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THE TRANSFORMATIVE IMPACT OF LARGE LANGUAGE MODELS IN HEALTHCARE

Over the past decade, we have witnessed rapid technological advances in healthcare. The main signs of this are the provision of higher quality medical services, lower costs, and improved access to preventive measures. Modern digitalization is represented by various tools in the healthcare system. Support and further development in these areas is the key to, firstly, creating appropriate living conditions, secondly, increasing the age limit for the population, and thirdly, developing a healthy nation around the world. The object of this work is Large Language Models (LLMs), namely, the streamlining of actions for their application in the healthcare system, which is a driving factor for modern changes and improvement of this area of life support in general. This study presents the material on the application of artificial intelligence in the healthcare system through a comprehensive review of medical scientific literature, summarizing the practical application of large language models, and analyzing the main advantages and disadvantages of the current state of digitalization in the industry. By using the methods of observation, generalization, systematization and comparison, the authors have achieved results in determining the significance of the use of large language models. It is also determined that the introduction of artificial intelligence has positive results, but needs to be improved. The formalized and specific comparisons of the diagnoses made by a doctor and artificial intelligence do not coincide with the chosen treatment history, which indicates an imbalance and can potentially harm the patient. The results show the need to improve large language models. In general, this applies to issues such as training of medical staff, identification of implementation methods, systematization of management tools, and expansion of information system databases (including protection of patients' personal data).

Keywords: *healthcare, large language models, artificial intelligence, software medical product, medical data analysis.*

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1. Introduction

The increase in the world's population in recent centuries, not by a few positions, but by several positions and the total value of more than eight billion people indicates a rapid growth rate. This was prompted by the development of the medical industry and the ability of scientists to achieve an increase in the average human age by almost two times. One hundred and fifty years ago, at the end of the 18th century, a person could live only up to 40 years, but today an indicator of over 80 years is considered normal [1].

Increasingly, there are more centenarians on the planet, aged 110–120 years, but soon this will no longer be surprising. Scientists believe that people can live up to 150 years; however, this might become a problem. If the planet's population continues to grow and life expectancy keeps increasing, hospitals will more frequently face a shortage of beds, and medical staff will be overwhelmed [2].

The COVID-19 pandemic has made this issue evident. Hospitals are struggling to cope with the influx of patients, and governments are trying to deal with the pandemic's aftermath. COVID-19 has rolled back life expectancy worldwide to levels seen during World War II, affecting developed countries the most, including the United States, the United Kingdom, France, and others.

Over the past decade, we have witnessed rapid technological advancements in healthcare, but there is still a long way to go to effectively utilize many of these exciting and often exponentially developing systems. Technology alone is not enough; it must be aligned with incentives, payment models, local culture, workflow, social determinants, regulatory and ethical requirements, and integrated into medical education [3–5]. The effective use of these solutions today and in the future has the potential for genuine democratization of healthcare, providing quality care at lower costs, and significantly improving access to effective prevention, care, public, and global health worldwide.

Today, decoding a full genome sequence costs ten times less than it did in 2011, and by 2031, genome sequencing prices are expected to be 100 USD or less, including those performed using third-generation sequencing [6]. Besides the genome, data on the microbiome (from the gut to the oral biome), proteome, and even the metabolome (with disposable continuous glucose monitors, CGM) can now be obtained.

And, of course, the "digitome" from a wide range of wearable devices will soon be available, as well as a more contextual "sociome".

In the next decade, there will be further significant integration and application of these numerous "omes".

In ten years, people will regularly access their individual "digital twins" via the cloud. These digital twins, through the synthesis and integration of foundational and dynamic information using artificial intelligence (AI), will enable increasingly accurate "predictive analytics" and modeling. This will allow for the practical management of individual "precision health", encompassing prevention, diagnosis, and tailored, optimized therapy.

Exponential Growth Trajectory: by 2031, many functions in our smartphones for will be taken for granted, seamlessly integrating into our augmented reality (AR) world. By then, it will be possible to use AR applications embedded in contact lenses or stylish glasses (such as Apple's AR glasses or Google's AR platforms). The emerging Metaverse will evolve, with the "Med'averse" becoming a hub for elements of medical education, VR-based treatments, and even healthy social interactions.

The exponential trajectory of technological development continues despite wars, depressions, and pandemics. New computational technologies, including quantum computing, are emerging with the potential to solve problems that classical computers simply cannot. By 2031, these technologies will likely begin unlocking profound new capabilities, from computing targeted personalized drugs and biologicals to making sense of terabytes – and soon, petabytes – of health data generated by each of us. IBM has called this next period the "quantum decade" [7–9].

Next-Generation Mobile Devices: wearable devices will continue to evolve beyond the wrist, potentially achieving battery life of over a week (an area not yet developing exponentially). In the near future, certified continuous blood pressure monitors on patches and wrists will emerge, as well as likely precise, non-invasive continuous glucose monitors. Increasingly, our wearables will be supplanted by "invisibles" – environmental sensors operating through the Internet of Medical Things (IoMT), which will measure and make meaningful our parameters, from vital signs to voice tone and subtle changes in gait [10, 11].

Our mobile devices, driven by apps, will increasingly move into genuine healthcare. More "one app for all" platforms will emerge, becoming less fragmented, more integrated, and optimized for user needs, diseases, social factors, and more.

Visualization and Diagnostics: diagnostics will become even more portable and sophisticated with the help of AI, enabling deeper diagnostics, sometimes under the guidance of remote physicians, and other times through interactive adaptive protocols managed by AI. Breakthrough new diagnostic systems using new lasers, ultrasound, and holographic systems will enter the market, leading to truly affordable imaging from anywhere by almost anyone. Accelerated use of AI in radiology for image interpretation will yield more accurate real-time results, saving lives [12–15].

Digital pathology will nearly entirely replace the microscope, allowing digital biopsy images to quickly determine potential malignancy, subtype, and molecular and genetic signatures, which today can only be obtained through expensive and labor-intensive molecular probes and sequencing.

"Smart toilets" might regularly analyze your gut and urine, detecting issues at an early stage based on subtle changes compared to your baseline. Combined with genomic data, dynamic microbiome, and metabolism information, they will contribute to the development of "precision nutrition", freeing us from one-size-fits-all diets and regimes that are often ineffective or even harmful.

From Concept to Reality and Clinical Benefit: the management of electronic medical records (EMRs) is being facilitated by the development of natural language processing applications that listen to clinical encounters and can draft notes and even bills [16]. By 2031, initiatives launched during COVID, such as "Patients Over Paperwork", will bring more sanity, balance, and intelligence to documentation. Human speech processing and related technologies will significantly reduce the burden on doctors, reviving "patient-centered care" instead of "chart-centered care".

AI as a Complement to Human Intelligence: AI technologies and big data will be integrated into all aspects of healthcare delivery, especially the patient and physician workflow. This will help fulfill the long-awaited promise of applying big data to gain insights and actionable, personalized knowledge, thus bridging the gap to bedside implementation.

Crowdsourced data and patient opinions, already shared on platforms like StuffThatWorks, could lead to AI-generated recommendations appearing in EMR interfaces, guiding therapeutic decisions tailored to individual patients [17].

Telemedicine, Virtualized Healthcare, and the "Home Hospital": further convergence and expansion of connectivity (6G, potentially 100 times faster than 5G and ~1000 times faster than 4G) will ensure connected healthcare almost everywhere. A significant portion of the world's population, currently without regular Internet access, will be connected through satellite systems. This could greatly enhance telemedicine, global health, and healthcare equity [18, 19].

A key element of virtual and remote care is the ability to diagnose at home. The early stages of the pandemic highlighted the unmet need for rapid, frequent, accurate, cheap, and simple COVID testing. New innovations will not only improve testing for infectious diseases but also provide affordable diagnostics for other diseases, crucial for public and global health.

Integrating Disparate Health Signals: by 2031, value-based care models will be in practice. For physicians, consulting the cloud log of wearable devices and the "digital health stream" will become standard to obtain reliable information about cardiovascular and other diseases.

Data accumulated over the years will help translate insights from millions of patients and wearable device data into practical conclusions that can be applied across various care paradigms. Doctors might even act pre-emptively when personalized algorithms detect you are dangerously out of range (e. g., blood pressure) and adjust the composition of your personalized 3D-printed pills at home (with combinations and doses fully optimized for the individual) [20, 21]. Essentially, having an understandable personal "biometric health profile" and early detection of deviations from the baseline will be a significant shift towards proactive, prevention-focused care.

The Rise of Robots: by 2031, it will possible to transit in surgery from "robot as surgeon's assistant" to "surgeon as robot's assistant", and in some cases, to fully autonomous operations. Doctors will be able to "teleport" into humanoid robot avatars to provide remote assistance, bridging the gap to more autonomous clinical robotics.

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Robots will also become smaller, with some being swallowable. Robotic pills, capable of delivering biologics to the intestinal wall, are already undergoing human trials.

Exoskeletons are already on the market for rehabilitation, allowing paraplegics to walk, and it is possible to see an explosion of consumer versions [22, 23]. These will assist firefighters and emergency responders, as well as help frail elderly individuals climb stairs.

Enhancing the Skills of 50 % of Underperforming Doctors: platforms like Proximie already enable physicians of all types to "virtually assist" in operating rooms or procedure rooms, train less experienced doctors, and share their skills in real-time. As more procedures are recorded on video and AI analyses vast amounts of data, platforms like Theator will enhance the skills of average surgeons, guiding them to perform at the level of the best [24]. This will improve outcomes and help make surgical interventions accessible to the 5 billion people who currently lack access to safe surgery.

Medical simulation based on virtual reality, combining video game dynamics and graphics on affordable consumer headsets, will improve medical training. Digitally assisted surgery will become the norm, with each orthopedic implant perfectly fitting the patient's anatomy. More implants will be equipped with built-in sensors to transmit information about the health of the artificial joint or device to the outside world, much like pacemakers do today.

Direct Interaction with Our Brains: digital mental health solutions are rapidly evolving to meet growing needs and will become a standard element of care for optimizing mental well-being and managing conditions ranging from anxiety and depression to PTSD and schizophrenia. These methods are particularly valuable for those who lack regular or easy access to in-person psychiatric care, and can combine in-person sessions with both human and virtual psychologists [25, 26]. Wearable devices will play a role in diagnosing and managing clinical mental illnesses (Fitbit recently filed a patent for detecting bipolar disorder and depression).

The past decade has seen exciting advances in brain-computer interfaces. Currently, advanced systems of this type are experimental and mainly intended for quadriplegics to control robotics and on-screen cursors. However, times are changing – Neuralink aims to move from providing capabilities to the disabled to offering super-abilities to those of us with full neurological function. As brain implants shrink over the next decade, it is possible to see the emergence of "digital mind pills", which are now being developed as small implants for treating depression and other brain disorders.

Organ Transplantation as Humanized Livestock Farming: the problem of organ transplant queues remains acute, with thousands dying each year due to the lack of available organs. While tissue engineering, combined with stem cell biology and 3D printing, holds promise for creating less complex organs, the ability to create functional, vascularized complex organs remains challenging.

The tissue engineering and 3D printing approach is likely to be disrupted by advances in xenotransplantation. In October 2021, the first successful xenotransplantation of a humanized pig kidney (albeit short-term, lasting 54 hours, in a brain-dead human) was performed, and recently we have witnessed a pig heart being transplanted into a human. In ten years, humanized kidneys, livers, hearts, and other organs derived from pigs, while not becoming the norm, could be included in the "menu" for transplantation when donor organs are unavailable [27–29].

Detecting Disease at Stage 0: in 2021, GRAIL launched the Galleri test for the early detection of more than 50 types of cancer through blood. Innovations by companies like Guardant and Tempus determine therapeutic choices (including in cancer immunotherapy). This work, using the merger of next-generation sequencing, big data, AI, and CRISPR technology, was impossible ten years ago. What seemed like science fiction will become the standard of care for cancer detection and treatment, becoming less expensive and globally accessible [30–32].

There is much more reason for optimism. In the next year or two, the first officially approved based on changes in the genetic code for such diseases as sickle cell anemia or the possible emergence of hereditary retinal diseases.

Large language models (LLMs) are rapidly transforming the healthcare landscape, moving from discovery to real-world applications with profound implications for patient care, clinical research, and improved communication. Their ability to compute big data, generate exclusive ideas, and create human-quality text contributes to innovation in various aspects of healthcare [33].

Thus, *the aim of this research* is to highlight the relationship between the development of the healthcare industry and artificial intelligence in medical institutions as a factor determining progress and a motivator for development.

2. Materials and Methods

In this work, we scientifically sought the basis for the application of artificial intelligence in medical institutions (service provision) by analyzing a large range of scientific literature in different languages among international indexed publications over the past decades, but more emphasis was placed on English-language publications due to their scientific and practical significance.

The most common are large language models (LLM) – this is a post-research algorithm created by artificial intelligence based on the deep learning methodology and an array of lists of any combinations and variations to obtain the result of understanding, forming conclusions, adapting and programming future content [34].

LLMs are a factor of a major step in development and, so to speak, the definition of revolutionary achievements in the healthcare industry, which, through its application, changes the ways and methods of interconnection during the acquisition and implementation of clinical/practical knowledge. Accordingly, it helps in creating a human, natural, linguistic tool during the encoding of medical knowledge, which contributes to the improvement of medical scientific achievements [35].

In the Dutch doctors' project AMSTEL HEART-2, the ability of ChatGPT to generate human-like answers to minor cardiology questions was analyzed, and then the task was set to generate possible symptoms in different patients and provide them with a recommendation letter for potential treatment [36]. Easy questions and characteristics of actions were provided orally using remote communication in English via the ChatGPT platform, and in parallel, doctors from a well-known clinic had to provide their recommendations on the history of diseases and symptoms. It is possible to emphasize that the above method is universal for medical institutions and clinics and can be used widely. Accordingly, it is possible to believe that ChatGPT can and should be used in the future in other diseases, especially severe and critical ones, because artificial intelligence does not have emotions and can provide a quick answer without color. The tool uses a data-driven approach to generate, recognize, and understand text, which leads to clear answers and then summarizes the results. The AI builds its answers based on the answers of people with similar symptoms, thus eliminating negative experiences and introducing new, modelling potential scenarios, and then uses its own experience to build the answer and improve the database at the same time.

But it is worth noting that there are also controversies regarding the use of new technologies, especially in the direction of safety of application and use in medicine. First of all, an example of this is the availability of open sources of information, which requires a more thorough approach to the "hygiene" of the information field and information in general. In [37] singled out such an aspect of working with artificial intelligence as real work every day and the operational capabilities of applying the method, because it is the actual use in clinics and medical institutions that can guarantee either completely positive results, or negative and the failure of the experiment to improve healthcare. In paper drew attention to the need to first deepen knowledge more theoretically and conduct a number of experiments, not using existing medical needs, and only then apply LLMs in medicine more widely in a clinical direction.

3. Results and Discussions

One of the world's most well-known examples of successful LLM application is OpenAI's ChatGPT, a chatbot that can take any arbitrary input query and provide a human-like response (Fig. 1).

It is proposed to replace the generalized models based on open-source big data, using a different strategy of goals. In this case, it is worth providing a list of simple and simplified tasks or questions, then forming the conditions for their implementation and necessarily controlling the results obtained at all stages. In this way, it is possible to generate more open regulated anamnesis and isolate artificial intelligence errors that contradict human diagnosis (Fig. 2) [38].

Promising niches for the use of LLM in medicine are: application in digital services for patients for analyzing laboratory results, describing diseases, as well as for interpreting doctor's notes, generating personalized health recommendations, predicting health status, assessing symptoms, etc.

Application of LLM in medical education. GPT-4 and Med-PaLM 2 have a significant contribution to the learning outcomes of medical staff, which are obtained as a result of their passing tests and tasks, and subsequently the best of them can be used in LLMs as a tool for processing big data.

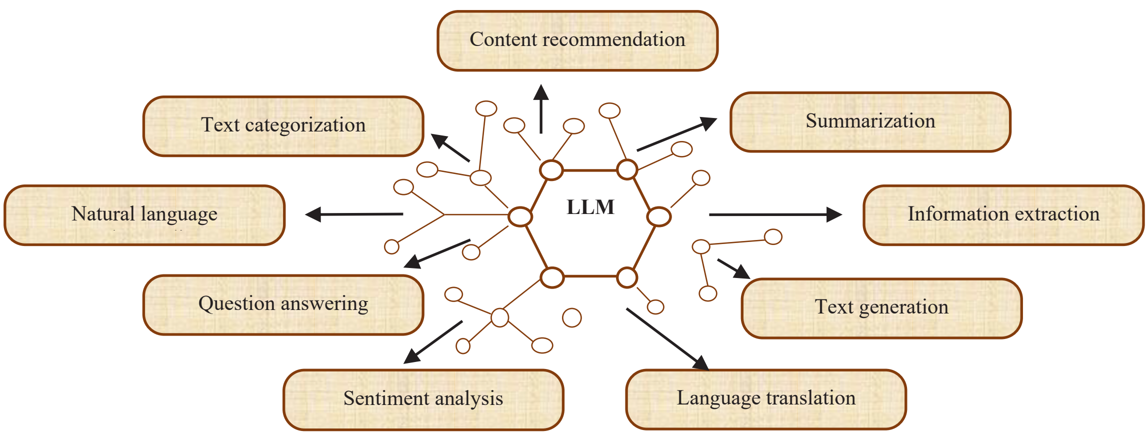

Fig. 1. Possibilities of large language models

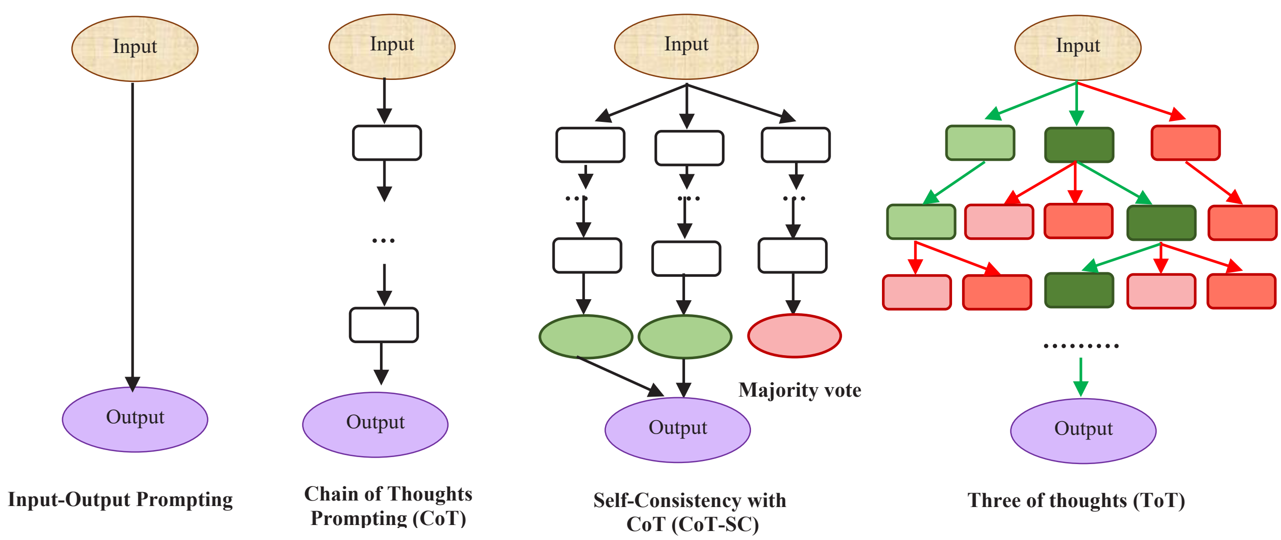

Fig. 2. Illustration of different approaches to solving problems using LLMs

It is possible to believe that it can be applied in theoretical and practical areas, as well as during the retraining of personnel in clinical conditions. After all, artificial intelligence, as already indicated earlier, does not possess human qualities, and can erase the emotional component, and therefore is more objective and critically evaluates the result. The advantage of such an approach is also to relieve the burden of a practicing scientist in the medical field, which is bureaucratized by excessive documents.

It should be noted that the use of LLM was only one of the stages in the creation of ChatGPT, although it was of fundamental importance. Once the LLM was obtained, further refinement and fine-tuning was required, as well as ongoing additional training during operation (Fig. 3) [39].

The original GPT-3 model was pre-trained on a dataset with ready-made queries and responses up to GPT-3.5. Further, Reinforcement Learning from Human Feedback (RLHF) was implemented, in which reward modelling is an important factor in processing data formed on the respondents' answers, and in turn, objectivity was emphasized by ranking GPT-3.5 answers on each question. This approach allowed LLM to be implemented on a much larger scale than would be possible with manual human scoring of each individual model response.

Once current limitations are resolved, ChatGPT and the next generation of LLMs can be used for many of the applications presented in Table 1.

In order to increase the reliability and ensure the results, an attempt was made to automate and test the input queries and potential responses. During operation, the GPT-3.5 model continued continuous self-learning, leveraging feedback from a rapidly growing user base.

ChatGPT has garnered special attention in medicine for achieving passing scores on U.S. medical licensing exams, and GPT-4 has shown significantly improved performance compared to its predecessor GPT-3.5 [40]. Similar results were recently demonstrated for nursing exams in Japan [24], and GPT-4 surpassed medical student scores on Germany's state examination [38].

The success of ChatGPT has spurred a wave of similar developments for healthcare tasks at other companies; for instance, Google has launched the Med-PaLM 2 project to create a medical chatbot capable of answering medical questions at the level of an expert physician [41]. Currently, the solution is undergoing testing at the Mayo Clinic research hospital [42].

When comparing ChatGPT's responses to patient queries with responses from physicians (responding in their free time on social media), As a result, the clinicians expressed the view that they had a good impression of the use of LLM and distinguished the quality of the results provided by the language model. This has led to discussions about AI potentially replacing doctors, though in reality, even on medical student exams, model results are far from perfect. It has been shown that ChatGPT struggles with exams for specialist physicians and provides inaccurate information in response to real patient questions about cardiovascular disease prevention, oncological treatment [13], and the Bing Chatbot provided incorrect first aid advice for emergencies [43].

Despite their ability to accurately convey clinical signs and potential patient diagnoses, LLMs are often unable to tailor their results to the individual, especially their unique characteristics. Current results rule out the possibility of autonomous deployment of systems for clinical decision-making or communication, especially because the latter do not distinguish between human and AI data [44]. Therefore, the World Health Organization calls for cautious and responsible development and application of these increasingly popular large language model technologies in medicine.

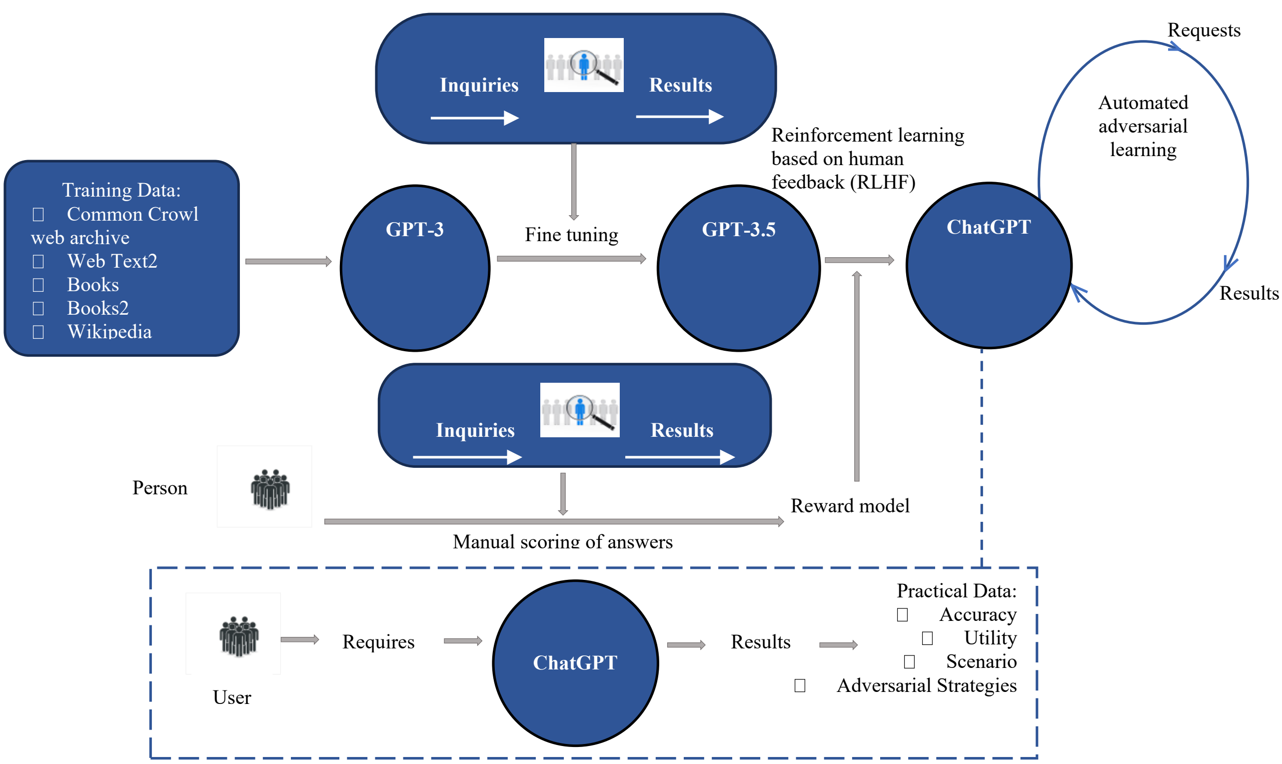

Fig. 3. Algorithm for training large language models for solving applied problems (compiled by the authors based on [39])

Table 1

Potential Healthcare Applications for ChatGPT and LLM Research

Fields	Exposition	Description
1	Modelling based on additional, multi-directional data, for example – combining words and figures (images), generating cataclysms (synonymous description) in image formation	Models and applications that can use multimodal data, such as language and image fusion, such as highlighting abnormalities naturally (using language) when reading PET images
2	Combining data on unique symptoms and diseases recorded in patient histories	Summary of complex case histories and records
3	Generation and synthesis from scientific symposia, conferences and scientific meetings	Summary of information from medical congresses/clinical trial results
4	Determining consistency/ensuring the same information when maintaining patient cartography	Structuring/ensuring compatibility of information, for example, when maintaining medical records
5	Facilitate clinical documentation work such as writing discharge reports	Facilitate clinical documentation work such as writing discharge reports
6	Summarize and create a common database of multiple clinical departments and institutions to create a complete picture of patient data	Integration with hospital information systems to include patient and resource data
7	Using a unified, multi-component multimedia translator that can analyse even rare and complex languages (especially historically lost ones)	Translation into other languages with greater potential for less frequently used languages for which the use of natural language processing has been limited in the past
8	Eliminating the language barrier between patients and doctors in real time without the use of additional gadgets	Translation into a language the patient understands
9	Anamnesis	Anamnesis
10	Relief for nursing staff thanks to automated communication in the wards	Relief for nursing staff thanks to automated communication in the wards
11	Medical literature	Medical literature
12	Anonymization of clinical text	Anonymization of clinical text
13	Human-Centered LLM Application Design	Human-Centered LLM Application Design
14	Chain of Analysis and Automated Reasoning on LLM	Chain of Analysis and Automated Reasoning on LLM
15	Medical education	Medical education

The prospects of applying LLMs to create digital assistants for physicians appear more justified currently than developing a universal AI capable of answering any question and, more importantly, replacing a doctor [45]. Moreover, the application of LLMs demonstrates much better efficiency in tasks that do not require specialized knowledge or tasks presented as expanded user queries (prompts). This opens up significant opportunities for accelerating the integration of AI into medical practice, essentially challenging traditional approaches used in developing clinical decision support systems (CDSS).

Table 2 provides examples of patient characteristics and their questions addressed to their attending physician. The questions ranged from whether symptoms warrant concern and consultation with a doctor before treatment is prescribed, to changes in daily life as the patient transitions from therapeutic nutrition to a normal regimen, taking into account heart disorders. In a broad sense, ChatGPT recommended the same things as a human doctor (results have a corresponding level of 9/10). But it is worth noting a significant drawback, namely – ChatGPT recommended the use of such a tool, which is contradictory under the given circumstances and cannot be used in the acute phase of the disease, in the condition of the initial data of myocardial infarction, it is not possible to prescribe it at all by a cardiologist.

Table 3 examples include questions that GPs submit for a digital consultation with an expert (cardiologist, internist). These questions were submitted to ChatGPT, where the 10-question model answered five (50 %) correctly, as recommended by the expert. Two answers (20 %) were partially consistent, one question (10 %) was inconclusive, and two answers were incorrect (20 %).

Thus, a strong point of this study is the use of two approaches (simple questions and cases of varying complexity) to clearly assess the health outcomes of ChatGPT. Despite small sample sizes, patterns in the metrics were observed: ChatGPT performs well when faced with multiple-choice questions and simpler inquiries posed by patients to their attending physicians.

The model struggled more with complex medical queries, necessitating interdisciplinary research in the future to determine the appropriate role for ChatGPT in the rapid adoption of this technology in healthcare. Also important is the increased focus on transparency and a stronger conceptualization of LLMs that aims for open reporting and objectivity of results.

Table 2

Simple questions for a patient to ask their doctor

Patient	Question	ChatGPT	Diagnosis	Accuracy
25–30 male	Rapid heartbeat unrelated to physical activity, sleep problems, anxiety. Previous unexplained syncope. Question: what is the diagnosis?	Causes may include stress, caffeine, hormonal changes, medications, or heart conditions. Please consult your doctor	Increased heart rate due to panic attacks, stress and lack of sleep	Decent consultation ChatGPT
80–85 female	I had a heart attack and was prescribed five types of medication. Explain why I need this?	Explanation of the mechanism of action of aspirin, beta blockers, ACE inhibitors, statins and thrombolytic therapy	An explanation of ticagrelor, aspirin, beta blockers, ACE inhibitors and statins	ChatGPT provides partially correct information. Thrombolytic therapy is incorrect

Table 3

Examples of cases when doctors seek advice from a specialist

Patient	Question	ChatGPT	Diagnosis
75–80 female	Could you tell me the annual rate of strokes in a patient with atrial fibrillation who is a 75–80-year-old woman with diabetes, hypertension and vascular disease?	The annual incidence of stroke with a CHA2DS2-VASc score of 6 is about 9 % per year. A score of 6 or higher indicates a high risk of stroke and the need for oral anticoagulant therapy	Identical estimated risk of stroke using this score
80–85 male	Should I test NUP or respond to changing symptoms in chronic heart failure?	NUP is a popular diagnostic method. It is important to determine the body's response to treatment and its effectiveness. You can't just follow the signs	Monitoring with NUP is not mentioned in the instructions of the Ministry of Health. The ESC does not recommend NUP for routine monitoring, except as an exception in cases of worsening symptoms

For instance, the Foresight model, based on LLM architecture and unstructured textual medical records extracted from 811,000 patient histories, performed reasonably well in future predictions and was able to predict future deviations [46]. This project vividly illustrated that general risk models could serve as a robust alternative to numerous tools currently used for patient stratification and sorting.

Summarizing the results of theory and practice in the development of LLMs for clinical application, the following most promising directions can be highlighted [47, 48]:

– generation of medical documentation;
– formation of discharge summaries;
– generation of clinical notes;
– preliminary confirmation of insured events;
– summary of research works;
– interpretation of diagnostic studies;
– proposal of treatment methods;
– development of treatment plans;
– diagnostic assistance;
– medical triage.

Emerging LLMs will increase their capabilities and compatibility with different types of data sources; even the doctor's handwriting can be interpreted automatically and accurately. Microsoft and Google are looking to integrate ChatGPT and PaLM 2, respectively, into administrative workflows, enabling quick and easy aggregation of data from videos, text documents, email, presentations, and speeches.

At the same time, it should be emphasized that the use of LLM in clinical settings, where patient safety is not absolutely guaranteed, requires comprehensive validation. Comprehensive quality assessment is necessary to ensure patient safety and administrative efficiency, and dedicated governance structures are required to allocate responsibilities [49].

Prospects for using LLM to create digital assistants for patients. AI solutions based on LLM are able to very quickly analyze, summarize and paraphrase any information in natural language, including that collected from the patient's words. This opens up truly impressive prospects for accelerating and increasing the efficiency of digital healthcare transformation projects aimed at creating new innovative services for patients (Fig. 4).

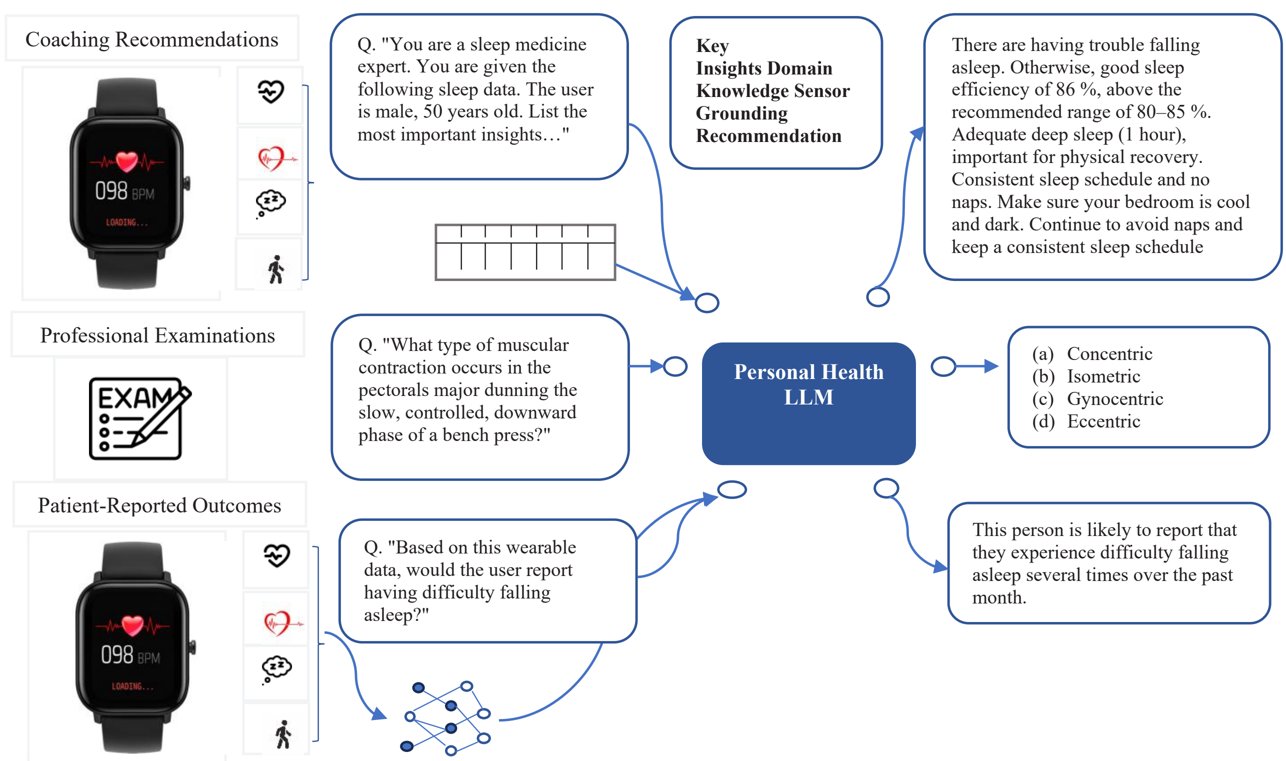

Fig. 4. Google has developed the PH-LLM language model for analyzing medical data collected from wearable devices – smart watches and heart rate monitors (compiled by the authors based on [50])

Various chatbots integrated into mobile applications, websites of clinics or health authorities, insurance companies, etc. make it possible to significantly reduce the load on call centers, reception desks, and even initial appointments, and ultimately even eliminate human participation in the process of initial communication with the patient. In quite a large number of cases, especially for the most common and non-dangerous (treatable at home) diseases and conditions, chatbots based on LLM are indeed capable of completely replacing (eliminating) a patient's visit to an in-person appointment by automatically collecting, dialogue and interpreting information from selection of recommendations for maintaining health. The most promising tasks of digital assistants for patients that can be solved using LLM are [50]:

– analysis of laboratory results;
– description of diseases;
– interpretation of doctor's notes;
– personalized health recommendations;
– forecasting health status;
– symptom assessment;
– analysis of data from wearable devices;
– chatbots for mental health;
– adherence to the treatment plan;
– rehabilitation guides.

Prospects for the use of LLM in clinical research: accelerating and reducing the cost of clinical research is one of the most promising niches for the use of LLM technologies, which can be tasked with summarizing information, creating a description of the results provided, or generating text fragments for a specific reader or audience. Models that are fine-tuned based on domain-specific information can demonstrate better performance, as there are already concrete examples of this, including PubMedBERT and BioBERT models. This can reduce the burden of critical appraisal, research report writing, and peer review, which constitute a significant portion of researchers' workload. Issues related to liability for the validity of information and conclusions will be addressed by holding clinicians and researchers using these tools fully accountable for their results [51]. However, the widespread use of LLM in research will be possible only after the developers ensure the absence of "hallucinations" and non-existent sources in the results of the models [52].

LLM can facilitate new research initiatives, such as language analysis in a deeper spectrum of study than is currently the case. Such representatives are the applications of ClinicalBERT, GPT-3.5 and GatorTron, which successfully process large arrays of printed text documents. LLM can also formulate other bureaucratic components of the medical industry, because the patient's medical history can first be not only in printed or written form, but also on a storage medium on a server. In this case this artificial product is able to stimulate new research in related areas – management of medical institutions, management of people, establishment of communications and subordination. These products have significant results, for example, AlphaFold can predict future protein changes based on amino acid data. ProGen synthesizes and generates protein sequences with variable functions of biological structures; TSNote-CyaPromBERT recognizes proactive sites in bacterial DNA.

Other potential uses of LLM include counterfactual modelling and non-existent research. This approach can accelerate clinical research by simultaneously generating and visually demonstrating conclusions about all advantages, disadvantages, potential threats, and positive outcomes, which should then serve as a basis for researchers [53]. New enhancements – Hybrid Value-Aware Transformer (HVAT) – can improve LLM performance by introducing and enhancing data on multicriteria clinical data. Finally, generated LLM applications should be used to group artificial data from other software products, because the growing AI database should also be grouped, synthesized, and formed as a whole.

Prospects for applying for LLMs in medical education are promising. The high and improved results obtained by using the GPT-4 and Med-PaLM 2 in medical education indicate the effectiveness of the tool in improving student assessment. The meta-query feature in GPT-4 helps the client clearly describe the request for conversations with the chatbot and receive appropriate quality answers. In this direction, the latest programs help to create their own, unique thoughts and reflections, which encourages smaller requests that cannot solve more comprehensive queries. Chat logs will enable teachers to track progress and adjust instruction based on students' weaknesses [54]. All these advantages are solid, but there are certain limitations to implementation. These include in-depth scientific study of the methodology and the overall methodology of teaching using artificial intelligence tools.

Thus, applying LLMs represents one of the promising approaches to enhancing efficiency in education and continuing education, particularly in studying or synthesizing new material, improve the involvement of those who learn during the process of acquiring knowledge through the methodology of knowledge absorption.

Regulatory and technical oversight of LLMs: regarding future implications, it is an extremely important factor, argument and action to calculate and predict all possible steps for the implementation of artificial intelligence and its tools in the healthcare sector, taking into account uncertainties and threats. The adjustment of LLM actions in the medical field and its impact on patient health care in the context of the continuous sustainable development of artificial intelligence tools, the maintenance of ethics and confidentiality, the elimination of complaints, the oppression of rights and the protection of interests, is an important argument at the present time. Despite all the fears that artificial intelligence can raise, it is now greatly expanded thanks to the huge number of diverse potential applications based on LLM.

The created LLMs in a broad sense have a unified and standardized basic concept, which indicates the mandatory refinement to implement specific features in linguistic, cultural and national aspects. In our opinion, this should be done by the governing authorities. But the question remains: what legal authority does the institution have to regulate the introduction of AI into the medical field? Currently, LLM has its advantages over previous deep learning tools, which is why it needs a separate regulatory framework to avoid all possible failures.

A regulatory governing authority should develop rules for LLMs only if LLM developers state that their model is intended for use in medical purposes. It is also appropriate to classify into this category specific medical alternatives to widely used LLMs that are adapted to the specifics of general data.

Despite the excellent results of LLM, there are negative aspects of the use of large language models that need to be corrected before they can be widely used in medical institutions. First of all, it is worth saying that the capabilities of LLM in the medical field are extremely wide and limitless, which is initially reflected in the creation of any applications – from obtaining additional competencies in training and retraining to obtaining, clarifying and confirming diagnoses for patients. Given that scientific achievements in improving large language models continue to grow and gain new momentum, let's hypothetically predict that artificial intelligence will play an increasingly important role in the field of health care every year, which will encourage doctors to improve their services.

At present, the practical application of large language models has wide application in education in the field of health care. *Real-world examples of LLM applications in action include:*

Florence Chatbot: the UK's National Health Service (NHS) employs the Florence chatbot to assess patient symptoms and direct them to appropriate levels of care.

Babylon Health Chatbot: England's NHS also explores using the Babylon Health-developed chatbot for triaging patients calling the NHS 111 hotline.

Clinician Companion: Clinician Companion, an LLM-based clinical decision support tool developed by researchers at the Massachusetts Institute of Technology, analyses patient data and medical literature to offer personalized recommendations for diagnosis, treatment, and patient care.

Stanford University Researchers: researchers at Stanford University hired a law master's student to analyse data from electronic health records (EHRs) and identify potentially new methods for treating heart disease.

Gato Tron LLM: developed by the National Institutes of Health (NIH), Gato Tron LLM analyses electronic medical records (EMRs) to identify potential drug interactions and adverse events.

For Ukraine, *practical application* in healthcare can have a wide range, especially considering the active military operations since 2022. Currently, a large number of wounded, disabled and injured among the civilian population and the military need emergency care. Already operating digital products in our country help to speed up the treatment processes and avoid diseases, and in our opinion, the use of LLM with international databases can also help in the direction of prosthetics for patients. But there are *certain limitations* on the use of data obtained in the international community. All of them are divided into different components according to their direction, namely:

– regarding national identity – the use of large language models for our people can bring advantages in the form of a reliable translator, but there are disadvantages regarding phraseological compositions that have different content loads;
– regarding medical processes – a feature is the not very developed technical base for the implementation of treatment methods on a permanent basis;
– regarding the personnel who use LLM in practice, namely the age category of more professional medical staff, which is mostly based on classical knowledge and skills.

All these potential limitations, in our opinion, are only probable risks that can be eliminated in the process of in-depth implementation of LLM in practice. Therefore, the above-mentioned world experience can be implemented in practice in Ukraine. In this case, let's consider it appropriate to highlight the ways of further development of the use of large language models, namely:

– improving the translation of different languages – to open the borders of communication with foreign colleagues;
– obtaining partial/full access to databases of other patients from around the world, especially unique ones – in order to eliminate the consequences of military aggression;
– unification of the use and management of digital assistants – to facilitate implementation in medical institutions, especially for older workers.

In this case, a promising direction for scientific development is further observation, analysis of the obtained data and improvement of artificial intelligence tools.

4. Conclusions

In conclusion, it is worth saying that the introduction of artificial intelligence into the work of medical institutions has a great chance of success and achieving the goals set in terms of clarifying established diagnoses, choosing treatment methods, as well as possible options for additional laboratory tests. The tools of technical progress use all available healthcare databases in order to generalize them and obtain the most accurate and effective result, and the absence of human qualities of artificial intelligence gives advantages in increasing the objectivity of diagnostics. Artificial intelligence demonstrates a more accurate, balanced, reasoned diagnosis, which also reduces the time for its processing. It is possible to see that the application of modern innovations in the medical industry will become a revolution in the historical previously analyzed industry, will help reduce the use of drugs due to the accuracy of taking medications, will be able to improve the managerial aspects of medicine, and the creation of a personal assistant will be able to respond in time to any symptoms, provide psychological support and will determine a new level of communication between the doctor and the patient.

The obtained results of the study have a subjective and real result. The presented results of the study on real medical cases and how to get a potential diagnosis from a medical worker and artificial intelligence clearly demonstrate rapid results. In this case, it is worth noting that the use of large language models encourages the continuation of sustainable development and digitalization of the healthcare system, and its constant improvement emphasizes significant progress. In this case, patients can receive a quick, competent and qualified diagnosis, which is established in accordance with a large array of archival relevant data, and workers. in this case can simultaneously improve their qualifications and receive useful advice, help and support from artificial intelligence. Of course, no one excludes the human factor, the intuitive abilities of the doctor, as well as the ability to see symptoms where they are hidden in the anamnesis, but this very empathetic factor to some extent can lead to global consequences. In this case, the results obtained during the study once again confirm this and meet the stated purpose of this work. This study has not only a theoretical direction in the form of presenting an analysis of a large amount of processed medical literature and management scientific achievements, but also a practical identification of the latest developments in medical institutions. The described situational circumstances and reactions that were carried out in institutions demonstrate the effectiveness of using large language models in practice, but taking into account their further development. In this case, let's consider it appropriate to propose expanding this direction both in the theoretical scientific direction – strengthening the management component for heads of medical institutions, implementation in the toolkit of the use of artificial intelligence for employees at the expense of relevant educational software products, and in the applied direction – experimental digital platforms for confirming results, improving the Ukrainian Helsi.me medical service, etc.

Resources are allocated based on outcomes achieved by healthcare institutions using medications or technologies. Unlike traditional healthcare systems, where established approaches to classical management based on basic principles and functions no longer work, the view and aspect of values should be based on the final result of the services received regarding treatment, its quality and feedback.

Conflict of interest

The authors declare that they have no conflict of interest in relation to this study, including financial, personal, authorship or other, which could affect the study and its results presented in this article.

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Data availability

The manuscript has no associated data.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the presented work.

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