool that eliminates the risks of unauthorised access and data falsification, as well as enhances the security of AI models in telemedicine environments. This is consistent with current research that the integration of AI with blockchain is a strategic direction for the formation of secure and resilient virtual medical platforms. It is advisable to create hybrid frameworks that combine ML, NLP, and computer vision with blockchain verification mechanisms to protect data and prevent adversarial attacks. Thus, the key trend is the formation of a human-centred healthcare model, where AI does not replace but complements the clinical thinking of doctors, ensuring accuracy, transparency and personalisation of medical care. The synergy between technological, regulatory, and ethical components will determine the transition to a new generation of intelligent healthcare systems focused on the safe, open, and fair use of data in the global medical environment, particularly in Ukraine.

Conclusions

The results of the study demonstrated that AI methods are fundamental in the structural analysis of medical data, including EHR, laboratory indicators, and clinical records. SVM, Random Forest, and Decision Trees algorithms ensure the interpretability of decisions and work effectively with limited data volumes. Deep learning based on CNN, LSTM, and Transformer architectures has become the core of virtual medicine, enabling automatic detection of patterns in images, time series, and texts. The combination of ML and DL approaches forms adaptive models with high accuracy and clinical relevance. Generative models create simulations and "digital twins" of patients, while LLM, as part of telemedicine CDSS, accelerate triage, report preparation, and reduces the cognitive load on physicians. The integration of different modalities through cross-modal attention mechanisms provides a comprehensive clinical picture, reducing the risk of wrong decisions in complex cases (comorbidity, rare conditions). The economic impact of AI is reflected in a reduction in readmissions and data annotation/processing costs (through synthetic data and automation), which increases the profitability of digital services.

Key risks remain the vulnerability of models to adversarial attacks, bias in training samples, and the opacity of deep networks, which undermines trust in clinical decisions and necessitates increased explainability and independent auditing. To scale virtual medicine across clinical institutions, the unification of clinical and laboratory data, the interoperability of electronic records, and federated training of AI models are key. Combining this with blockchain ensures data immutability and transparency of access to medical informatiofdn. The EU regulatory vector sets requirements for transparency, certification, and risk management for medical AI systems. Ukraine should harmonise its legislation with the AI Act through the phased implementation of assessment, audit, and ethical control procedures. The priority steps for implementing AI in virtual medicine are Explainable AI approaches in critical tasks, RAG architectures for LLM with controlled knowledge sources, data policies (federated learning + blockchain) and continuous ethical monitoring. Further research should address the integration of explanatory and generative models, the development of secure and transparent AI frameworks, and the creation of a global regulatory and ethical ecosystem for virtual medicine.

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Conflict of Interest

None.

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Використання інтелектуальних алгоритмів у комп'ютерних системах віртуальної охорони здоров'я: від діагностики до персоналізованого лікування

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Анотація. Метою дослідження було теоретично обґрунтувати підходи до ефективного впровадження інтелектуальних алгоритмів у віртуальну медицину. Методологія ґрунтувалась на теоретичному, аналітичному та нормативно-прогнозному аналізі ефективності й розвитку інтелектуальних технологій у цифровій охороні здоров'я. Встановлено, що штучний інтелект (ШІ) трансформує підходи до збору, аналізу та використання медичних даних. Віртуальна медицина застосовує машинне й глибоке навчання для діагностики, прогнозування та персоналізованого лікування, підвищуючи точність рішень і зменшуючи навантаження на лікарів. Методи машинного навчання ефективні для роботи з електронними медичними записами та лабораторними даними, тоді як глибоке навчання формує основу віртуальної медицини, автоматизуючи аналіз великих обсягів інформації. Генеративні моделі створюють синтетичні медичні дані й клінічні сценарії, підтримуючи розвиток персоналізованої медицини та концепції «цифрових двійників». Мультимодальні системи поєднують різні типи даних, забезпечуючи комплексний аналіз стану пацієнта й точніші клінічні прогнози. Переваги впровадження ШІ у підвищенні точності діагностики на 18–25 %, зменшенні часу роботи лікарів на 20–30 %, розширенні доступу до медицини у віддалених регіонах, зниження вартості медичних послуг. Основними ризиками є проблеми безпеки даних, пояснюваності, етики, упередженості та довіри лікарів, що зумовлює потребу у прозорості, контролі й правовому регулюванні. У Європейському Союзі діє спеціальне законодавство, яке встановлює вимоги до безпеки та прозорості медичних ШІ-систем, тоді як в Україні нормативна база перебуває на етапі формування. Для вдосконалення віртуальної медицини доцільно впровадити пояснюваний ШІ, інтегрувати Large Language Models із захистом даних, застосовувати федеративне навчання, генеративні симуляції та блокчейн із дотриманням етичних і правових стандартів. Результати дослідження можуть бути викоритстані фахівцями при прийнятті рішень щодо вибору і застосування інтелектуальних алгоритмів у медичних закладах, дослідницьких центрах т а ІТ-сфері охорони здоров'я

Ключові слова: мультимодальна аналітика медичних даних; цифровий моніторинг; генеративні моделі для симуляцій; пояснюваність клінічних рішень; дистанційна медицина; безпека та приватність медичних даних