

Concept of Artificial Intelligence-oriented Public Health Model in Cancer Care

Research Article

Oleksandr Ivashchuk*, Serhiy Hovornyan

*¹Bukovinian State Medical University, Department of Oncology and Radiology,
58002, Ukraine, Chernivtsi, Teatralnaya Square, 2*

Received 19 October 2023; Accepted 10 April 2024

Abstract: In recent years, the escalating volume of essential information for oncologists has created a challenge, making it arduous to stay abreast of the latest developments in the multifaceted field of cancer care. Although Artificial Intelligence (AI) is increasingly applied in healthcare, particularly for tasks like image recognition and big data analysis, we advocate for an AI-centric public health model tailored to comprehensive cancer care. This model aims to guide patients from their initial doctor's visit to the conclusion of treatment, thereby minimizing direct doctor involvement. Results. The proposed AI system comprises distinct units: Regional AI (RAI) for patient management and coordination with healthcare specialists and facilities in specific areas, General AI (GAI) to oversee healthcare processes on a broader scale, and Scientific AI (SAI) for data analysis and hypothesis generation, essential for scientific research and clinical trials. To enhance cost efficiency, we suggest introducing an intermediate layer, Teacher AI (TAI), facilitating the development of AI systems like GAI or RAI based on human needs without necessitating extensive specialist intervention. Conclusions. Implementing this model can simplify oncologists' daily tasks, reduce errors, improve treatment outcomes, and lower the cost of cancer care while maintaining its high quality. The Human-TAI-AI development model can streamline the system's development and implementation, making it more cost-effective.

Keywords: Artificial Intelligence • machine learning • self-improvement algorithms • cancer care • public health

1. Introduction

According to the World Health Organization's data, cancer ranks as the second-leading cause of global mortality, responsible for estimated 9.6 million deaths in 2018, accounting for 1 in 6 deaths. Ischemic heart disease stands out as the most common cause of mortality. Given this scenario, one might expect cardiological research to be at the forefront of medical science in addressing this issue, but surprisingly, it is not. Data from EBSCOHost, searched within the MEDLINE with Full-Text database, limited to publications since 2010, and tagged as "Cardiology," reveal only 201,798 results. In contrast, a search with the "Oncology" tag yields 354,539 results. A similar trend is observed with Google Scholar, where a search for "Cardiology" since 2010 returns 1,130,000 results, while "Oncology" fetches more than 1,640,000 results. These statistics highlight oncology as one of the most innovative and prevalent fields in medical science^[1].

The multifactorial nature of oncological diagnostic procedures, coupled with the diversity of treatment approaches, screening methods, and notably, the inadequacy of treatment, may contribute to the observed phenomenon. These challenges drive the continuous development and enhancement of healthcare methods^[2, 3, 4].

Cancer not only stands as the second most common cause of death but also exerts a profound impact on the economy. In 2010, cancer-related expenses amounted to approximately 1.6 trillion dollars. However, early detection of cancer has the potential to save both money and human lives. As Jeremy Howard aptly stated, "If cancer is detected early, the probability of survival increases tenfold"^[5].

According to Bernard Marr, over 90% of investigations and information have been generated in the last three years alone. Presently, humanity generates as much information every two days as

* E-mail: ivashchuk@bsmu.edu.ua

was created in the entire period before 2003. Breda Corish, Clinical Solutions Director for Elsevier's Health Solutions in the UK and Northern Europe healthcare markets, proposes a theory that by 2020, all medical knowledge and data will double every 73 days. Simultaneously, the exponential increase in information, particularly in the field of medical science, renders it nearly impossible to consider all of it for informed treatment decisions. Traditional analytics and machine technology face limitations in handling vast datasets, commonly referred to as "big data." Consequently, there is a pressing need for the development of technologies that can address the challenges of decision-making and data processing posed by the overwhelming volume of information^[6,7].

The innovation process in oncological science generates a substantial amount of information, concurrently involving an increasing number of individuals in this dynamic field. Typically, these novel findings and data are shared and presented at conferences or congresses^[8].

There are over 1000 specialized oncology congresses and conferences organized worldwide, accompanied by an even larger number of oncology-specific journals. According to the 2017 Scopus report, the count of oncology journals increased to 318 from 260 in 2011, marking a significant rise of about 24.2%. The majority of these journals contain crucial data on new findings in the field of oncology. Due to the vast number of patients and the intricate nature of oncologists' work, it becomes challenging for any physician, be it an oncologist, family doctor, surgeon, gynecologist, etc., to stay consistently updated and work with the latest recommendations, guidelines, and essential scientific data and findings.

While guidelines play a crucial role in the medical field, accessing them can be problematic. Additionally, the extensive information contained in these guidelines poses a challenge for doctors to efficiently integrate into their professional activities. Moreover, guidelines often present various treatments or diagnostic options, making the selection process daunting for a specific clinical case. An additional challenge arises from the diversity of recommendations. In some instances, there may be a lack of consistency, particularly when it comes to governmental treatment recommendations for specific cancer types or locations. However, it is noteworthy that substantial guidance is provided by global organizations such as WHO, ESMO, NCI, and NCCN. Despite these challenges, efforts are continuously made to enhance the accessibility of information, facilitating doctors in their pursuit of self-improvement and the implementation of new findings on the doctor-patient level^[9,10].

Frequently, improvements in this process rely solely on orders or laws from governmental structures. Unfortunately, the implementation process is often prolonged due to bureaucratic hurdles and the intricacies of the healthcare structure. These factors contribute to delays in the implementation and hinder the potential for improved treatment outcomes^[11].

Currently, we encounter a global challenge in oncological practice, where individuals struggle to manage the overwhelming volume of information and execute daily practices in line with inadequate governmental guidelines^[12].

These issues give rise to the following problems:

- High frequency of doctor mistakes and misdiagnosis;
- Inadequate utilization of new findings and up-to-date information;
- Absence of a feedback relationship among family doctors, surgeons, gynecologists, internal medicine doctors, and oncologists;
- The significance of a doctor's concentration on scientific research processes and correct research design;
- Limited use of computer technology, mostly confined to specific tasks such as image analysis, data storage, and attempting to establish correlations between genome data and specific diseases^[13].

2. Background

At the current stage of oncology development, challenges stem from the physical constraints of the human body and the multitude of tasks at hand, necessitating a qualitative transition for further progress. This challenge is not unique to oncology; in the military, timely decision-making is crucial, especially in operations where time is a decisive factor. For instance, in air forces, pilots play a pivotal role, making decisions in extreme conditions with only seconds to spare. To enhance capabilities, military developers are increasingly integrating AI elements, enabling swift decision-making in milliseconds and monitoring tasks performed by humans. The deployment of AI units facilitates the creation of coordinated "swarms" of drones or system units, ensuring continued productivity even in the face of unit loss^[14].

AI has become pervasive across various sectors, transforming industries beyond military and oncology. In healthcare, AI is revolutionizing diagnostic processes, drug discovery, and personalized treatment plans. Autonomous vehicles leverage AI for navigation and real-time decision-making, shaping the future of transportation. Finance relies on AI for fraud detection, risk assessment, and algorithmic trading, enhancing

efficiency and security. In manufacturing, AI-driven automation optimizes production processes, improving precision and productivity. Education benefits from AI applications in personalized learning, adaptive assessments, and virtual classrooms, tailoring education to individual needs. Returning to the military context, AI's ubiquity in various applications raises concerns about potential misuse. Figures like Elon Musk have voiced worries about autonomous machines, prompting calls for international regulation to prevent destabilizing impacts on world peace^[15, 16].

A distinctive feature between military and oncology lies in their approach to technology. The military predominantly employs AI for targeting and aiming, often leading to the complete elimination of enemies. In medicine, these technologies are harnessed to protect, heal, and reduce mortality rates.

2.1. The goal of this investigation

The purpose of this paper is to analyze the current applications of AI in healthcare, particularly in cancer care. The goal is to identify possible ways to optimize healthcare processes in oncology using AI-oriented technologies and, as a result, propose a new healthcare model in oncology.

2.2. Importance

The significance of this paper lies in demonstrating potential avenues for enhancing AI technologies to streamline the efforts of medical specialists in cancer care. The aim is to reduce the overall cost of the treatment and improve the management of patients with this condition by implementing an AI-oriented healthcare model.

2.3. Material and methods: Study design and setting

To achieve the aforementioned goals and identify the current applications of AI technologies, we employed the literature review method using EBSCO Host and other search technologies. The specified criteria for our search included AI-oriented models, AI in oncology, AI in medicine, and AI in healthcare. Additionally, we utilized descriptive methods, software engineering logistics methods, and machine learning methods.

2.4. Results: cases and applications of AI technologies in oncology

In modern oncology, a multitude of methods is widely utilized. Xiaoxuan Liu and co-authors observed this fact, listing 31,587 reports, with 82 included in their meta-analysis, describing 147 patient cohorts. The study revealed that the predictive quality of deep-learning models was comparable to that of healthcare professionals. However, one of the key findings is that few experiments have demonstrated externally validated outcomes or measured the performance of deep learning systems against health workers on an equivalent level^[2].

The early detection of cancer relies on profound learning. According to an NVIDIA study, deep learning has been shown to decrease error rates for breast cancer diagnoses by 85 percent^[17].

In many cases, contemporary methods leverage principles of image recognition, classification, and diagnostics to develop trained models for predicting new cases. Co-founders Jeet Raut and Peter Njenga applied this type of image recognition and aligned with deep learning, when developing the AI imaging medical platform Behold.ai^[18].

A research paper published in *Nature* by scientists from the Stanford University demonstrated the performance of neural networks in classifying skin cancer. Google's platform has shown its capability to accurately classify malignant skin cancers, thereby expanding the testing scope beyond the hospital setting. This allows for the use of service-based apps that adapt to the increasing trend of remote access worldwide. Additionally, a program at Case Western Reserve University has been developed to surpass doctors in diagnosing brain cancer^[19, 20].

Scientists in China have evaluated the segmentation of brain tumors in MR images, achieving more stable results compared to those of doctors^[21].

A team led by Dr. Qi Zhang from the University of Shanghai has discovered that deep learning can accurately distinguish between benign and malignant breast tumors on ultrasound shear-wave elastography. The method achieved over 93% elastogram accuracy for more than 200 patients^[22].

Deep learning can also be applied to determine the size and identify new metastases of tumors. This is a focus of research conducted by scientists at the Fraunhofer Institute for Clinical Image Computing in Germany. The deep learning algorithm becomes more accurate as clinicians scan CT and MRI images^[23].

Google Research has actively worked on developing deep educational tools that can “naturally complement the workflow” of pathologists. In their efforts to identify breast cancer tumors that have spread to adjoining lymph nodes, images were utilized to train their deep learning algorithm, Inception (also known as GoogLeNet). The algorithm achieved an accuracy rate of 89%, surpassing the pathologist’s accuracy rate of 73%^[24].

Diagnostic protocols must prioritize effectiveness and accuracy to handle the increased workload and complexity of histopathologies in cancer diagnosis. To enhance the effectiveness of histopathological diagnosis, researchers in the Netherlands have employed deep learning to alleviate the workload of pathologists and enhance the objective nature of diagnoses. The scientists hypothesized that machine learning could improve the efficiency of cancer diagnosis^[25].

The prognosis indicates the severity or advancement of the cancer stage, directly impacting the chances of survival. Cancer staging systems play a crucial role in determining the patient’s outlook but have certain limitations. South Korean researchers employed an in-depth modeling to construct a forecasting framework for predicting outcomes in gastric cancer patients, particularly in the context of diagnoses like gastrectomy. Deep learning has demonstrated superior predictive abilities for survival compared to that of other prediction models^[26].

Studies conducted in Finland and Sweden have delved into comprehensive research on the quantification of tumor-infiltrated immune cells in breast cancer. The emerging prognostic biomarker for immune cell infiltration in tumors is considered the gold standard for quantifying immune cells in tissues using a microscope^[27].

In addition to image identification, the efficacy of cancer detection has been demonstrated through data mining and in-depth data analysis. Owing to its substantial size and complexity, gene expression data present challenges for cancer detection. However, researchers from Oregon State University have conducted thorough investigations to extract valuable characteristics from gene expression information, enabling the classification of breast cancer cells. This innovation has led to the identification of genes considered useful for prediction and potentially valuable biomarkers for future breast cancer detection^[28].

Researchers in China have developed an innovative in-depth learning cancer classification system tailored to the complexities of current cancer classification studies based on somatic mutation. The results indicate that this tool outperforms three well-adopted current classifiers, as it can extract high-level characteristics

from combinatorial somatic point mutations associated with specific types of cancer^[29].

The pathology laboratory located in Hengelo, the Netherlands, in collaboration with a renowned technology company, is planning to build the world’s largest pathology database. This database will include annotated photographs of tissues for deep learning^[30].

In an effort to accelerate cancer research, researchers at the Oak Ridge National Laboratory are utilizing deep learning to automate the documentation of cancer-related information across a national cancer registry system^[31].

A well-known American multinational technology corporation already employs machine learning algorithms to deliver crucial information to experts involved in all stages of the treatment process, including guidelines and AI tips^[32].

Early detection and prognosis of cancer represent crucial areas in healthcare where deep learning technology has found application. The utilization of deep oncology technology raises the prospect that scientists may one day be assisted by machines in discovering effective cures and methods for preventing cancer growth.

In April 2019, the US Food & Drug Administration (FDA) issued a request for comments on new proposals for regulating medical equipment incorporating AI and machine learning components. The FDA acknowledges the necessity for a change in the approach to technology enforcement from traditional practices^[33].

In the modern approach to software development, we observe a direct bilateral relationship from humans to AI (Fig. 1). At the inception of any medical project, it is imperative to engage highly skilled developers specializing in AI to define methods, along with software engineers tasked with creating the product. In addition to these specialists, the current software creation process requires hiring additional staff such as Project Managers, Quality Assurance Engineers, and others, to organize and evaluate the overall process.

Another challenge in software creation processes is the necessity to involve a specialist in the field of product usage. In our case, an oncologist and healthcare specialist are required to review the created product and specify future tasks for developers. Misunderstandings between software engineers and the specialist may lead to conceptual errors that can compromise the efficiency of results.

The primary objective of the graphic user interface (GUI) is to simplify the user experience for individuals interacting with the project. However, a simplified GUI may lead to reduced complexity, which is undesirable in many intricate scenarios. Increasing the complexity of

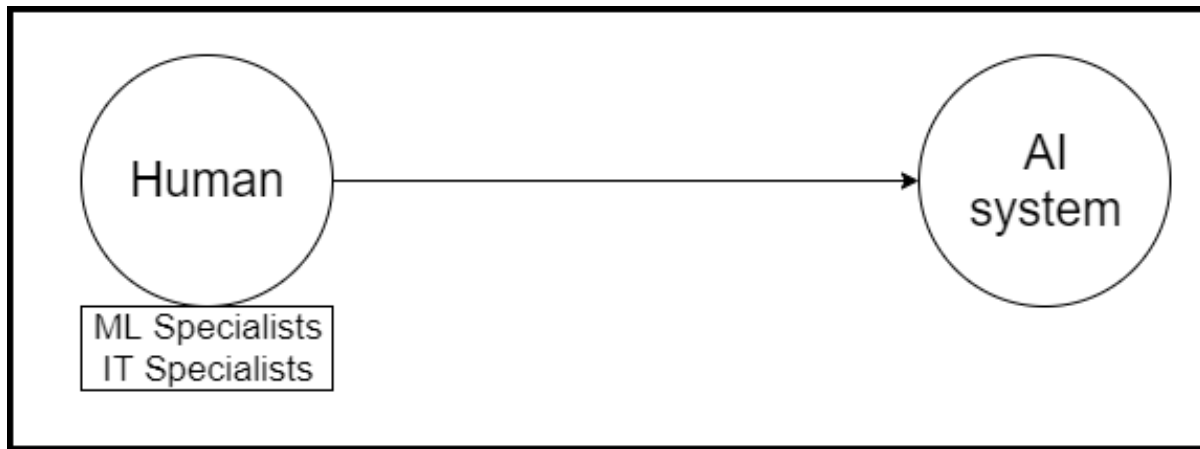


Figure 1: Modern approach of software developing (ML specialists, machine learning specialists; IT specialists, informational technologies specialists).

the GUI necessitates more skilled and trained personnel to effectively operate the created product. For a medical specialist, acquiring extensive knowledge beyond daily tasks and a significant patient load is impractical.

Currently, there is no universally recognized classification or terminology among scientists, leading to occasional misunderstandings in the development process.

Models, as a product of machine learning, are trained on datasets and can subsequently process additional data to make predictions. Various methods exist for creating models, and AI systems can be classified based on these methods. In most cases, this process is often referred to as the “Black Box,” encapsulating the learning processes involved^[34].

Given the multitude of tasks and intricate processes involved in achieving the objectives, developers must specify algorithms for each model, which is practically impossible, and assemble teams for each algorithm (protocol) in the system. This can result in significant time and financial expenditures.

In this context, the current software creation approach exhibits both positive and negative aspects.

- Pro:
 - The highly task-specific purpose enables the resolution of almost all the requirements for a specified task.
 - The interaction between developers and software allows for the quicker resolution of errors and bugs.
- Cons
 - High costs in development, continuous support, and customization.
 - A large number of staff and a more complex work organization process.
 - Involvement of specialists that leads to additional costs.

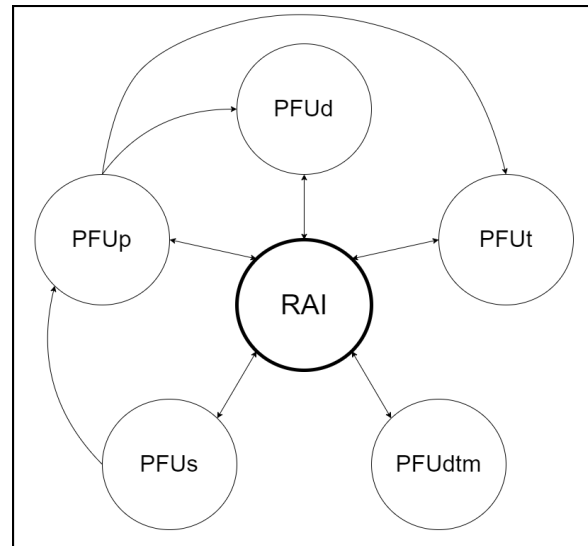


Figure 2: First organizational level (RAI, Regional Artificial Intelligence; PFU, Physical-Functional Units; PFUs, healthcare specialist; PFUp, patient; PFUd, diagnostic component; PFUt, treatment component; PFUdtm, diagnostic and treatment model sources (guidelines, journals, conferences, etc.)).

- A complex GUI for intricate tasks results in a high entry-level for personnel.
- Non-multidisciplinary use: a project designed for comorbid pathology in oncology care is applicable in rare cases.

In the examples described above, it is evident that AI is utilized in oncology primarily for specific practical applications. It functions as a tool or, in some cases, as a diagnostic instrument. Unfortunately, in the literature, we did not find publications dedicated to the use of AI in the management of public health in cancer care.

3. Discussion

Due to a lack of applicable methods in healthcare, we would like to propose a concept of an AI-oriented public health model as an alternative to the current patient-oriented model. This model comprises Physical-Functional Units (PFU) and Artificial Intelligence Units (AIU). We present two levels of structural organization.

At the *first organizational level* (Fig. 2), Regional AI (RAI) interacts with the basic physical-functional units of the healthcare process, including general specialists, family doctors, surgeons, and gynecologists, who initiate cancer diagnoses or suspicions, forming the first Physical-Functional Units (PFUs) and interacting with the patient (PFUp). The treatment component is executed by healthcare structures combined into PFUt, while the diagnostic component is realized by various laboratories and healthcare structures dedicated to this purpose, all grouped under PFUd.

RAI collects all data related to treatment and diagnostic processes from PFUd and PFUt. Scientific data about diagnostic and treatment models are gathered by RAI from various sources, such as scientific journals with high impact factors, governmental guidelines, and materials from scientific meetings, forming the last PFU – PFUdtm. RAI provides PFUd and PFUt with guidelines and patient-based instructions.

We propose the creation of a system that automatically generates Diagnostic and Treatment Models (DTM) without human interaction, extracting information from scientific papers and other informational sources generated by humans.

At the *second organizational level* (Fig. 3), General AI (GAI) and Scientific AI (SAI) are introduced. GAI collects data from RAI, oversees the healthcare processes generated by RAI, and communicates information to humans. All data collected from RAI are encrypted and depersonalized before being transferred to GAI. GAI maintains a bilateral connection with SAI, which analyzes findings, operates with various structures to conduct clinical trials, and generates new hypotheses.

We propose the following functional relative structures for the implementation of the above-described levels. The *first organizational level* of the AI system must be realized at the patient interaction level. The RAI system will be deployed in small administrative units at the primary level of healthcare organizations, such as Primary Health Centers in rural areas. In urban areas, it can be implemented in Health Posts, Family Welfare Centers, special oncological clinics, and other healthcare structures (PFUs). This approach allows for the consideration of ecological, climatic, and socio-

economic factors, enabling the treatment not only in individual form but also considering regional diversity.

The objective of this level is to collect patient data at the time of the first cancer diagnosis or suspicion and provide the patient with necessary information. After registration in the system, the patient must be equipped with a special “system communication tool” (SCT), which may be presented in the form of a mobile application or a specially designed smartwatch. The SCT’s task is to deliver notifications to patients about treatment, medication schedules, medical staff visits, and diagnostic appointments. Simultaneously, it provides RAI with the capability to monitor the patient’s status and collect necessary data.

The first level guides the patient throughout the diagnostic and treatment processes by connecting them with two additional physical-functional units: the examination laboratory unit with the diagnostic component (PFUd) and the treatment procedure cabinets (or surgery rooms) with the treatment component (PFUt), sending notifications to SCT and/or email. These two units are designed to collect and analyze the necessary patient’s health status and diagnostic conclusions, storing the data.

RAI should supervise the diagnostic and treatment outcomes. In the case of a reduction in treatment effectiveness, RAI triggers special processes that lead to a redesign of the treatment or diagnostic procedures, generated by GAI based on data from all RAI of the system.

The recommendations about the treatment and diagnostic design performed by RAI are collected from the PFUdtm. The RAI unit is designed to analyze and digitize new findings in the scientific field by examining and digitizing the treatment and diagnostic designs, generating diagnostic and treatment models.

The *second organizational level* consists of GAI and SAI and will be based at the state or country level or another administrative territory depending on the governmental organization of the healthcare structure of the country.

The main task of this level is to operate with data from all RAI. GAI is the general control unit of the second organizational level, responsible for collecting diagnostic and treatment data from all RAI, summarizing the DTM, and verifying recommendations for each region.

GAI will serve as the information source for governmental structures, small scientific groups, or big pharmaceutical companies. It will be enhanced with a special interface that provides unique access to crucial data for the above-described units. Governmental structures responsible for healthcare will be able to access statistical data on diseases, summarized

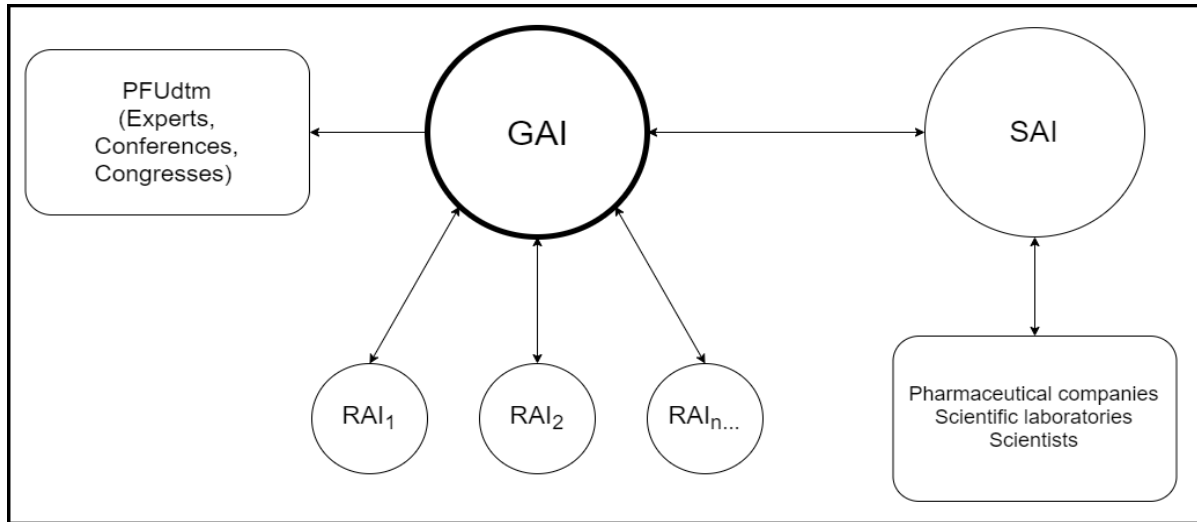


Figure 3: Second organizational level (RAI, Regional Artificial Intelligence; GAI, General Artificial Intelligence; SAI, Scientific Artificial Intelligence).

information about the effectiveness of treatment programs, and the number of drugs needed to maintain a secure and stable healthcare environment in the regions and the country as a whole.

The access guarantee for scientists will provide the opportunity to work with different forms of statistical data. The authors of scientific papers that “inspired” RAI to create DTM will be able to monitor the effectiveness of their findings to create new or optimize existing ones.

Pharmaceutical companies will have access to information about their drugs, including effectiveness, manifestations of side effects, and the number of drugs used for each disease in the treatment process. In this way, companies will have a special opportunity to better understand the needs of the healthcare process, ultimately allowing them to create new drugs and conduct new clinical trials.

The moderation of clinical trials falls under the purview of SAI. Pharmaceutical companies will be able to collaborate with SAI to initiate new clinical trials. The trial designs will be uploaded to SAI. Subsequently, SAI, utilizing machine learning technologies, will analyze the potential of uploaded trials and the existing patient database eligible to participate in these trials, describing the needs and criteria for each trial. This information and criteria will be shared with all RAI systems through GAI to facilitate the trials and invite potential patients. This process is designed to simplify and reduce the costs of new drug trials by collecting and operating with precise information without human interaction or mistakes.

Besides clinical trials, SAI, utilizing special cognitive learning methods, will be able to generate new hypotheses, scientific findings, and clinical programs

just like humans. This information will be published in different scientific sources like journals and presented at specialized forums and meetings to provide scientists with new ideas and a better understanding of the ongoing healthcare process.

In this way, with the modernization of the healthcare structure and the implementation of our model, combining GAI+SAI, we can elevate scientific research and governmental supervision to a new level. Simultaneously, with RAI technology, we can increase the quality of medical services and reduce the number of doctor visits. To calculate the saved amount of money by reducing doctor visits and implementing our model, we propose the following formula:

Formula 1. Cost-effectiveness of implementation of the AI-oriented model in oncology care.

$$\Delta_1 = (N_{\max} - N_{\min}) \cdot P - O_{AI}$$

Δ_1 - Cost-effectiveness; $N_{\max}$ - Number of doctor visits with traditional non-AI approach; $N_{\min}$ - Number of doctor visits with new AI approach; P - Average payment cost for doctor services; O_{AI} - Cost spent to develop and integrate the AI systems.

With this formula, we can clearly see that reducing doctor visits can decrease the cost of medical services. However, another obstacle in this process is the costs incurred to develop and integrate AI systems. We understand that this model can be expensive in realization and implementation. To address the issues of the modern approach in the software-making process described above, we propose replacing engineering teams with AI systems that will establish and develop other subsystems.

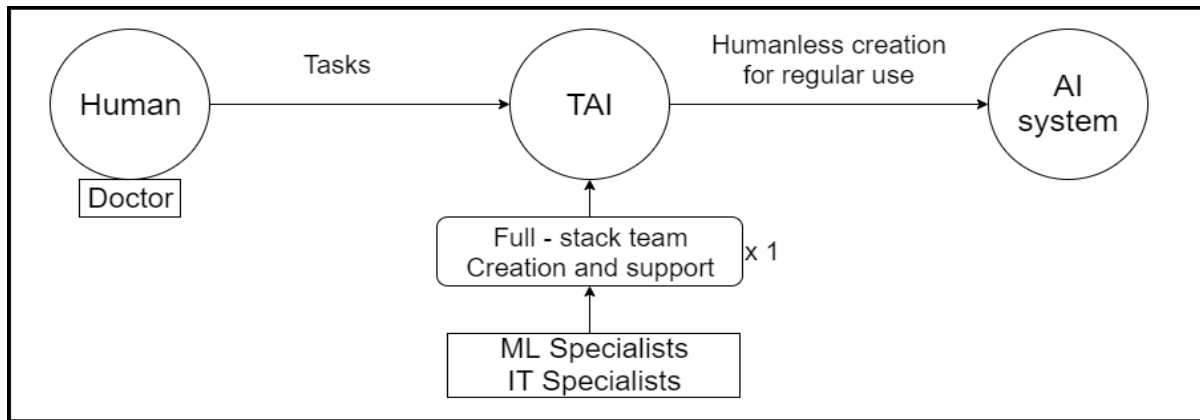


Figure 4: The new approach of the software developing process with an intermediate object – Teacher for Artificial Intelligence.

In this way, to realize all the functionalities of RAI and GAI and to reduce the costs of development processes, we suggest establishing an intermediate object – Teacher for Artificial Intelligence (TAI) (Fig. 4).

The functional features of this intermediate object give rise to the next possible variants of names: “AI-framework management environment,” which is more familiar to developers, or “Teacher AI,” which is more simplified and understandable for a medical specialist.

Regardless of the name, this system shall be governed by a robust and sophisticated AI capable of understanding the needs and operational tasks demanded by humans. From the required tasks, “Teacher AI” (TAI) will create objectives, “teach,” and guide other AI sub-systems like RAI to perform and realize those objectives. In addition to this process, TAI must learn from humans and undergo self-improvement operations to incorporate the newest methods created by machine learning scientists.

Our goal is to create a simple GUI in which doctors and healthcare specialists can interact, set tasks for TAI, and, in turn, receive reports of performed tasks by sub-system AI like RAI or GAI, all without the need for software engineers and at lower cost rates compared to a modern approach.

According to the data from a software company, the development cost for an AI project at the minimal viable product level, using the modern approach in 2019, ranges from \$100,000 to \$300,000 depending on the purpose. The project’s complexity is directly correlated with the price. This cost estimate is for one AI system designed for one localization. To cover all 98 localizations of cancer described by ICD-10, the expenditure would be almost \$15 billion USD^[34].

The cost of creating a new approach is obviously greater than the cost for one project designed for a specific localization, but it is smaller than the price

for developing individual localizations. Since all expenditures are directed toward the development of TAI, the profitability of this development approach will be realized when the saved amount on creating sub-system AI surpasses the cost of developing TAI. To quantify this result, we would like to introduce the following formula to calculate the cost-effectiveness of developing with a new approach:

Formula 2. Cost-effectiveness of implementation of the new approach.

$$\Delta_2 = (P + O_{AI}) \cdot n - (P_n + O_{TAI})$$

Δ_2 - Cost-effectiveness; P - Average payments cost for doctor services for specific nosology; O_{AI} - Cost spent to develop and integrate modern AI systems; n - Number of nosologies; P_n - Average payments cost for doctor services for all nosologies; O_{TAI} - Cost spent to develop and integrate new TAI systems.

The newly proposed approach undoubtedly simplifies the tasks of medical workers and introduces a novel pathway in healthcare management, yet it still possesses various advantages and disadvantages.

- Pro:
 - Universality and multidisciplinary use for oncology and comorbid diseases.
 - The economy of funds: Newly created sub-system AI is free to use.
 - Decreased the number of engineering teams to one.
 - Resolving complex tasks with a simplified GUI.
 - Processing of big data.
 - Continuous monitoring and task performance in non-human conditions.
 - Financial support for this product equal to the traditional one.
- Cons:
 - High entry-level cost in development.

- High complex system architecture.
- AI–AI interactions may lead to complex errors and bugs.
- Violation of ethical and juridic aspects of the healthcare process.

The realization of the new approach in the software-making process, in consideration of our AI-oriented healthcare model, opens new ways in medicine and patient management. With these new systems, there is no longer a necessity for dedicated oncological clinics for patient management, or at least, it is possible to minimize their number and the need for specialized oncologists.

4. Conclusions

We understand that this approach can raise ethical and human concerns. However, our main idea is to free up medical specialists from routine tasks while maintaining high-quality cancer care. We hope that AI will not replace doctors and other specialists but rather will find its place alongside them in a supportive role.

References

- [1] World Health Organization. (n.d.). Cancer. World Health Organization. <https://www.who.int/health-topics/cancer>
- [2] Liu, X., Faes, L., Kale, A. U., Wagner, S. K., Fu, D. J., Bruynseels, A., ... & Ledsam, J. R. (2019). A comparison of deep learning performance against health-care professionals in detecting diseases from medical imaging: a systematic review and meta-analysis. *The Lancet Digital Health*, 1(6), e271-e297.
- [3] Tan, D. S., Mok, T. S., & Rebbeck, T. R. (2016). Cancer genomics: diversity and disparity across ethnicity and geography. *J Clin Oncol*, 34(1), 91-101.
- [4] Ung, K. A., Campbell, B. A., Duplan, D., Ball, D., & David, S. (2016). Impact of the lung oncology multidisciplinary team meetings on the management of patients with cancer. *Asia-Pacific Journal of Clinical Oncology*, 12(2), e298-e304.
- [5] Stewart, B. W. K. P., & Wild, C. P. (2019). World cancer report 2014. Public Health.
- [6] Marr B. (2018, May 21). How Much Data Do We Create Every Day? The Mind-Blowing Stats Everyone Should Read. Retrieved from <https://www.forbes.com/sites/bernardmarr/2018/05/21/how-much-data-do-we-create-every-day-the-mind-blowing-stats-everyone-should-read/#49a4c84a60ba>
- [7] Corish B. (2018, April 23). Medical knowledge doubles every few months; how can clinicians keep up? Retrieved from <https://www.elsevier.com/connect/medical-knowledge-doubles-every-few-months-how-can-clinicians-keep-up>
- [8] Mathew, A. (2018). Global survey of clinical oncology workforce. *Journal of global oncology*, 4, 1-12.
- [9] ESMO (2019). ESMO Clinical Practice Guidelines. Retrieved from <https://www.esmo.org/Guidelines>
- [10] NCCN (2019). NCCN Guidelines® & Clinical Resources. Retrieved from https://www.nccn.org/professionals/physician_gls/default.aspx
- [11] Begun, J. W., & Thygeson, M. (2015). Managing complex healthcare organizations. Handbook of healthcare management. Northampton: Edward Elgar, 1-17.
- [12] Loftus, G. R., & Loftus, E. F. (2019). Human memory: The processing of information.
- [13] Uhlen, M., Zhang, C., Lee, S., Sjöstedt, E., Fagerberg, L., Bidkhori, G., ... & Sanli, K. (2017). A pathology atlas of the human cancer transcriptome. *Science*, 357(6352), eaan2507.

A list of abbreviations

AI – Artificial Intelligence;
 GUI – graphic user interface;
 ML – machine learning;
 RAI – Regional Artificial Intelligence;
 GAI – General Artificial Intelligence;
 SAI – Scientific Artificial Intelligence.

Conflicts of interest

none.

Source of funding

none.

- [14] Altshuler, Y., Pentland, A., & Bruckstein, A. M. (2018). The cooperative hunters—efficient and scalable drones swarm for multiple targets detection. *Swarms and Network Intelligence in Search*, 187-205.
- [15] Flin, R., Salas, E., Straub, M., & Martin, L. (2017). Decision-making under stress: Emerging themes and applications.
- [16] Gibbs S. (2017, August 20). Elon Musk leads 116 experts calling for outright ban of killer robots. Retrived from <https://www.theguardian.com/technology/2017/aug/20/elon-musk-killer-robots-experts-outright-ban-lethal-autonomous-weapons-war>
- [17] Kontzer T. (2016, September 19). Deep Learning Drops Error Rate for Breast Cancer Diagnoses by 85%. Retrived from <https://blogs.nvidia.com/blog/2016/09/19/deep-learning-breast-cancer-diagnosis>
- [18] Behold AI (2019). Pioneering artificial intelligence in healthcare. Retrived from <https://behold.ai/how-it-works/>
- [19] Esteva, A., Kuprel, B., Novoa, R. A., Ko, J., Swetter, S. M., Blau, H. M., & Thrun, S. (2017). Dermatologist-level classification of skin cancer with deep neural networks. *Nature*, 542(7639), 115.
- [20] Case Western Reserve University (2019, September 21) Computer program beats physicians at brain cancer diagnoses. Retrived from <https://thedaily.case.edu/computer-program-beats-physicians-brain-cancer-diagnoses/>
- [21] Xiao, Z., Huang, R., Ding, Y., Lan, T., Dong, R., Qin, Z., ... & Wang, W. (2016, October). A deep learning-based segmentation method for brain tumor in MR images. In 2016 IEEE 6th International Conference on Computational Advances in Bio and Medical Sciences (ICCABS) (pp. 1-6). IEEE.
- [22] Zhang, Q., Xiao, Y., Suo, J., Shi, J., Yu, J., Guo, Y., ... & Zheng, H. (2017). Sonoelastomics for breast tumor classification: a radiomics approach with clustering-based feature selection on sonoelastography. *Ultrasound in medicine & biology*, 43(5), 1058-1069.
- [23] Jäger, P. F., Bickelhaupt, S., Laun, F. B., Lederer, W., Heidi, D., Kuder, T. A., ... & Schlemmer, H. P. (2017, September). Revealing hidden potentials of the q-Space signal in breast cancer. In *International Conference on Medical Image Computing and Computer-Assisted Intervention* (pp. 664-671). Springer, Cham.
- [24] Stumpe M., Peng L. (2017, March 3). Assisting Pathologists in Detecting Cancer with Deep Learning. Retrived from <https://ai.googleblog.com/2017/03/assisting-pathologists-in-detecting.html>
- [25] Litjens, G., Sánchez, C. I., Timofeeva, N., Hermsen, M., Nagtegaal, I., Kovacs, I., ... & Van Der Laak, J. (2016). Deep learning as a tool for increased accuracy and efficiency of histopathological diagnosis. *Scientific reports*, 6, 26286.
- [26] Hyung, W. J., Son, T., Park, M., Lee, H., Kim, Y. N., Kim, H. I., ... & Kim, J. (2017). Superior prognosis prediction performance of deep learning for gastric cancer compared to Yonsei prognosis prediction model using Cox regression. *Journal of Clinical Oncology*, 35(4_suppl), 164-164.
- [27] Turkkı, R., Linder, N., Kovanen, P. E., Pellinen, T., & Lundin, J. (2016). Antibody-supervised deep learning for quantification of tumor-infiltrating immune cells in hematoxylin and eosin stained breast cancer samples. *Journal of pathology informatics*, 7.
- [28] Danaee, P., Ghaeini, R., & Hendrix, D. A. (2017). A deep learning approach for cancer detection and relevant gene identification. In *PACIFIC SYMPOSIUM ON BIOCOMPUTING 2017* (pp. 219-229).
- [29] Yuan, Y., Shi, Y., Li, C., Kim, J., Cai, W., Han, Z., & Feng, D. D. (2016). DeepGene: an advanced cancer type classifier based on deep learning and somatic point mutations. *BMC bioinformatics*, 17(17), 476.
- [30] Driessen H. (2017, March 6). Philips and LabPON plan to create world's largest pathology database of annotated tissue images for deep learning. Retrived from <https://www.philips.com/a-w/about/news/archive/standard/news/press/2017/20170306-philips-and-labpon-plan-to-create-worlds-largest-pathology-database-of-annotated-tissue-images-for-deep-learning.html>
- [31] Oak Ridge National Laboratory (2016, November 14) Accelerating Cancer Research With Deep Learning. Retrived from <https://cacm.acm.org/news/209708-accelerating-cancer-research-with-deep-learning/fulltext>
- [32] Ross, C., & Swetlitz, I. (2018). IBM's Watson supercomputer recommended 'unsafe and incorrect' cancer treatments, internal documents show. *Stat News* <https://www.statnews.com/2018/07/25/ibm-watson-recommended-unsafeincorrect-treatments>.
- [33] FDA (2019, May 11). Artificial Intelligence and Machine Learning in Software as a Medical Device. Retrived from [37](https://www.fda.gov/medical-
</div>
<div data-bbox=)

devices/software-medical-device-samd/artificial-intelligence-and-machine-learning-software-medical-device

- [34] Azati Software (2019, January 23). How much does Artificial Intelligence (AI) cost in 2019? Retrived from <https://azati.ai/how-much-does-it-cost-to-utilize-machine-learning-artificial-intelligence/>