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Implementation of digital technologies in the medicine of the future

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Abstract

The parallel development of digital and telecommunication technologies in recent years has created ample opportunities to improve traditional healthcare delivery systems. New models of healthcare services are supported by scientific developments and digital innovations.

Objectives: To improve doctors' expertise and healthcare managers with the main achievements of digital technologies introduction in practical medicine and the possibilities for further development of technologies in this area.

Methodology: A review of articles from professional peer-reviewed journals in the online medical literature search system MEDLINE from the US National Library of Medicine for 2018-2022 was conducted. The article concerns the use of digital innovations in clinical medicine, their achievements in oncology, cardiology, medical imaging and other healthcare fields.

Results: The article discusses the main digital strategies that are part of the practical work of doctors and create new workflows and interactions between patients and specialists of medical institutions. Attention is paid to the advances in computer technology and the challenges they pose to the quality of medical care. The introduction of telemedicine, problems of validation of results and clinical use of artificial intelligence applications, as well as opportunities for their development in the future are discussed.

Conclusion: New technologies, including artificial intelligence algorithms, machine learning, image recognition, radiomics, and telemedicine, are creating the prerequisites for the development of new forms of healthcare delivery. The combination of telemedicine, server-based applications, and machine learning algorithms can provide a synchronised solution to the challenges faced by modern society in ensuring a healthy future around the world.

Keywords: artificial intelligence; machine learning; radiomics; telemedicine; computer model; healthcare;

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Introduction

The widespread introduction of digital technologies in modern medicine in recent years has created a favourable atmosphere for reviewing possible directions for future clinical trials. New theoretical advances and clinical observations pose new challenges in the healthcare sector. The issues of disease surveillance, timely and early detection, improving the efficiency of diagnosis and treatment, search for new methods of treatment and rehabilitation, bringing healthcare closer to the patient and personalising medicine are being rethought.

Research Problem

The factors of digitalisation's impact on the patient-physician relationship need to be studied, as well as the impact of computer technology on the ability to predict the course of diseases and the state of public health. The limits of artificial intelligence application in diagnostics, treatment planning, and patient monitoring, as well as the ethics and transparency of the impact of machine learning systems on the work of healthcare institutions are being discussed.

Research Focus

The ever-increasing flow of data in the form of clinical images, continuous biometric data, and IoT devices is driving a steady increase in the number of studies on the impact of digital technologies on the state of future medicine. Large volumes of data that cannot be processed by traditional methods of human intelligence have significant potential to expand both theoretical knowledge of pathogenic processes in the human body and the practical application of machine learning systems in the diagnosis and treatment of patients.

Research Aim and Research Questions

Improving the familiarity of doctors and healthcare managers with the main achievements and challenges of implementing digital technologies in practical medicine will contribute to the further development of technologies in the provision of medical services to the population. To achieve this goal, it is necessary to find answers to the following questions:

1) What are the main digital strategies that are part of doctors' practice and how do they affect the interaction between patients and healthcare institutions?

2) How computer technologies used in healthcare delivery processes affect the quality of medical care.

3) What has already been implemented in the field of clinical application of artificial intelligence and telemedicine technologies, what prospects for their development are expected in future research.

Research Methodology

General Background

The growth of interest in digitalisation is clearly illustrated in Figure 1, which shows the number of publications in the US National Library of Medicine over the past 20 years. The number of such publications for the key words “digital technology healthcare” has increased from 3-5 per year at the beginning to 1276 this year.

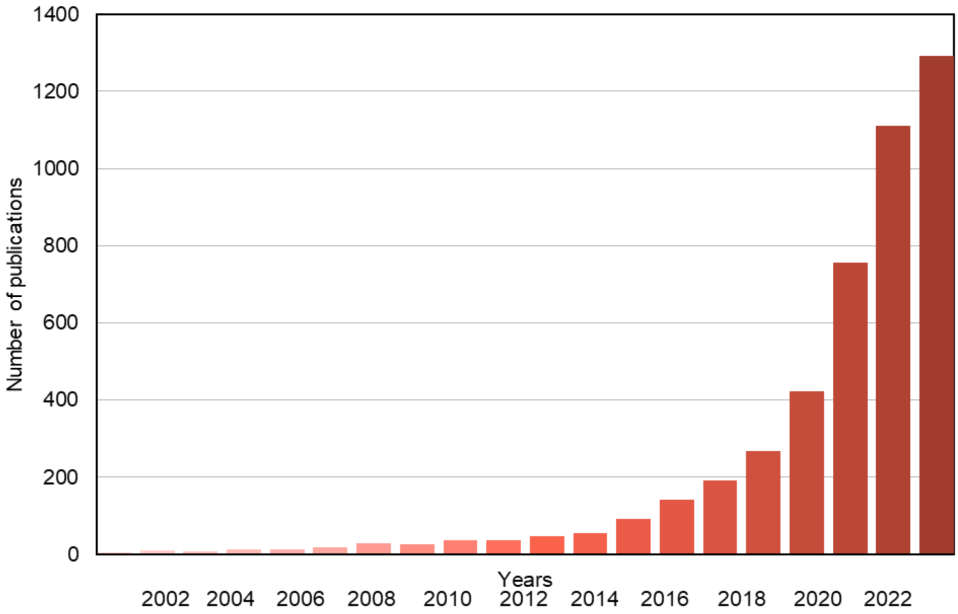

Figure 1. Dynamics of publications concerning the topic over the past 20 years

Data Analysis

To address these research questions, articles from professional peer-reviewed journals using the online medical literature search system MEDLINE from the US National Library of Medicine for 2018-2022 were reviewed. The limitations of the last five years are due to significant technological changes that make it incorrect to compare the capabilities of a decade-old machine park with modern computer equipment. The genders were selected by keywords: "digital technologies", "healthcare", "machine learning", "and computer model". Preference was given to review articles with the maximum coverage of the use of digital innovations in clinical medicine; there were no restrictions on the healthcare sector or the choice of medical specialties. Purely technical articles describing the mathematical justification for the choice of computer technologies were excluded from the review in order to keep the review accessible to practicing physicians and healthcare managers.

Research Results

The rapid introduction of digital changes in the field of medicine is based on artificial intelligence, the development of new mathematical algorithms for data processing, the development of consumer technologies, and the improvement of communication systems. Here are the definitions of the main concepts in the field of artificial intelligence [1], in hierarchical order:

- Artificial intelligence is the ability of a machine to imitate intelligent human behaviour: to learn, solve problems, and find the relationship between facts.
- Machine learning is a branch of artificial intelligence that enables programs to learn solely from collected data without explicit human programming.
- Representational learning is a type of machine learning that algorithmically explores the features necessary for data classification.
- Deep learning is a branch of machine learning that uses multilayer artificial neural networks to solve various problems. The definition of "deep" emphasises the fact that learning goes throughout the entire depth of the neural network, rather than concentrating on any specific level of it.

The results of the distribution of the selected sources by topic are shown in Figure 2. The following presentation of the information is divided into three subsections, in accordance with the research objectives.

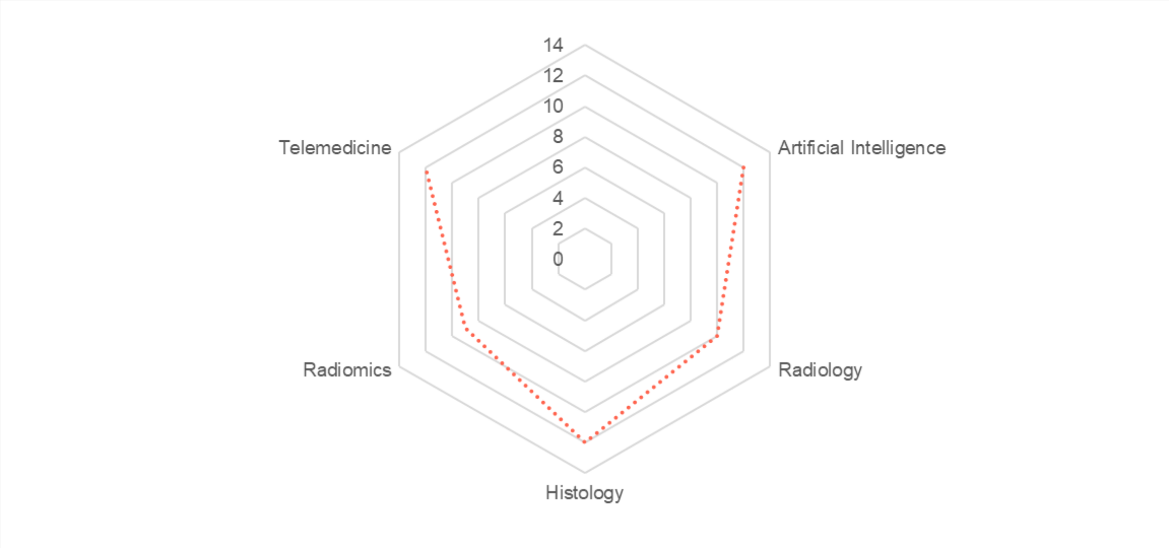

Figure 2. **Breakdown of the number of publications by topic**

Key digital technologies

Analysing the benefits that these modern computer technologies provide to the healthcare system it is visible that: while positively assessing the overall impact of artificial intelligence, many researchers [2-4] consider the simplification of the most common routine tasks of healthcare professionals to be the overall effect of digitalisation. According to H. Shimizu, K. Nakayama [5], deep learning algorithms have revolutionized practical oncology in the field of medical image analysis of clinical radiology and histopathology and successfully solve the problems of image classification in oncodermatology. The use of digital technologies not only eliminates routine human labour, but also reorients the work of image classification specialists to manage a larger volume of individualised care, requiring their attention only in cases that were not classified by artificial intelligence.

Deep learning algorithms can dramatically affect almost all aspects of oncology [6], from improving diagnostics to personalising treatment and discovering new anti-cancer drugs. Drawing on the development of digital technologies, A. Ibrahim et al. point out [7] that new knowledge about the complex nature of breast cancer and the availability of individualised treatments open up fundamentally different possibilities for diagnosing and treating this pathology. If a computer model can provide a better life expectancy prediction for a particular patient than existing risk stratification systems, it will be widely used in the future.

D.A. Hashimoto et al. [8], discussing the use of artificial intelligence in anaesthesiology, summarise six promising areas of its application: 1) monitoring the depth of anaesthesia, 2) control of medical anaesthesia, 3) prediction of intensive care risks, 4) ultrasound assistance in regional anaesthesia, 5) intraoperative pain relief, and 6) operating room logistics. Artificial intelligence demonstrates a decrease in the number of errors in clinical practice, not because it has surpassed humans, but because it narrows the field of attention for a specialist, allowing him or her to focus on the main thing. The authors are confident that the development of technologies that can help monitor the depth of anaesthesia, support drug infusions, or predict hypotension during surgery will allow practicing anaesthesiologists to be more efficient and effective.

Evaluating some of the applications of artificial intelligence methods in cardiology to date, K.W. Johnson et al. [9] identify how cardiovascular medicine can use artificial intelligence in the future. As the amount of possible patient data continues to increase due to the introduction of new research into the clinic, artificial intelligence systems will soon become an integral part of clinical practice. Algorithms will allow for the better treatment choices, eliminating much of the unproductive work of a cardiologist.

After considering the applications, potential limitations, and challenges of computer technology, R. Wang et al. [10] highlight the future prospects of artificial intelligence in the context of reproductive medicine. A medical expert system based on diagnostic algorithms will become the most important tool that can help practitioners solve complex medical problems.

In the era of universal digitalisation, the rapid development of artificial intelligence brings new ideas to forensic medicine [11]. Y.T. Fang et al. in their work present the results of many studies of forensic experts in recent years based on artificial intelligence technology, such as face recognition, age and gender identification, DNA analysis, postmortem interval estimation, identification of injuries and causes of death, demonstrating the feasibility and benefits of using artificial intelligence technology to solve problems of forensic practice.

Computer image recognition

A classic example of the effective use of digital technologies in healthcare is the analysis of data obtained from medical imaging systems, among which, due to their prevalence, radiological images predominate [12-14]. The potential for computer technology to help analyse and interpret X-rays is of particular value, as X-rays are the most common imaging test performed in most medical facilities.

The progress of digital technologies in clinical medicine has made it possible to improve the level of diagnosis of bone and joint fractures of the extremities through the use of multi slice spiral computed tomography post-processing technology. W. Yang and F. Wang [15] conducted routine plain film X-ray radiography in 80 adult patients, followed by a computerised examination. The frequency of pathology detection on X-rays was 69%, and after applying post-processing technologies to computed tomography scans, the frequency of diagnosed pathology was 96%, 98%, and 99% in these 3 groups, respectively.

The role of artificial intelligence systems is vividly illustrated in the work of A. Rodríguez-Ruiz et al. 16, when they compared the effectiveness of breast cancer detection based on a retrospective cross-sectional multicenter study of 240 women. 14 qualified radiologists evaluated the standardized reporting system for analysing breast images for the likelihood of a malignant process twice - independently and with the support of an artificial intelligence system. Decision support included interactive interactions: a click on a breast area provided a computerised estimate of the local cancer probability, traditional lesion markers were used for algorithmically detected abnormalities, and an estimate of the cancer probability based on the examination. As a result, sensitivity with AI-assisted systems increased from 83% to 86% ($p = 0.046$), specificity tended to improve (79% vs. 77%, $p = 0.06$), and the time to analyse one case was similar (unassisted - 146 seconds; AI-assisted - 149 seconds; $p = 0.15$).

In order to determine the potential of artificial intelligence to improve the accuracy of mammography screening by reducing the number of missed cancers and false positives, an international competition was held between the United States and Sweden to develop algorithms [17], with more than 1,100 participants. To train and test the algorithms, 144,231 screening mammograms of 85,580 American women and 166,578 examinations of 68,008 Swedish women were used. An ensemble method was developed and evaluated that combines the best artificial intelligence algorithms and radiologists' judgment. As a result, the most effective algorithm achieved an area under the error curve of 0.858 (USA) and 0.903 (Sweden) and a specificity of 66.2% (USA) and 81.2% (Sweden), while maintaining sensitivity values typical of general radiologists. The combination of a set of selected best artificial intelligence algorithms and radiologists' assessments allowed to achieve significantly better specificity (92.0%) with the same sensitivity.

The introduction of digital artificial intelligence systems is gradually changing the clinical workflow. E.J. Hwang et al. [18] in their study present the results of the development of a deep learning algorithm that can classify normal and abnormal chest X-ray results with major chest diseases, including lung malignancies, active tuberculosis, pneumonia, and pneumothorax. The developed algorithm demonstrated significantly higher efficiency than that of all doctors both for image classification (0.983 vs. 0.814; $p < 0.005$) and for lesion localization (0.985 vs. 0.781; $p < 0.001$). The same picture can be observed in the work of H. Yoo et al. [19], when an artificial intelligence algorithm based on deep learning improved the sensitivity of lung cancer diagnosis for residents (from 0.61 to 0.72; $p = 0.016$) and specificity for radiologists (from 0.17 to 0.24; $p < 0.001$) in detecting pathology. Thanks to artificial intelligence, doctors were able to recommend more chest CT scans to patients with cancer (from 54.7% to 70.2%; $p < 0.001$), and the percentage of incorrectly prescribed tests for healthy patients decreased from 16.7% to 11.7% ($p < 0.001$).

Promising possibilities for detecting brain metastases through the introduction of high-tech algorithms are demonstrated by M. Zhang et al. [20] in a retrospective study of 361 brain scans in 121 patients. First, a computer model detected abnormal areas of high intensity that could be tumour metastases, and at the second stage, the model's classifier analysed the data to reduce the number of false positives. Testing of the brain images demonstrated 96% sensitivity, with 20 false-positive metastases per scan and 0.24 false-positive metastases per slice. The authors conclude that the deep learning method has a high potential for detecting brain metastases with high sensitivity and sufficient specificity. This result is also confirmed by the work of P. Azimi et al. in [21], in which the artificial neural network showed the best result of 95.3% accuracy in similar conditions. We can be sure that the introduction of artificial intelligence technologies in the future will significantly improve the quality, value and efficiency of the radiology service in providing medical care to the population and preserving the public health of future generations [22, 23].

The rapid development of digital technologies has created a new area of computer image analysis called radiomics [24]. If we think of a diagnostic image as a digital array, then, in addition to the features visible to the researcher, algorithmic analysis can be directed to the quantitative characteristics of the array and thus obtain valuable diagnostic information. Understanding the main types of radiomarkers can facilitate the perception of the results of modern research and their selection for practical clinical use. Here is a brief description of the most common radiomarkers, the full list of which is far beyond the scope of this review and requires special mathematical knowledge. The main radiomic features include: statistical descriptors of the gray-level histogram (mean, maximum, minimum, variance, and percentiles), second-order features (symmetry and kurtosis, which describe the shape of the data intensity distribution), texture features (absolute gradient, grey-level matrices, lengths of segments and zones by grey level, neighbourhood tone matrices), features of parameterized and autoregressive models, fractal analysis data (dimensionality, lacunarity), features based on transforms (Fourier, Gabor and Haar wavelet transforms, quadrature mirror filters) and features based on shape (compactness, sphericity, density). Thus, in addition to morphological features visible to humans, many hundreds of radiological features correspond to one medical image, which greatly expands the analysis capabilities but requires complex mathematical calculations [24, 25].

Recent studies [26] have demonstrated the potential usefulness of radiomics for staging liver fibrosis, detecting portal hypertension, identifying characteristics of focal liver lesions, and predicting liver malignancies. Radiomics is actively used to analyse computerised lung images [27] for the timely detection of early forms of malignant tumours. By analysing quantitative information from diagnostic images that cannot be recognized or evaluated with the naked eye, it can be used to record tissue properties such as the shape and heterogeneity of their structure, their changes over time during serial imaging [25].

In oncology, the assessment of tissue heterogeneity, for example, during treatment or follow-up, is of particular interest [27, 28] as a prognostic determinant of survival and a marker of tumour aggressiveness. It has been suggested that radiomic features are directly related to genomic, transcriptomic, or proteomic characteristics of tumours [24, 27, 28]. For example, in a retrospective multicenter study [28], radiomic signatures were identified and validated in 803 patients to assess the condition of axillary lymph nodes in breast cancer. The multiple signatures, which included magnetic resonance imaging data of the tumour and lymph nodes, clinicopathological characteristics, and molecular subtypes, demonstrated a high level of prediction of lymph node status (AUC 0.93). A correlation was found between the obtained radiological features and the features of the tumour microenvironment, including immune cells and types of methylated sites.

The result of the differential diagnosis of early stages of nasopharyngeal carcinoma, which is relevant for modern oncology, was demonstrated in a recent study by L.M. Wong et al. For the screening selection of patients for malignancy among patients with benign hyperplasia, an ensemble method of processing radiomarkers was developed on magnetic resonance imaging data of 442 patients, which achieved 85% efficiency in separating pathologies ($p = 0.05$). And in the work of H. Bae et al. [30], a retrospective study of 502 patients who underwent computed tomography with contrast was conducted to differentiate between cysts, haemangiomas, and colorectal metastases to the liver. The diagnostic performance of the developed model for assessing radiological features was compared with the diagnostic performance of 4 qualified radiologists. The model demonstrated lower efficiency and specificity for haemangiomas and metastases than the doctors, but comparable diagnostic efficiency (84.36%, AUC 0.9426) for distinguishing between metastases and benign liver lesions.

However, the capabilities of new technologies are widely used not only in leading oncology clinics around the world. For example, Chinese experts [31] investigated the possibilities of preoperative differential diagnosis of tuberculous granuloma and lung adenocarcinoma, which manifest as a separate solid dense nodule in the lung. A deep learning model was built to segment the nodule on plain computed tomography images of 426 patients, of which a training cohort ($n = 123$), an internal validation cohort ($n = 121$), and an external validation cohort ($n = 182$) were identified. A comprehensive model was developed with clinical factors such as age, gender, and subjective computed tomography data (lesion size, localization, margin, multifocality, and spicules) and individualized radiomicrographs were constructed to confirm diagnostic capability. As a result, the developed diagnostic model showed 96.6%, 93.4%, and 90.6% efficiency for the training, internal validation, and external validation cohorts, respectively.

The results of the preoperative diagnosis of osteoporosis by Y.W. Jiang et al. are also optimistic [32]. In their study, a radiomarker signature based on computed tomography of 386 vertebral bodies was developed and validated for screening osteoporosis of the lumbar spine. The 3D slice module automatically extracted 1040 radiological features from the scans and created a specific signature. The sensitivity, specificity, accuracy and area under the receiver operating characteristic curve (AUC) of the Hounsfield model and the radiomic signature were calculated. The AUCs of the radiomarker and Hounsfield model were 0.96 and 0.88 in the training sample and 0.92 and 0.84 in the test sample, respectively ($p < 0.05$). Thus, the computed tomography-based radiomic signature can differentiate patients with osteoporosis before lumbar spine surgery, providing valuable information for surgical decision-making without additional costs and radiation exposure.

Important changes in medical image analysis capabilities occurred with the advent of whole slide imaging (WSI), which is the result of scanning a microscope slide with a high resolution suitable for clinical use. Specialized clinical scanners for producing such digital images became available more than 20 years ago [33, 34]. Progress in this area has improved the resolution and throughput of slide scanning, and software tools for viewing the images on a monitor screen and integrating them with medical information systems have developed [34, 35].

M.G. Hanna et al. [35] present the results of their own randomized study of the equivalence and effectiveness of the use of PCR, in which the overall diagnostic equivalence for primary diagnosis was 99.3% between the standard method and PCR. The digital method showed an increase in the time required creating a clinical report by an average of 19% per case, and no significant difference was found in terms of the researcher's personality, specialisation, or sample type.

The vast majority of publications positively characterize the use of CCD, demonstrating that their use is sufficiently appropriate in comparison with traditional light microscopy for diagnosis [36-38]. However, it is worth identifying and evaluating possible artefacts and technological risks that may affect the study result. This approach is demonstrated by P.C. Rizzo et al. [39], who present the results of a systematic literature review to analyse possible technical or diagnostic problems with the use of PCR. Of the 45 studies analysed, technical problems were reported in 15 (33%), diagnostic problems in 8 (18%), and 22 studies (49%) reported both types of problems. Technical problems included slide scanning failures, longer viewing times, and the need for higher image resolution. Diagnostic problems included cases of diagnosing dysplasia, determining the edge of invasive growth, reliable assessment of mitoses, and issues of microflora identification.

The integration of CCD technology with algorithms for detecting quantitative image data significantly increases the diagnostic capabilities of the method [40]. The software tool "HistomicsML2" of the histological pattern classifier in the detection of tumour-infiltrating lymphocytes in breast carcinoma and skin melanoma improved the recognition accuracy to 88.9%-92.4%. An important result is demonstrated by the application of a deep learning system for preliminary pretreatment marking of breast cancer [41]. When the system was applied to 44,732 BCIs from 15,187 patients with prostate cancer, basal cell carcinoma, and breast cancer metastases to the axillary lymph nodes, 65-75% of images were excluded with high confidence, while maintaining 100% diagnostic sensitivity. The impact of digital technologies on breast cancer imaging has a multifaceted effect [42], including the education of specialists with the creation of training datasets, ensuring the quality of diagnosis in terms of providing alternative viewing and the ability to archive and provide access to clinical information.

Telemedicine

The active expansion of communication networks and the increasing availability of mobile devices have prompted the rapid development of telemedicine services. Telemedicine, as the use of digital communication technologies to provide medical care to the population, has proven [43-45] to be at least equivalent to face-to-face care, improving access and reducing costs with a high level of patient satisfaction. Telemedicine can be a component of prevention, providing patients with information about their health status, monitoring chronic diseases such as diabetic retinopathy, glaucoma, and macular degeneration. The spread of ophthalmology programs has improved the quality of care for diabetic retinopathy and retinopathy of prematurity [43]. Family doctors can take advantage of a standardised approach to the assessment and diagnosis of musculoskeletal problems through telemedicine visits [45]. In oncology, telemedicine interventions include [44] remote diagnostics, remote chemotherapy monitoring, symptom management, and palliative care. Digitalisation of communication is widely used to expand access to clinical trials of cancer drugs, some of which can be used with mobile technologies. Telemonitoring of patients avoids long queues and reduces the number of hospitalizations, and electronic prescriptions reduce the number of possible errors in prescription, patient age, or dosage [43, 44].

This year's coronavirus pandemic has exacerbated the need for alternative methods of providing modern medical care. An analysis of 97614 visits by employees of 6 general and emergency medicine clinics at Stanford University [46] showed a positive attitude of stakeholders toward video consultations during the coronavirus pandemic. In 3 weeks after the almost complete transition to video visits, 53 semi-structured interviews were conducted and critical issues for further use of the program were identified. Participants emphasised the need to simplify the technology, introduce multi-party video conferencing, enable the connection of narrow specialists, and introduce trainings for doctors on virtual examination and diagnosis of patients at home.

In order to study patient characteristics that influence the choice of a video visit over a hospital visit, M.E. Reed et al [47] conducted a study of data from 1,131,722 patients who made an appointment with a primary care physician through the Kaiser Permanente Northern California patient portal. Out of more than 2.2 million appointment requests, 86% were scheduled as hospital visits, 14% as telemedicine services, and half of them as video visits. The choice of telemedicine services had a statistically significant dependence on the socio-demographic characteristics of patients: people aged 65 and older were less likely to choose telemedicine than those under 44; patients from areas with high internet access were more likely to use video visits, and even the availability of paid parking near the clinic encouraged people to choose a telemedicine visit.

Active research is ongoing to identify and remove barriers to the widespread use of telemedicine technologies [44, 45, 48], and to assess patients' attitudes and needs. Thus, C.E. Hawley et al. [6t] in 2019-2020 assessed patients' personal needs through telephone interviews after the visit. Only 68% of patients indicated an interest in home video visits, 64% of respondents had the technical capabilities to do so, and only 42% of patients were confident that they would be able to participate. The authors divided all patients into 4 cohorts based on the principle of "interested and able," "interested and unable," "not interested and able," and "uninterested and unable" and developed special trainings for each group to overcome barriers to patient acceptance of telemedicine services. Given the cost of technical equipment and training for medical staff and patients, further research is needed to understand the scaling up of efforts and integration of telehealth visits into the population health care system [43, 45, 48].

The economic component of telemedicine services was investigated by A. Buvik et al. in a randomised controlled trial of 389 patients (559 consultations) who were referred to the University Hospital of Northern Norway for an outpatient consultation with an orthopaedist. The intervention group of 199 patients received 302 video-assisted remote consultations, and the control group of 190 patients received standard outpatient care in the hospital (257 consultations). The quality criterion was a comprehensive assessment of "quality-adjusted life years gained" (QALYs), and costs were calculated after 12 months by analysing medical records. The authors concluded that orthopaedic video consultations were cheaper than standard outpatient visits to a specialist if the total number of consultations exceeded 151 per year. With a hospital workload of 300 consultations per year, the calculated annual cost savings amounted to 18,616 euros. Thus, this work proves that, if properly organized, providing video consultations by specialists for remote facilities instead of patients coming to the center is a cost-effective measure, both from the point of view of society and healthcare institutions.

Artificial intelligence technologies have proven to be promising in many studies, but the success of clinical application depends on the conditions of patients' response to modern changes in the healthcare system. H.A. Haenssle et al. [50] conducted a patient survey to assess patients' attitudes toward artificial intelligence in melanoma diagnosis in Germany. The anonymous survey assessed patients' expectations and concerns about the use of artificial intelligence in medicine in general, as well as about various applications. About 94% of the respondents supported the idea of using artificial intelligence in clinical approaches, and 88% even expressed their willingness to anonymously provide data on their health status for the further development of telemedicine applications in medicine. As for the disadvantages of using AI-based software in medicine, patients were concerned about insufficient data protection, impersonality, and the likelihood of errors, and expected more accurate and objective diagnostics, and fewer diagnostic errors.

In a more recent study in 2021 [51], researchers assessed the potential acceptance of digitalisation by the younger generation. An anonymous online survey was conducted of the preferences and concerns of people under the age of 35 via three social networks (Facebook, LinkedIn, and Xing) regarding remote diagnosis on mobile applications for skin cancer. 66.5% of respondents expressed a positive attitude toward the use of telemedicine technologies, more so among participants living in urban areas and those who already use mobile health and fitness apps. Analysis of the responses of negative participants showed that data security, lack of trust in the app, and lack of personal interaction were the dominant problems with telemedicine use. Thus, in order to move from experimental work to clinical practice, patients of all age groups expressed demands for greater transparency and clarity of digitalisation-based tools. The critical preferences and concerns of people of all ages were similar when compared to each other and to the results.

A 2018 Cochrane systematic review [52] noted that telemedicine technologies can currently correctly identify most malignant skin lesions, but research participants' concerns about obtaining images from smartphones of sufficient quality should be taken into account. Telemedicine enables general practitioners to receive timely specialist advice on suspicious lesions of visual localisation by sending data for delayed review or interactive consultations using video conferencing to communicate between the patient, general practitioner, and specialist in real time. For the correct diagnosis of skin cancer based on photos, the average sensitivity was 94.9% and the specificity was 84.3%. For the detection of invasive melanoma or suspicious variants, the sensitivity ranged from 59% to 95% and the specificity from 30% to 93%, including the decision to refer to a specialist or excise the lesion for further diagnosis.

New perspectives for healthcare institutions and the general population arise from the interpenetration of digital wearable technology and machine learning. G.L. Farina et al. [53] studied the accuracy of automated obesity detection by deep learning using a smartphone camera. Digital lateral images of men and women were analysed in comparison with dual-energy X-ray absorptiometry. The authors developed a qualitative model for predicting fat mass based on two-dimensional digital images, which greatly simplified the practical task of identifying the obesity phenotype in adults. The gender-specific features of smartphone images and the type of obesity were significantly correlated ($R = 0.99$, $p < 0.05$) with the results of absorptiometry. And if we combine this approach with the results of a pilot study by S.A. Alsareii et al. [54] on the creation of a new Internet of Things platform that offers ultra-reliable communication for monitoring patients' condition, we can confidently assert the enormous potential for transforming traditional healthcare systems through artificial intelligence.

Discussion

The analysed works generally reveal the positive nature of the changes caused by the widespread use of digital technologies in the field of medicine. The optimistic expectations for improving the quality of disease detection, timely diagnosis, creation of individualised treatment plans, and monitoring of prevention are generally being met in many areas of professional interest to healthcare professionals.

Eliminating many routine tasks frees up the attention of healthcare professionals and the ability to apply unique human skills. The introduction of artificial intelligence systems in healthcare facilities improves doctor-patient relationships, promotes empathy and interpersonal communication. In recent years, significant progress has been made in the development of algorithms for analysing radiographic examination methods, large amounts of publicly available image data have been collected, and artificial intelligence methods have been developed that demonstrate accuracy and efficiency equivalent to that of qualified radiologists. Smart systems in portable wearable devices based on artificial intelligence will play a key role in creating the future of healthcare.

However, some problematic issues were not covered. First of all, we are talking about one of the richest sources of clinical data - the patient's electronic medical record. The possibilities of processing natural unformalised medical records are underutilised. The unstructured text, high level of information noise, sparse and inconsistent data have not found methods for special data processing and cleaning. Inefficient technologies for keeping records should be replaced by the use of databases with standardised disease codes and harmonised vocabulary, and user-friendly software.

It's also worth noting that both researchers and practitioners are concerned about the inability to identify the criteria used by deep learning systems to achieve high performance. Several hundred criteria fed into neural networks turn into a complex system of neural output weights distributed throughout the network and cannot be analysed by humans. This creates the phenomenon of a "black box" in which we can only track input and output data, and the decision-making mechanism itself remains unclear. A shocking fact [55] was the ability of artificial intelligence to determine a patient's race based on impersonal radiological data, in which researchers could not identify any race-related features (constitutional and phenotypic features, prevalence of specific diseases, tissue density, etc.) Although the arbitrary determination of a person's race when he or she does not want it does not pose an immediate threat, the evidence that there is currently no way to control the undesirable behaviour of deep learning models requires solutions to a whole range of legal and ethical problems in the future application of artificial intelligence.

Digital technologies in the healthcare system still require public awareness, detailed testing, and further clinical trials. Before widespread implementation for direct use in clinical practice, it is necessary to ensure that computer systems are adapted to the real working conditions in medical institutions, which should include not only mechanisms for assessing accuracy and efficiency, but also rules for the safety of patients' access to the healthcare system.

Conclusions and Implications

In conclusion, the following conclusions can be drawn:

1. New technologies, including artificial intelligence algorithms, machine learning, image recognition, radiomics, and telemedicine, create the prerequisites for the development of new forms of healthcare delivery.

2. The progress of computer image recognition technologies already makes it possible to achieve diagnostic accuracy and specificity comparable to the results of experienced specialists.

3. The ability to simultaneously process large amounts of patient data using sophisticated mathematical algorithms is leading to the creation of new technologies in medicine, such as full-slide digital image visualisation or radiological signature analysis.

4. Thanks to the availability of high-quality communication and the prevalence of mobile devices, patients and doctors can interact virtually through telemedicine technologies, remotely receiving, storing, and sending clinical data.

5. The combination of telemedicine and machine learning algorithms can provide a synchronized solution to the healthcare challenges faced by modern society to ensure a healthy future for its citizens.

Declarations

Data Availability Statement

All data contained in this publication is publicly available and can be accessed via the links provided.

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The work was carried out by the authors independently without additional sources of funding.

Institutional Review Board Statement

D The study is a literature review and does not have grounds for review by an ethics committee.

Informed Consent Statement

The nature of the study does not require informed consent.

Conflicts of Interest

There is no evidence of a possible conflict of interest in relation to the study. Ethical issues, including plagiarism, informed consent, misconduct, data falsification, double publication, and duplication, were fully complied with.

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