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# Integrating Artificial Intelligence in Radiotherapy: Challenges and Opportunities in Clinical Workflows

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**Abstract**

**Background**: Radiation therapy is crucial in cancer treatment, yet access remains limited due to inadequate infrastructure and workforce shortages. The integration of artificial intelligence (AI) in radiological workflows holds the potential to enhance efficiency and improve patient outcomes.

**Methods**: This review analyzes the current landscape of AI applications in radiation oncology, focusing on various stages of the treatment process, including decision-making, treatment planning, and quality assurance. We evaluated the capabilities of AI techniques, particularly deep learning algorithms, in automating tasks such as image segmentation and dose optimization.

**Results**: The findings indicate that AI can significantly improve the accuracy and consistency of treatment planning by facilitating automated tumor delineation and enhancing image registration processes. Moreover, AI-driven predictive models have shown promise in forecasting treatment responses and optimizing radiation doses tailored to individual patient anatomies. However, the clinical adoption of these technologies is hindered by challenges, including the black-box nature of AI algorithms, the need for extensive validation, and concerns regarding data privacy.

**Conclusion**: While the potential of AI to revolutionize radiation oncology is evident, significant barriers must be addressed before widespread implementation can occur. Future efforts should focus on developing interpretable AI systems, establishing robust validation frameworks, and integrating AI tools into existing clinical workflows to enhance the quality of cancer care globally.

**Keywords**: Artificial Intelligence, Radiation Therapy, Clinical Workflow, Cancer Treatment, Deep Learning.

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## 1. Introduction

Radiation therapy is an essential component of cancer treatment and is recommended for around 50% of patients. Estimates suggest that millions of patients now lack access to this essential therapy method due to obstacles such as insufficient infrastructure, technology, and human resources, including treatment facilities, equipment, and trained personnel. Moreover, radiation treatment has become increasingly intricate in recent decades due to technological advancements, leading to a near-total dependence on human-machine interactions including both software and hardware [1-4].

Notwithstanding technological advancements, a significant portion of the radiation treatment process continues to need laborious, manual input from a varied team of healthcare experts, including radiation oncologists, medical physicists, medical dosimetrists, and radiation therapists. The increasing intricacy of human-machine interactions, along with the rising prevalence of cancer, has resulted in global shortages in the radiation oncology workforce and heightened diversity in service quality [5-8]. Variations in the radiation treatment-planning process have been shown to adversely impact overall survival, even within clinical trials, when efforts are made to standardize methodologies. The disparity in radiation treatment knowledge and experience between well-resourced and under-resourced healthcare systems represents a significant worldwide inequality in cancer care and is a substantial public health concern.

Artificial intelligence (AI) encompasses the creation and use of intricate computer algorithms to execute activities often necessitating human intellect, including visual perception, pattern recognition, decision-making, and problem-solving, at an equivalent or enhanced level of efficacy. Artificial intelligence is revolutionizing several medical disciplines and can tackle various issues encountered in radiation therapy, thereby enhancing the accessibility and quality of cancer treatment globally [9,10]. This study examines the potential of AI to revolutionize radiation oncology by detailing each phase of the clinical workflow and illustrating instances where AI could improve the efficiency, accuracy, and quality of radiation therapy, thereby augmenting value-based cancer care in contemporary resource-constrained healthcare settings. The potential uses of AI in radiation oncology are many, and this article does not include them all. We want to provide an overview of the revolutionary potential of AI in radiation treatment and our insights about the future of the radiation oncology workforce.

## 2. Techniques of artificial intelligence

Initial AI platforms were built on rule-based reasoning executed by a computer system following a series of processes and procedures established by human specialists. Nonetheless, the applicability of these methodologies to variations in input data and job scope is sometimes constrained by the absence of 'intelligent' components capable of addressing 'edge situations' not expressly outlined in the knowledge base [11-14]. These rule-based AI systems have attained differing levels of therapeutic value. In the last ten years, a significant transformation has taken place in the algorithms driving the automation of image-related operations. This transition has been characterized by the resurgence of neural networks; a category of machine learning algorithms loosely grounded on our assumed comprehension of human brain functionality [15].

Research on neural networks has progressed from the mathematical formulation of the backpropagation algorithm in the 1960s, which serves as the primary training method for neural networks by utilizing known outputs for each input to adjust the network's weights, to simpler networks in the 1980s. The growing volume of available data, coupled with enhancements in computational power and algorithmic advancements, has rekindled interest in this research domain, resulting in the creation of 'deeper' neural networks featuring multiple intermediate hidden layers between the input and output layers [16,17]. Hidden layers serve to execute non-linear transformations of input data to obtain feature information for the output layer. The use of these algorithms has eliminated the need to predefine reasoning principles, since the configuration of 'hidden neurons' connecting input and output nodes may be autonomously acquired from the training data. This method endows deep learning algorithms with enhanced learning capacity compared to earlier AI algorithms, hence enabling them to identify intricate, non-linear correlations in data. Consequently, deep learning may start to mimic or even exceed human skills in very complicated tasks and has been used in several medical contexts [18,19].

The radiation treatment process encompasses several intricate activities, such as tumor and organ segmentation, dose optimization, outcome prediction, and quality assurance (QA), which have seen differing levels of digitization and subsequent automation throughout time. This variability is also evident in the variety of data used, including radiographic pictures, radiation dosage maps, device calibration log files, and maintenance records. The multimodal characteristics of deep learning architectures facilitate the integration of diverse data streams, cross-modality learning, and algorithmic generalizability, thereby enhancing clinical decision-making and hence improving treatment quality for all patients [20].

## 3. Utilization in radiation oncology

The radiation therapy process consists of various stages: initial treatment decision-making, treatment planning and preparation, quality assurance, administration of radiation therapy, and subsequent follow-up care (Figure 1). The following sections delineate the principal responsibilities at each stage, the personnel engaged, and significant instances of AI's possible facilitative functions. In process stages where we do not foresee a significant role for AI, such as the actual administration of radiation, we have omitted instances [21].

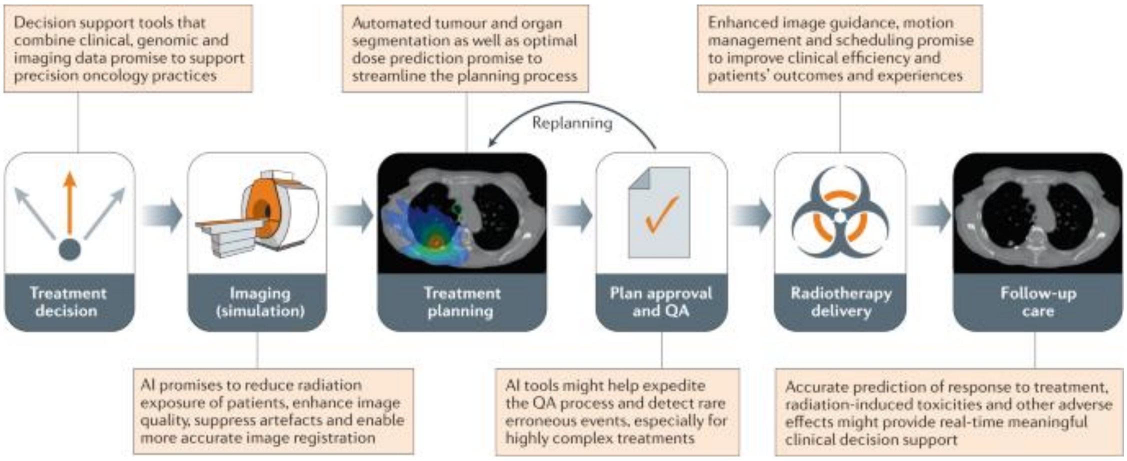


**Figure 1. Utilization of AI inside the radiation treatment process.**

## 4. Preliminary treatment decision-making

The clinical radiation treatment process starts with patient admission and assessment. This stage generally entails consultation with the radiation oncologist, encompassing an evaluation of the patient's symptoms, medical history, physical examination, pathological and genomic information, diagnostic assessments, prognostic considerations, comorbidities, and potential radiotherapy toxicities; the radiation oncologist then proposes a treatment plan derived from a synthesis of these data [22-24]. A burgeoning issue for doctors engaged in this procedure pertains to the incessant collection of data, beyond levels that humans can swiftly assimilate and comprehend. AI-driven techniques capable of autonomously identifying essential clinically actionable attributes will be vital for developing decision support systems for physicians at the primary point of care. Artificial intelligence methodologies for medical imaging evaluations and natural language processing for electronic medical records have shown preliminary potential in informing therapy choices and/or the clinical care of cancer patients. The prediction of the pathological response of affected lymph nodes in patients with non-small-cell lung cancer undergoing chemoradiotherapy may guide the therapeutic choice to either continue with the therapy or advance to surgical intervention. Furthermore, AI-based models have shown the capacity to enhance prognostication and predict treatment outcomes; nevertheless, they have not yet been integrated into standard clinical practice [25-27].

The radiation oncologist establishes the recommended radiation dosage to the tumor and the dose limitations for adjacent organs before treatment planning, by nationally recognized standards and clinical trial data. Nonetheless, disparities in tumor biology may lead to significant variances in radiation sensitivity, even within the same cancer type [28,29]. Moreover, the geometrical configuration of the tumor and adjacent organs may render the target dosage unattainable, a fact often overlooked until the planning phase is almost finalized. AI systems may facilitate the customization of radiotherapy by forecasting the radiation sensitivity of the tumor and determining the best dosage prescription attainable with a particular treatment plan, depending on the outlines of the tumor and surrounding organs [30,31].

## 5. Planning and preparedness for treatment

Simulation sessions are conducted to prepare for treatment planning, during which the patient is immobilized to minimize significant movement, and medical photographs are typically obtained to aid in developing the treatment plan. The complexity of this procedure varies by cancer location, and appropriate patient immobilization is subjective; thus, it often necessitates the collaboration of a radiation oncologist and a medical physicist [30-32]. Special care must be given to assess possible interference between the immobilization device and treatment beam angles, as well as patient-specific factors that may lead to collisions with the treatment equipment. Analogous to the utilization of AI in accelerating treatment planning predicated on a patient's anatomy, we hypothesize that AI may assist in recognizing potential challenges during treatment simulation by leveraging prior anatomical knowledge acquired through diagnostic imaging. Furthermore, it could propose solutions informed by algorithm training data, thereby streamlining and enhancing the planning process [33].

Numerous patients slated for radiation therapy need several medical imaging modalities for treatment planning, including CT pictures for radiation dosage calculation and MRI scans for tumor segmentation. Typically, these pictures are obtained with the patient in diverse postures (in the treatment position during CT, but in other positions during diagnostic imaging with other modalities), which adds ambiguity when aligning the images. One approach to reducing this uncertainty is to eliminate the need for CT by obtaining MRI data that may also provide electron density information, known as synthetic CT [34]. Artificial intelligence has been used to produce synthetic CT images from MRI scans of the brain and pelvis, with negligible dosage discrepancies seen between treatment plans developed using synthetic CT and actual CT. This strategy may enhance clinical efficiency and save costs by decreasing the number of imaging visits required for patients, while simultaneously minimizing their exposure to radiation from CT scans [35,36].

Technological advancements have resulted in the novel use of MRI in directing radiation therapy, including the integration of MRI scanners with linear accelerators into a unified treatment modality (MR Linac) [36-38]. High-resolution, low-noise MRI pictures need extended acquisition durations; hence, a trade-off must be established about the resolution and signal-to-noise ratios attainable within the allotted time for image collection and other clinical activities. Artificial intelligence may decrease MRI scan durations by facilitating the reconstruction of intricate features from under-sampled MRI data, as shown by the use of deep learning algorithms to produce high-resolution, high-contrast, and low-noise brain and heart MRI pictures from under-sampled data. Due to the intricacies involved in merging MRI scanners with radiotherapy linear accelerators—specifically, the distorting influence of the magnetic field on radiation beams and the artifacts produced by linear accelerator components on the magnetic field—current MR Linac systems are constructed with low-strength magnets, generally ranging from 0.35 to 1.5 T, which diminishes image quality relative to the high-resolution images acquired from conventional high-field-strength MRI scanners. Artificial intelligence may facilitate the reconstruction of high-signal, high-resolution pictures from low-field-strength MRI scans (for instance, generating 7-T MRI-like images of the brain from 3-T MRI data) to enhance tumor visibility during therapy [39,40].

Image registration is a crucial component of the radiation therapy workflow, utilizing data from multimodal and longitudinal imaging not only during treatment planning but also immediately before the administration of each treatment fraction, as well as for real-time monitoring of radiation delivery [41-44]. Commercially available automatic image-registration algorithms are generally optimized for modality-specific registration issues and exhibit sensitivity to image artifacts, which undermines accuracy and frequently necessitates supplementary manual adjustments to attain clinically acceptable registration. AI tools have been developed to identify the sequence of motion activities that provide the best picture alignment; these algorithms demonstrate superior accuracy and resilience compared to several state-of-the-art registration approaches and are applicable across numerous imaging modalities [45-47]. Moreover, AI methodologies have demonstrated efficacy in alleviating the impact of image artifacts, such as those present in X-ray images of the spine due to metal screws and guide wires, as well as motion artifacts frequently observed in fetal MRI, on registration precision. AI tools have been created for preliminary applications in MRI, X-ray, CT–MRI, and MRI–PET image registration. While several algorithms were not explicitly designed for radiation treatment, the issues they tackle are also encountered in this domain; so, these algorithms might enhance the radiation therapy process [48].

## 6. Image segmentation and dosimetric treatment planning

At present, the manual delineation of the main tumor and involved lymph nodes constitutes one of the most labor-intensive but essential responsibilities undertaken by the radiation oncologist. The precision of tumor segmentation may directly influence outcomes: an inaccurately defined tumor may result in underdosing or overdose, hence diminishing the probability of tumor control or increasing the risk of toxicities, respectively. Tumor segmentation exhibits inter-observer variability, even among professional radiation oncologists, potentially resulting in discrepancies in treatment plan quality and subsequent survival results [49,50]. Present semi-automated segmentation systems that use past information from reference pictures, such as segmentation atlases, are sometimes inaccurate or unavailable to most radiation oncologists due to exorbitant pricing and still need considerable human input [51]. Artificial intelligence can significantly enhance the efficiency, reproducibility, and quality of radiation treatment planning through the implementation of nearly fully automated segmentation techniques, exemplified by those created for the delineation of nasopharyngeal carcinomas, primary lung tumors, and oropharyngeal carcinomas. The efficacy of these segmentation algorithms closely parallels that of human specialists. However, further research, especially prospective studies, is necessary to directly evaluate the efficiency, accuracy, and repeatability of these AI tools in comparison to the existing gold-standard methods in the radiation therapy clinical workflow [52-55].

In radiation therapy planning, nearby organs to the tumor are segmented to assess the radiation dosage administered to these vital organs and to ensure it remains below acceptable thresholds. Initial AI tools have shown potential in identifying various organs in the body, including the intricate anatomy of the head and neck, thoracic organs, kidneys, liver, and cardiac substructures; however, these results are constrained by small training datasets, leading to possible overfitting of the AI algorithms [56,57]. The most extensive instance of this methodology documented thus far pertains to a collaboration between the University College London Hospitals Department of Radiotherapy and Google DeepMind, utilizing a training dataset of CT images from 663 patients to create an algorithm proficient in segmenting organs in the head and neck region, achieving performance akin to that of human experts. As commercially available AI-driven auto-segmentation technologies are increasingly integrated into treatment planning systems, supplementary tools are necessary for quality assurance to detect inaccuracies. The quality assurance of auto-segmentations is a labor-intensive and time-consuming endeavor, representing another domain where AI-based QA solutions might diminish the necessary time and resources [58-62].

Upon receiving medical imaging, tumor, and organ segmentations, and the dosage prescription, the medical dosimetrist endeavors to create the ideal treatment plan for the patient, aiming to maximize the dose administered to the tumor while preserving adjacent organs. Treatment planning is a laborious, iterative procedure in which the dosimetrist formulates the dosage distribution, implementing modifications via trial and error to meet the objectives specified in the dose prescription [63,64]. The radiation oncologist thereafter assesses the treatment plan before its clearance for execution. The efficacy of radiation therapy regimens is contingent upon several human variables, including the selection of radiation beam angles and optimization parameters, leading to significant variances both within and across institutions [65].

Existing methodologies for standardizing and enhancing the effectiveness of dosimetric treatment planning are not reliant on artificial intelligence; rather, they include the automation of repetitive operations via rigidly specified rules and/or the optimization of planning parameters by predetermined goals using statistical techniques. The used procedures are often tailored for certain anatomical locations and possess a restricted ability to accommodate changes in plan complexity and patient-specific considerations [66,67].

AI techniques for automating treatment planning consist of two primary steps: 1) forecasting the ideal dosage distribution, and 2) determining the necessary treatment machine settings to realize that distribution [68]. Numerous research indicates that deep learning algorithms can anticipate appropriate dose distributions for individual individuals based on their anatomy and expedite dosage computations [69-72]. For AI-driven treatment-planning algorithms to produce a high-quality plan, it is essential to incorporate information about the intricate decision-making process into the foundational model, akin to the methodologies employed in the creation of AI algorithms capable of playing Atari games or the board game Go. In retrospective studies, researchers have utilized gamification concepts to autonomously create treatment plans for high-dose-rate brachytherapy in cervical cancer patients or radiation dose modification in non-small-cell lung cancer patients, achieving performance comparable to or exceeding that of human planners. AI techniques possess the capacity to significantly enhance this vital phase of the radiation workflow, initially by forecasting achievable radiation dose distributions to enable radiation oncologists to determine the most effective treatment strategy, and subsequently by formulating the treatment plan for the administration of the optimal radiation dose. Consequently, AI may facilitate the complete automation of the treatment-planning process shortly [73].

## 7. Obstacles to clinical execution

The clinical use of AI in radiation oncology presents a significant obstacle to its potential; using AI tools necessitates an initial commitment of time and money, alongside efforts to comprehend their value and limits, and to reconfigure existing clinical processes. Numerous AI technologies are still in the proof-of-concept phase and require external validation, leading to a sluggish integration into standard practice, hence rendering the demonstration of generalizability and efficacy unachievable [75]. Establishing confidence in AI systems is essential due to the 'black box' characteristics of several machine learning techniques, particularly deep learning. Despite ongoing research into the 'interpretability' and 'explainability' of AI—referring to the comprehension of an algorithm's operations and its underlying mechanics, respectively—the opacity of AI impedes our capacity to comprehend outputs, anticipate failures, and address generalizability challenges. Failure to regularly monitor the performance of deployed AI tools and to continuously evaluate the suitability of training data for the specific issue may lead to a rise in mistakes due to the introduction of systematic biases into these systems [76].

Present AI tools lack perfect accuracy, and three criteria can assess their viability for clinical application: 1) the time allotted for and the user's capacity to evaluate the accuracy of the results; 2) the possibility of rectifying erroneous outcomes; and 3) the implications of errors for a patient. A clinical implementation may be quite simple, even in instances with potentially grave implications, provided that model mistakes are identified and rectified before advancing to the subsequent phase of the radiation process [77]. The feasibility of clinical application will diminish if the time and skill needed for the user to assess the correctness of the results surpass the efficiency or accuracy benefits provided by the AI tool. Moreover, the risk-to-benefit ratio of using the AI-based tool is much more difficult to ascertain in scenarios where the user is unable to evaluate the accuracy of the outcome (for instance, when a tumor is not discernible in an image and an AI tool is used for auto-segmentation). AI-assisted or completed tasks that significantly impact a patient's therapy provide a distinct difficulty for clinical application because of their possible consequences for the patient.

A comprehensive legal framework for regulating algorithmic decision-making remains undeveloped, particularly with patients' rights to receive explanations for algorithmic outputs and the ramifications of data protection legislation. Artificial intelligence can diminish medical mistakes, however, it is likewise anticipated to transform the legal framework concerning clinical liabilities and obligations. The heightened use of AI will alter the dynamics of the patient-doctor connection, presumably transitioning towards a patient-healthcare system interaction, hence potentially diminishing the doctor's responsibility for the patient. Ethically, algorithms used for face recognition and estimating recidivism risk have shown intrinsic racial prejudices, and the implementation of AI in healthcare is beginning to reveal analogous issues. Furthermore, immoral AI methodologies may be devised by entities with hidden agendas to manipulate outcomes for financial advantage. All these issues must be resolved to allow the successful general clinical deployment of AI-based solutions [20,45].

## 8. Consequences for medical dosimetrists

Medical dosimetrists now execute several manual treatment-planning jobs that are likely to be replaced by AI methodologies. Research indicates that discrepancies in the quality of treatment plans are mostly due to the overall 'planning competence,' rather than factors such as experience, certification, or education. This discovery emphasizes the prospective advantages of automating dosimetrists' responsibilities, particularly the potential to reduce the variability of treatment provided. The feasibility of automating treatment planning to alleviate the labor of medical dosimetrists is purportedly contingent upon the clinical precision of the produced plans [36,67]. Additional evidence is needed to instill enough confidence for a transition to full automation; nonetheless, results from preliminary experiments have shown encouraging promise. Shortly, we anticipate that the responsibilities of dosimetrists will concentrate on higher-risk and more intricate scenarios that pose challenges for existing AI methodologies. We anticipate that AI-driven automation will significantly disrupt this profession in the long future. The 2017 American Association of Medical Dosimetry salary survey indicated that 45% of respondents said they were impacted by understaffing. Automation may reduce the workload of dosimetrists to achieve optimal staffing levels, while it might result in significant decreases in the number of dosimetrists employed [78].

Radiation therapists act as the ultimate safeguard in treatment administration to maintain patient safety and prevent the misadministration of radiation. As previously stated, AI has the potential to offer software tools that assist radiation therapists in delivering precise and safe treatment while enhancing efficiency and patient accessibility; nonetheless, we contend that radiation therapists will maintain a crucial role in overseeing the operation of these automated systems and the patient [54].

## 9. Conclusions

In addition to improvements in accuracy, repeatability, and consistency, the collaboration between human intuition and AI's ability to use extensive data from huge datasets might significantly enhance efficiency and throughput in radiation treatment. These advantages have attained paramount significance in the contemporary context of cost reduction, alongside the transition from fee-for-service to value-based care.

The global health landscape is poised to gain from AI-based initiatives. More than fifty percent of cancer patients reside in low-income or middle-income nations. In resource-constrained environments, workforce and equipment shortages have resulted in over 50% of patients anticipated to benefit from radiation lacking access to this treatment, with figures reaching as high as 90% in some low-income nations. AI software solutions aim to mitigate some shortages by delivering specialized expertise across various illness locations and treatment approaches. The potential of AI to resolve hardware equipment shortages is uncertain; nonetheless, it may assist in maintaining current equipment by enhancing the interpretation of machine quality assurance data.

The introduction of AI tools will significantly alter the composition and skill set of the radiation oncology workforce; however, these modifications are expected to be largely beneficial, facilitating enhanced efficiency and improved quality of care while reducing costs.

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**دمج الذكاء الاصطناعي في العلاج الإشعاعي: التحديات والفرص في سير العمل السريري**

**الملخص**

**الخلفية :**يُعد العلاج الإشعاعي عنصرًا أساسيًا في علاج السرطان، ومع ذلك، يظل الوصول إليه محدودًا بسبب نقص البنية التحتية وقلة الكوادر المتخصصة. يحمل دمج الذكاء الاصطناعي (AI) في سير العمل الإشعاعي إمكانات كبيرة لتعزيز الكفاءة وتحسين نتائج المرضى.

**المنهجية :**تحلل هذه المراجعة الوضع الحالي لتطبيقات الذكاء الاصطناعي في علم الأورام الإشعاعي، مع التركيز على مراحل مختلفة من عملية العلاج، بما في ذلك اتخاذ القرارات، تخطيط العلاج، وضمان الجودة. قمنا بتقييم قدرات تقنيات الذكاء الاصطناعي، لا سيما خوارزميات التعلم العميق، في أتمتة المهام مثل تقسيم الصور وتحسين الجرعات.

**النتائج :**تشير النتائج إلى أن الذكاء الاصطناعي يمكن أن يحسن بشكل كبير دقة وتناسق تخطيط العلاج من خلال تسهيل تحديد الأورام تلقائيًا وتعزيز عمليات تسجيل الصور. علاوة على ذلك، أظهرت النماذج التنبؤية التي تعتمد على الذكاء الاصطناعي وعودًا في التنبؤ باستجابات العلاج وتحسين جرعات الإشعاع المخصصة بناءً على تشريح كل مريض. ومع ذلك، فإن تبني هذه التقنيات سريريًا يواجه تحديات، بما في ذلك الطبيعة "الصندوق الأسود" لخوارزميات الذكاء الاصطناعي، الحاجة إلى التحقق الشامل، والمخاوف المتعلقة بخصوصية البيانات.

**الخلاصة :**على الرغم من أن إمكانات الذكاء الاصطناعي لإحداث ثورة في علم الأورام الإشعاعي واضحة، يجب التغلب على عوائق كبيرة قبل أن يصبح تنفيذه واسع النطاق ممكنًا. يجب أن تركز الجهود المستقبلية على تطوير أنظمة ذكاء اصطناعي قابلة للتفسير، وإنشاء أطر تحقق قوية، ودمج أدوات الذكاء الاصطناعي في سير العمل السريري الحالي لتعزيز جودة رعاية مرضى السرطان على مستوى العالم.

**الكلمات المفتاحية :**الذكاء الاصطناعي، العلاج الإشعاعي، سير العمل السريري، علاج السرطان، التعلم العميق.