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Review

Artificial Intelligence in Oncology

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Abstract: The aim of the article is to highlight the key role of artificial intelligence in modern oncology. The search for scientific publications was carried out through the following web search engines: PubMed, PMC, Web of Science, Scopus, Embase and Ebsco. Artificial intelligence plays a special role in oncology and is considered to be the future of oncology. The largest application of artificial intelligence in oncology is in diagnostics (more than 80%), particularly in radiology and pathology. This can help oncologists not only detect cancer at an early stage but also forecast the possible development of the disease by using predictive models. Artificial intelligence plays a special role in clinical trials. AI makes it possible to accelerate the discovery and development of new drugs, even if not necessarily successfully. This is done by detecting new molecules. Artificial intelligence enables patient recruitment by combining diverse demographic and medical patient data to match the requirements of a given research protocol. This can be done by reducing population heterogeneity, or by prognostic and predictive enrichment. The effectiveness of artificial intelligence in oncology depends on the continuous learning of the system based on large amounts of new data but the development of artificial intelligence also requires the resolution of some ethical and legal issues.

Keywords: artificial intelligence; intelligent oncology; cancer prediction; cancer screening; clinical trials

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1. Introduction

The search for scientific publications was carried out through the following web search engines: PubMed, PMC, Web of Science, Scopus, Embase and Ebsco.

The idea of artificial intelligence (AI) has been discussed since at least 1943, although the term AI itself was first used in 1956. The origins of AI are linked to neurophysiology and date back to the 1940s, when Warren McCulloch, and Walter Pitts proposed a model for artificial neurons (1943). The artificial neuron, according to this concept, mimics biological neurons and accepts and produces binary outputs based on a certain threshold value, which can be adjusted [1]. The father of artificial intelligence is also often credited as Alan Turing, a British mathematician, philosopher, logician, theoretical biologist and cryptologist. In an article published in the journal *Mind*, he asked the question, "Can machines think?" He believed that there is no convincing evidence that machines cannot think intelligently as humans do [2]. Turing became famous as the creator of the so-called "Turing machine", a device capable of performing a programmed mathematical operation.

The phrase "artificial intelligence" was first introduced into scientific terminology at a conference in 1956 by John McCarthy. The 2-month conference hosted by McCarty at

Dartmouth College was attended by 20 distinguished scholars, who were to debate how to use this rapid development for the good of the people. This special conference was an eight-week workshop sponsored by the Rockefeller Foundation entitled *Dartmouth Summer Research Project on Artificial Intelligence*.

There are different definitions of AI, but it is commonly defined as a field of knowledge that focuses on the study of computers that solve the tasks that humans normally use their intelligence for. According to Dobrev, an AI is a program that performs no worse than a human in an arbitrary world [3]. Russell and Norvig defined AI as "a system that imitates cognitive functions generally associated with human attributes such as learning, speech and problem solving" [4].

According to Kaplan and Haenlein, artificial intelligence is the ability of a system to correctly interpret external data, learn from it and achieve specific goals through adaptation [5].

According to another definition, AI is the ability of a machine to recognize and make connections from learned examples and use them to make decisions [6].

AI terminology includes two main terms: machine learning and deep learning. Machine learning is a subset of artificial intelligence that helps people build AI-driven applications. Machine learning focuses on programming, automation, scaling, and the inclusion and storage of results. Deep learning is a subset of machine learning that uses vast volumes of data and complex algorithms to train a model. It uses artificial neural networks in the same way the human brain processes information. Deep learning imitates human thinking by combining multiple layers of algorithms to process data. As data moves through each layer, algorithms convert some of the data elements into a numeric format, making it easier to process them in successive layers.

The interdependence between artificial intelligence, machine learning and deep learning is best illustrated in the figure (Figure 1) published by Shimizu and Nakayama [7].

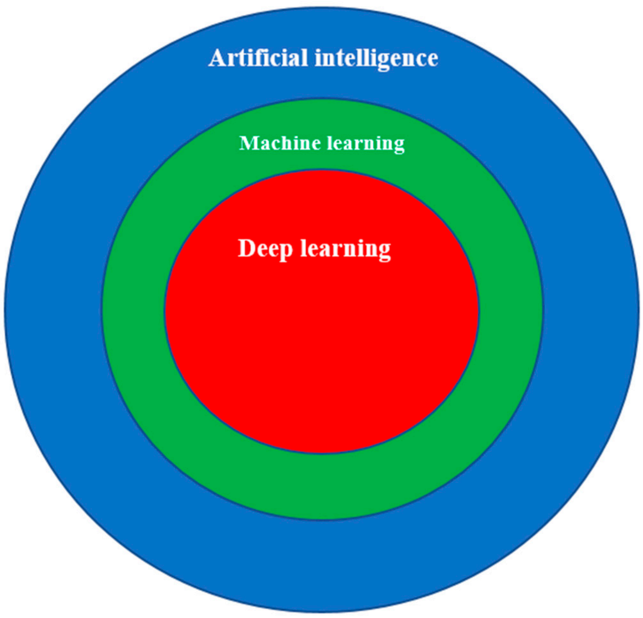

Figure 1. The relationship between artificial intelligence, machine learning and deep learning according to Shimizu and Nakayama [7].

AI can be used in healthcare in various aspects of medicine, including clinical practice (diagnostics, therapy, prognosis of disease development and treatment outcomes, virtual patient care, rehabilitation) and medical research (preclinical research, drug discovery) and can change nearly all aspects of medicine [8,9]. The rapid development of AI in medicine is probably best evidenced by Chat GPT (Chat Generative Pre-trained Transformer) [10,11].

Since its launch in November 2022, this application has already been used by over a billion subscribers. ChatGPT is based on a deep learning algorithm to generate human-like responses. Chatbots are becoming an integral part of our daily lives and are increasingly used in the health care systems, including in oncology, despite many limitations [12–18].

Chua et al. distinguished three groups of data that AI analyses in medicine: patient-related data, medical data and contextual data [19]. According to the authors, the first group refers to socio-demographic data, problems, procedures, medications, images from radiology and pathology, clinical data, test results, clinical notes and reports, scanned documents, patient generated health data, electronic health records, medical devices, billing/ancillary systems and data warehouses. On the other hand, medical data concern medical literature, textbooks, internet sources, professional meetings, clinical evidence (levels: I, II, III), guidelines, opinions and pre-clinical evidence. Contextual data deal with characteristics of the hospital, clinicians, neighborhood, insurance and quality measures.

2. Intelligent Oncology and Clinical Practice

AI plays a special role in oncology. The growing role of AI in oncology is best illustrated by the publication by Denysenko et al., who performed a bibliometric analysis of publications on AI in prostate cancer in the years 1987–2022 [20]. The authors found that, in the last 7 years of the analyzed period (2015–2022), there was a sharp increase in publications on this topic, especially in the United States, Canada and the United Kingdom. Lin et al. introduced a new term "intelligent oncology" to paraphrase the concept of "artificial intelligence", replacing the word "intelligence" with "oncology" to describe the interdisciplinary fusion of different medical disciplines with AI [21]. This holistic and structured concept is the fusion of AI with oncology to help create a chain of oncology care, including cancer prevention, screening, early diagnosis, and treatment [21].

Sebastian and Peter identified three areas where AI may be particularly useful in oncology [22]. These are early diagnosis of cancer, therapy, and prediction, also covering three domains: cancer incidence, recurrence and survival. However, there are also some other areas where AI is of special importance, namely cancer screening and clinical trials. The largest application of AI in oncology is in diagnostics (more than 80%), particularly radiology and pathology. AI algorithms can process and interpret complex imaging data from X-rays, CT scans, and MRIs much more quickly and more accurately than humans. These algorithms can detect subtle patterns and anomalies that might be missed by the human eye, leading to early and accurate diagnosis [23]. Generative Adversarial Networks (GANs), containing two interoperating artificial neural networks, a generator and a discriminator, enable the creation of new radiological images, detecting changes previously overlooked by radiologists [24,25]. In addition, GANs improve the education of radiologists and can be used in scientific research. A novelty in the use of AI in oncology is the use of the term metaverse, or "medical technology and AI" (MeTAI). In this method, radiological scans of a patient are first simulated using virtual machines to obtain the best result before the actual scan is analyzed. Based on the result, the actual scan is performed [26–28].

The role of AI in the early detection of cancer is most commonly employed in breast cancer, lung cancer and colorectal cancer. Sharma et al. drew attention to the key role of AI in the early radiological detection of cancers, especially breast cancer, lung cancer, lymph node metastasis, and colorectal cancer detection [29].

The most widely developed AI technologies address the five key cancers: breast, lung, prostate, pancreas and cervix [30]. Cancer diagnosis using AI focuses mainly on gene characterisation of tumours and tumour imaging techniques [31]. Based on AI algorithms, it is possible to determine how often a patient should be screened for breast cancer to avoid its development in the next 5 years. One of the AI models used in breast cancer oncology is Mirai [32]. This model was validated in seven hospitals across five countries [33]. The Mirai model is more modern and effective than the two earlier models developed by Tyrer-Cuzick and colleagues and Gail and co-workers [34–36]. The Mirai was better at predicting the development of breast cancer [32]. In lung cancer diagnosis, AI allows the detection of precancerous lesions that mimic cancer from actual cancerous lesions. This makes it possible to reduce the number of false positives, thereby reducing the costs of further diagnostics and stress for patients.

Sybil is a model used in prediction of the risk of lung cancer when low-dose CT scans are made [37]. So far, the results of lung cancer screening are disappointing. In the United States, for example, less than 10% of the eligible population is screened [38–40]. The use of the Sybil model makes it possible to assess lung cancer risk based on only one CT scan. However, the Sybil model still requires further validation work, as it is based on data from 2002–2004 obtained from predominantly Caucasian patients (92%). It is also important to take into account the technological changes in CT that have occurred since 2002, e.g., the use of scans that are now thicker than 2.5 mm. In addition. AI accurately predicted some parameters of clinical response to treatment of non-small cell lung cancer with PD-1 inhibitors [41]. The effectiveness of AI in the diagnosis of colorectal cancer was studied at different stages: blood testing, colonoscopy and examination of samples taken during colonoscopy. Turkbey and colleagues have developed an AI model that allows radiologists to detect potentially aggressive prostate cancer using a new type of MR, multiparametric MRI. Reading scans from this type of MRI, however, require long-term learning by radiologists [42]. AI plays an important role in the detection of pancreatic cancer. This topic was addressed at the conference in 2020 entitled *AI and Early Detection of Pancreatic Cancer Virtual Summit*, organized by the Kenner Family Research Fund and the American Pancreatic Association [43]. There are many aspects to the early detection of pancreatic cancer with the help of AI.

The use of AI in the early detection of pancreatic cancer includes patient diagnostic tests, radiological, laboratory and demographic data [43–50]. These procedures are then subjected to an integrative analysis, risk assessment for pancreatic cancer and diverse data to train the system. There are two ways to acquire data to train AI: centralisation and federation [44]. The centralised databases come from multiple sources and are stored in central repositories while. in the second model, data is stored in local repositories and then transferred to the central system.

AI makes it possible to detect precancerous lesions of the cervix that can be removed or treated. In the search for precancerous lesions of cervical cancer with the visual inspection method, AI achieved better results than those obtained by specialists [51].

Thanks to artificial intelligence methods, it is possible to discover new biomarkers in oncology. This is especially relevant in cancer immunotherapy. However, despite an encouraging number of studies indicating the significant importance of AI in the search for predictive biomarkers, none of these studies has so far provided high-level evidence to enable their rapid implementation in clinical practice [52].

AI can help oncologists to predict the possible development of the disease. Early cancer detection includes computer aided screening, sensor based detection, molecular biomarker detection and self-diagnosis application. In turn, in cancer therapy, AI helps in drug discovery and repurposing, assisted surgery, precision medicine, clinical decision support systems and cell programming. In cancer therapy, the key issue is knowledge of the dynamics of a given disease, the possibility of its recurrence, or potential sites of dissemination [53]. AI enables doctors to plan the appropriate timing of restaging, and to select the appropriate doses of oncological drugs or radiotherapy. This is particularly evident in glioblastoma, a cancer with very poor prognosis. AI allows the use of high doses of chemotherapy and radiotherapy and reduces the risk of side effects. AI helps to avoid overtreatment and unnecessary surgeries. AI makes it possible to distinguish precancerous from non-cancerous lesions. AI is also instrumental in supporting the selection of the optimal therapeutic pathway. It can analyse a patient's medical history, genetic information, and health status to recommend the most effective treatment plan. This personalised approach increases the chances of successful treatment and reduces the risk of adverse side effects.

3. AI in New Drug Synthesis and Clinical Trials

The development of a given drug is a complicated process. One of the ways to improve this process is to study the reuse of previously used drugs. The traditional method of creating drugs is based on finding targets that are the starting point for further research into their relationship with a given disease. The second approach is the synthesis of new drugs. The use of new technologies, including AI, to create new drugs is not only a result of the development of new technologies, but has even become a necessity when the traditional synthesis of new drugs has proven to be time-consuming and costly. Four directions can be distinguished in the use of AI in the development of new cancer drugs: assessment of the properties of the molecule under investigation, prediction of its activity, its synthesis from scratch, and drug–receptor interactions and prediction of drug response [54]. In the construction of new oncological drugs, different models developed by AI are used, which take into account such parameters as tumour growth kinetics, molecular profiling and pharmacological properties [55]. This is done by detecting new molecules, e.g., proteins and nucleic acids important in the process of tumour growth, making it possible to design new drugs oriented towards the above-mentioned molecules, e.g., tracking the interaction between KRAS proteins and cell membranes in more detail than before. AI's task is to analyse biological data to identify potential targets, such as proteins or genes, important in the process of tumour growth related to a given disease [56]. AI also has the ability to analyse patient data and predict potential treatment outcomes and potential toxicity. Potential targets in AI research on the synthesis of new cancer drugs include the STK 33 pathway (serine/threonine kinase). STK 33 is involved in the process of cancer initiation, progression and resistance to treatment. Nada et al. described the use of AI in the creation of potential EGFR inhibitors for breast cancer therapy [57]. Using the prediction model developed, they applied the technique of hybridizing the N-substituted quinazolin-4-amine scaffold with EGFR inhibitors, resulting in the synthesis of 18 new molecules, of which, after further selection, one had the highest activity against EGFR [57]. Although AI is accelerating the development of new drug research, it comes with certain limitations, well described by Alshawwa et al. [58].

The role of AI in clinical trials includes clinical trial design, patient enrichment, recruitment and enrolment, investigator and site selection, patient monitoring, medication adherence and retention.

The way clinical trials have been conducted to date can be described as linear and sequential. Unfortunately, this has disadvantages, such as suboptimal patient selection and difficulties in effectively managing and monitoring patients, resulting in prolonged trial duration and leading to high failure rates and high costs [59]. This traditional approach is lengthy, with only a 10% success rate [59]. AI plays a special role in clinical trials. When constructing new oncological drugs, attention is paid to the variability of the genome of cancer cells and the potential activity of new drugs. This can be achieved by constructing various AI models that predict drug activity and disease prognosis depending on the state of gene mutations in various cancers [60–73].

AI enables patient recruitment by combining diverse demographic and medical patient data to match the requirements of a given research protocol by using methods such as population heterogeneity reduction and prognostic and predictive enrichment [74]. Reduction of population heterogeneity implies selection of patients with baseline measurements of a disease or a biomarker characterising the disease in a narrow range, while excluding patients whose disease or symptoms improve spontaneously or whose measurements are highly variable, in order to increase study power. This requires the selection of patients whose disease is characterized by a narrow spectrum of parameters and the exclusion of those whose health condition improves spontaneously or whose health parameters are variable. The heterogeneity of the study population can be reduced by harmonizing data obtained from electronic medical records and by using electronic phenotyping [74].

Prognostic enrichment, on the other hand, enables the selection of candidates for clinical trials who are more likely to settle an endpoint or to experience a significant deterioration in health status.

Analysis of tumor biomarkers can be useful for prognostic enrichment and allows the selection of patients who are more likely to have a favorable trial endpoint. Similarly, AI enables predictive enrichment by selecting the population participating in a clinical trial [73]. This beneficial effect of AI on trial enrolment was described by Leventakos et al. [75]. AI-based matching showed a 58. 4% increase in recruitment in lung cancer study.

One of the new technologies used in clinical trials is Deep Match, which improves patient recruitment [76].

In the search for applications of AI in clinical trial research, AI may become indispensable in improving clinical documentation. AI in clinical trials can clean, aggregate, code, store and manage clinical trial data and reduce errors in data collection.

4. Ethical Aspects and Other Limitations of AI

It is not clear whether AI fits the current ethical and legal criteria or whether AI requires the development of new criteria [77]. Artificial intelligence raises some ethical and legal concerns. Some authors draw attention to the problems that may be encountered in the implementation of ethical principles to AI. So far, unlike existing ethical and legal guidelines in the healthcare system, there are no such guidelines for AI, although the European Union has developed the *European Ethics Guidelines for Trustworthy AI* [78]. According to these Guidelines, trustworthy AI should be lawful—respecting all applicable laws and regulations; ethical—respecting ethical principles and values; and robust—both from a technical perspective, while also taking into account its social environment. In its recommendations, in particular in Policy Area 6 and Policy Area 11, UNESCO highlighted several aspects related to the use of AI, especially in the medical field such as gender bias, explainability, responsibility, accountability, health and social well-being [79]. AI systems should be based on seven pillars: (1) human agency and oversight, (2) technical robustness and safety, (3) privacy and data governance, (4) transparency, (5) diversity, non-discrimination and fairness, (6) environmental and social well-being and (7) accountability. In a systematic literature review, Möllmann and co-authors identified five key ethical issues connected with AI in medicine: beneficence, non-maleficence, autonomy, justice and explicability [80]. The first of these principles, i.e., beneficence, addresses the problem of how AI can best use patient data, to what extent medical knowledge can be enriched by AI, how to combine the knowledge of a doctor with AI, and how to prevent bias, for example, associated with belonging to a particular minority. The second ethical issue raised by the authors is non-maleficence. What is this and how is it different from beneficence? Non-maleficence means that medical personnel should not cause or allow any harm to the patient through neglect. There are two main differences between non-maleficence and beneficence. First of all, non-maleficence acts as a threshold for treatment. If a treatment causes more harm than good, then it should not be considered. This is in contrast to beneficence, where all valid treatment methods are considered. Second, as against beneficence, where the best method of treatment is chosen in a particular situation, non-maleficence is constant in clinical practice.

The next ethical problem connected with AI is autonomy. Autonomy mainly affects the problems of AI threats to medical staff such as accountability for algorithm-based decisions derived by AI, factors influencing perceptions of losing individual autonomy, and differences between AI and other technologies.

The next ethical issue i.e., justice, concerns psychological support for medical practice in the case of making morally unacceptable decisions by AI, using AI to improve the patient–doctor relationship, and creating guidelines to develop AI. The last principle identified by Möllmann et al., i.e., explicability, implies that the data obtained by AI should be presented, especially to medical staff, in an understandable way [80]. It is also important to determine which data are particularly useful for AI in communicating understandable medical decisions. The ethical aspects of AI according to Mőllmann et al. are shown in Table 1.

Table 1. Ethical aspects of AI according to Mőllmann et al. [80].

Key Ethical Issues	What Does it Mean?
beneficence	how AI can best use patient data
non-maleficence	to do no harm to a patient
autonomy	accountability for algorithm-based decisions
justice	psychological support for morally unacceptable decisions by AI
explicability	to present data in an understandable way

Similar principles to those of Möllmann et al. were proposed by Jonsen, who outlined four main ethical pillars for putting AI into clinical practice: medical indications (beneficence and non-maleficence), patient preferences (respect for autonomy), quality of life (beneficence, non-maleficence and respect for autonomy) and contextual features (justice and fairness) [81]. Floridi states that introducing ethical principles into AI practices may be connected with problems such as ethics lobbying, ethics dumping and ethics evasion [82].

According to Gerke et al., in order to observe the beneficial effects of AI in the healthcare system, four key elements must be taken into account: (1) informed concern regarding the use of data, (2) safety and transparency, (3) algorithmic fairness and biases, and (4) data privacy [83].

There are various limitations of artificial intelligence. One is systematic error, which can lead to false results. This error depends on the input or non-entry of certain data into the system. If certain data is omitted, this may cause errors. This is perfectly illustrated by the example given by Parikh and colleagues, who described that the probability of testing for gene mutations among black women is much lower than among white women, although these mutations are equally common in women of both races. The consequence of this is an incorrect assessment of breast cancer risk in black women [84]. The output result depends on what data has been entered.

In addition to the above mentioned ethical aspects, there are some other ethical aspects connected with the use of AI in oncology, such as dehumanization, deidentification, depersonalization, lack of transparency, creativity, emotion, safety, biased programming and unclear legal regulations.

A problem of special importance is dehumanization, which plays a special role in the elderly population and can lead to a deterioration in the quality of interpersonal relationships, ultimately leading to a decline in the quality of life. Manzeschke et al. drew attention to four aspects that constitute an obstacle to the access of older people to new technologies: low socio-economic status, impaired cognitive abilities, living in geographically distant areas, and differences in the ability to use information technologies in medicine [85].

De-identifying patient data using AI is still an unresolved issue and, as Safdar et al. point out, de-identifying data to protect patient privacy seems unrealistic [86]. Although modern automatic data de-identification methods have been introduced, even the most up-to-date examples cannot remove all protected medical data. Even techniques designed to protect the visualisation of the patient (a pixilated photograph) are not a guarantee that the patient will not be identified [87,88]. Similar problems apply to non-image data [86,89].

Depersonalization is another problem. Since artificial intelligence uses large datasets, there is a risk of under-representation of the needs of people with specific health needs.

Lack of transparency is another problem for AI. This concerns limited validation in research. Lack of guidelines and limited experience with methodology for research into AI may influence scientific evidence regarding this method.

Another problem related to transparency is the lack of reproducibility of functions and results in practice. The development of a uniform standard could be the solution to this problem.

One of the problems related to the use of AI in oncology is patients' access to various applications and the use of chatbots. These are undoubtedly a valuable source of information for patients, especially when access to a medical team is limited. However, different chatbots answer the same question in different ways, which means that the information obtained by patients should be verified and treated with caution [90–92]. There are also other problems such as poor understanding of patients' problems and the resulting difficulties in answering specific questions, exclusion of certain patient target groups, predominance of AI systems based on text instead of speech or voice making access more difficult for the elderly, and safety and regulatory issues.

Meyer et al. highlighted several aspects related to the use of Chat GPT, including looking for ways to use this technology effectively, quantifying deviations, and realizing poor performance [93]. However, attention is drawn to the lack of transparency of Chat-GPT and the risk of propagating false health information [17,18]. Chen and co-authors examined chatbots in communicating information regarding cancer treatments and found that, although they would be able to pass the U. S. Medical Licensing Examination and are better at diagnosing cancer than people without medical training, they are poor at making therapeutic recommendations [90].

Despite various dilemmas, including ethical ones, not applying Ai would be unscientific and unethical, according to Naik et al. [77].

5. Discussion

Although AI is considered as the future of oncology and Lin et al. introduced the concept of "intelligent oncology", it is certainly only the beginning of a challenging yet exciting development path for oncology [21]. The use of AI in oncology requires constant improvement of the system and its continuous learning. AI's acquisition of new data enables its development and improvement in solving medical problems. This is particularly evident in the case of pancreatic cancer, where researchers are trying to collect data in two ways: centralization and federation. So far, AI is mainly used in the most common cancers (breast, lung, cervical, pancreas, colon and prostate cancers). There are fewer studies on less common cancers or so-called rare cancers. This is probably due to the smaller amount of data on less common cancers. An unsolved problem so far is not that of only self-learning AI, but that of the medical personnel using AI in oncology. There is another phenomenon related to this. There are concerns in the medical community as to whether there will still be room for doctors when using AI in oncology.

The issue of multi-morbidity in relation to cancer presents a new challenge for AI. Alsaleh and co-authors noted that detecting multimorbidity using AI requires several steps, which include incorporating clinical knowledge and stakeholder input at all stages of model development and validation, standardisation of approaches to data collection, management, phenotyping and validation of models to enable replication and informed comparison between studies, creation of transparent and understandable predictive models to increase clinical utility and assess bias, integrating other types of data, such as genetic, to increase efficiency, and promoting open data [94].

While research into the use of AI in adult oncology is growing rapidly, the pace of development of AI technology in pediatric oncology is much slower, and this should be changed. Ramesh et al. in their systematic review highlighted several difficulties with AI in pediatric oncology, such as the heterogeneity of methodologies and samples, limited use of validation cohorts, data standards, and a wide array of reporting metrics [95]. AI algorithms used in adult oncology cannot always be applied to pediatric oncology, which is particularly evident in imaging techniques (CT, MRI, PET, etc.) There are two main problems with the use of AI in diagnostic imaging of pediatric oncology, etc.: lack of large data and appropriate memory power [96]. This is why it is necessary to develop new AI algorithms that can be applied to pediatric cancers [96].

6. Conclusions

1. The development of oncology is closely related to AI.
2. The application of AI in oncology concerns not only various aspects of daily oncological clinical practice (cancer prevention, screening, diagnosis and treatment), but also research activities including biotechnology (biomarkers) and clinical trials
3. Intelligent oncology is a new term that describes the interdisciplinary integration of clinical oncology, radiology, pathology, molecular biology, and multi-omics with AI.
4. The effectiveness of AI in oncology depends on continuous learning of the system based on large amounts of new data.
5. The development of AI in oncology requires the resolution of some current issues, including ethical and legal ones.
6. To obtain medical information, AI applications used by patients, especially the elderly, need to be tailored to their capabilities

7. Future Directions

The introduction of AI into oncology presents an opportunity to improve the fate of cancer patients by using AI for screening, early diagnosis, treatment and predicting treatment outcomes. There is also a great potential for AI in clinical trials, not only in the design and development of new drugs, but also in improving organisation, including patient recruitment, and investigator and site selection.

AI can be helpful in studying the phenomenon of multimorbidity. Cancer mostly affects the elderly population, who also suffer from other conditions. The impact of these diseases on the course of cancer is very significant. AI is essential in creating a database on the coexistence of cancer with other diseases of epidemiological importance and tracing the relationship between these diseases, especially in tracing the influence of non-cancer diseases on the survival and mortality of cancer patients. Future directions for

AI development should include expanding the database so that the AI system can train itself and suggest the most beneficial actions for quick detection of cancer.

AI needs to be developed in diagnostic areas other than pathology and radiology. AI's ability to detect all cancers early should be expanded, not just the most common ones, but also so-called rare cancers and cancer in children.

Therapeutic decisions by multidisciplinary teams regarding the choice of therapy should be supported by AI. The numerous ethical and legal aspects of using AI in oncology need to be resolved. It needs to be clarified who will be responsible for possible errors resulting from the use of AI in oncology. The use of AI in oncology requires further investigations of the ethical aspects of AI and perhaps the development of not only new legal regulations, but also ethical ones.

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