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Artificial Intelligence in Radiation Oncology: Current applications, clinical impact, and future perspectives. A Narrative Review

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ABSTRACT

Radiation oncology is a highly digital and data-intensive discipline in which artificial intelligence (AI) is increasingly being incorporated into the clinical workflow. From image analysis and automatic segmentation to treatment planning, adaptive radiotherapy, radiomics, and outcome prediction, AI has the potential to improve efficiency, reproducibility, and treatment personalization. This narrative review summarizes the principal concepts underlying machine learning and deep learning and examines their current applications across the radiation therapy pathway. Particular attention is given to automated contouring, knowledge-based and automated planning, cone-beam computed tomography (CBCT)- and magnetic resonance imaging (MRI)-guided adaptive radiotherapy, toxicity and tumor-control prediction, and the integration of radiomic, clinical, dosimetric, and molecular data. The available literature suggests that AI can reduce repetitive workload and inter-observer variability and may facilitate more consistent treatment planning. However, technical performance alone does not establish clinical benefit. Major challenges include data quality, dataset bias, limited external generalizability, interpretability, cybersecurity and data governance, and the need to define responsibility when AI-generated outputs are used in patient care. Prospective, multicenter validation and continuous quality assurance are therefore essential. The future of AI in radiation oncology is unlikely to be the replacement of the radiation oncologist, but rather a human–AI partnership in which automation supports clinical expertise. If AI successfully releases clinical time, this resource should be reinvested in patient communication, shared decision-making, research, innovation, and education.

KEYWORDS

Artificial intelligence; machine learning; deep learning; radiation oncology; auto-segmentation; automated treatment planning; adaptive radiotherapy; radiomics; precision medicine

MAIN ARTICLE

Introduction

Radiotherapy is a cornerstone of cancer treatment and is delivered to a substantial proportion of patients during the course of their disease. Over recent decades, radiation oncology has evolved from two-dimensional techniques to three-dimensional conformal radiotherapy, intensity-modulated radiotherapy (IMRT), volumetric modulated arc therapy (VMAT), stereotactic radiotherapy, image-guided radiotherapy, and adaptive radiotherapy. This technological progress has improved the ability to conform dose to target volumes while limiting irradiation of organs at risk (OARs). At the same time, increasingly sophisticated workflows have generated substantial amounts of imaging, dosimetric, clinical, and longitudinal data [1,3,4].

The radiotherapy workflow remains time-consuming and dependent on human expertise. Contouring, treatment planning, image registration, verification, and adaptive decision-making are all susceptible to inter- and intra-observer variability. Artificial intelligence has therefore emerged as a potential decision-support and automation tool. Rather than representing a single technology, AI encompasses a family of computational approaches, including machine learning, deep learning, image analysis, pattern recognition, predictive modeling, and, more recently, generative and multimodal models [3,4,9].

The objective of this narrative review is to describe the current applications of AI in radiation oncology, assess their potential clinical and organizational impact, and discuss the limitations and requirements for safe implementation. A central question is not simply what AI can technically perform, but whether its integration produces meaningful improvements for patients and healthcare teams.

Methods

This work was designed as a narrative review of the literature. The source thesis reports searches of PubMed, Scopus, Cochrane, and Google Scholar performed between July and August 2026 using combinations of the terms “artificial intelligence,” “machine learning,” “deep learning,” “radiotherapy,” “radiation oncology,” and “radiomics.” Additional recent publications and conference communications were considered to identify emerging technologies. The literature was organized thematically around AI fundamentals, medical imaging, segmentation, treatment planning, adaptive radiotherapy, radiomics, predictive models, ethics, regulation, and clinical implementation.

The review deliberately distinguished three levels of assessment: algorithmic performance, clinical performance, and organizational impact. This distinction is important because a high technical metric does not necessarily translate into improved clinical outcomes. No formal systematic-review screening process or quantitative meta-analysis was performed, and the source thesis does not report a numerical count of records identified or included.

Artificial Intelligence Fundamentals in Radiation Oncology

Machine learning and deep learning

Machine learning (ML) enables computational models to learn relationships from data rather than relying exclusively on explicitly programmed rules. A typical ML workflow includes data collection, preprocessing, feature selection or extraction, model training, validation, and testing. Classification models may be assessed using sensitivity, specificity, precision, F1 score, or area under the receiver operating characteristic curve, whereas segmentation commonly relies on Dice similarity coefficient, Jaccard index, and Hausdorff distance. Regression tasks may be evaluated using mean absolute error, root mean squared error, or R^2 [12,17,22,26].

Deep learning (DL) is a subset of ML based on multilayer neural networks capable of learning hierarchical representations directly from complex data. Convolutional neural networks (CNNs) have become particularly important for medical image analysis. The U-Net architecture and its variants are widely used for biomedical segmentation because encoder–decoder structures and skip connections preserve spatial information while extracting increasingly complex features [13,29–32]. Transformers and vision-transformer approaches are newer architectures that may capture long-range spatial relationships and are being investigated for medical image segmentation and classification.

Learning strategies and data sources

Supervised learning remains the dominant strategy in radiation oncology because expert-annotated datasets are available for many tasks, including segmentation, toxicity prediction, tumor response, and survival modeling. Unsupervised learning can identify clusters or latent patterns without predefined labels and has applications in patient stratification and radiomic exploration. Reinforcement learning remains more experimental but may eventually support treatment optimization and adaptive decision-making.

Radiotherapy generates heterogeneous digital data, including simulation CT, MRI, PET/CT, contours, three-dimensional dose distributions, dose-volume histograms, treatment parameters, electronic health records, pathology, molecular data, and longitudinal outcomes. The combination of these modalities is particularly attractive because treatment response and toxicity are determined by interactions between anatomy, dose, biology, and patient-specific factors rather than by any single variable [16,17,39].

Current Applications of AI in Radiation Oncology

Automated contouring

Contouring of target volumes and OARs is a fundamental step in radiation treatment planning. Manual delineation is labor-intensive and can vary substantially between clinicians. Modern AI systems, particularly DL-based segmentation models, can generate initial contours rapidly and reproducibly. Applications include head-and-neck structures such as the spinal cord, brainstem, parotids, submandibular glands, larynx, and oral cavity, as well as pelvic, thoracic, abdominal, and intracranial structures [34,56,58,59].

Target segmentation is more challenging than OAR segmentation because the GTV may be defined from multimodal imaging, whereas the CTV reflects not only visible anatomy but also microscopic extension risk, tumor stage, histology, and known patterns of spread. AI can therefore assist with a preliminary segmentation, but the final CTV definition remains a clinical decision. The PTV can generally be generated from the CTV according to institutional margins and setup uncertainties [56–58].

The principal advantage of auto-segmentation is not the elimination of the clinician, but reduction of the total contouring workload. The clinical value of a contour cannot be inferred from the Dice coefficient alone: a small geometric error involving a small OAR adjacent to a high-dose target may have major dosimetric consequences. Accordingly, current practice is best characterized as “human-in-the-loop,” with AI generating an initial segmentation followed by expert review and correction [34,58,61].

AI-assisted treatment planning

Treatment planning is another major area of AI development. Knowledge-based planning (KBP) uses previously generated high-quality plans to learn relationships between patient anatomy and achievable dose distributions. For a new patient, the model can predict expected dose-volume objectives and help guide optimization. This approach may improve plan consistency and reduce dependence on individual planner experience [62–64].

Automated planning and dose prediction extend this concept by using ML or DL to estimate three-dimensional dose distributions or optimization parameters directly from anatomy and contours. These approaches are particularly relevant to IMRT and VMAT, where numerous beam or delivery parameters must be optimized simultaneously. AI is also being explored in stereotactic body radiotherapy (SBRT), where rapid generation of high-quality plans may be useful but where the consequences of segmentation or optimization errors are particularly important.

Importantly, an automatically generated plan is not automatically a clinically acceptable plan. Target coverage, OAR constraints, plan robustness, machine deliverability, and independent quality assurance must still be evaluated by the radiation oncology team.

Adaptive radiotherapy

Adaptive radiotherapy (ART) aims to modify treatment according to anatomical or biological changes occurring during a course of irradiation, such as tumor regression, weight loss, organ filling, or deformation. AI may shorten the interval between daily imaging and adaptation by automating image enhancement, segmentation, registration, dose estimation, and plan generation [65–70].

CBCT is widely used for daily image guidance but is affected by noise, artifacts, and limitations in quantitative density information. DL-based image enhancement and synthetic CT generation may improve its suitability for adaptive workflows [66,68]. Deformable image registration can transfer contours and support dose accumulation across fractions, although substantial anatomical deformation may introduce registration errors that require clinical review [67].

Online adaptive radiotherapy is particularly attractive on MR-guided treatment systems. MRI provides superior soft-tissue contrast and can support daily visualization of structures such as the prostate, bladder, and rectum. AI-assisted segmentation and planning may reduce the time required for daily adaptation, potentially making highly individualized treatment more practical [45,46,69]. Similar principles are relevant to head-and-neck cancer, where weight loss and tumor regression may substantially alter anatomy during treatment [70].

Predictive modeling, radiomics, and precision radiotherapy

AI can integrate clinical, imaging, dosimetric, and biological information to estimate the probability of treatment-related toxicity, tumor response, local control, recurrence, and survival. For toxicity prediction, models can combine OAR dose-volume parameters with age, comorbidities, treatment characteristics, and other patient-specific variables, extending traditional normal tissue complication probability (NTCP) approaches [39,52].

Radiomics transforms medical images into quantitative features describing intensity, shape, texture, and heterogeneity. These features may reveal information not readily apparent to visual inspection and can be combined with clinical and dosimetric variables to construct predictive models [36,42,71]. Radiogenomics seeks associations between imaging phenotypes and molecular or genetic characteristics, with the long-term objective of obtaining non-invasive biomarkers of tumor biology and radiosensitivity [72,74].

The most promising direction is multimodal modeling, in which CT, MRI, PET, electronic health records, pathology, genomics, radiomics, and dosimetry are analyzed together. Such models could help stratify patients according to individualized risks and potentially support treatment intensification, de-escalation, surveillance, or adaptive strategies. However, prediction must not be confused with causation: identifying a high-risk patient does not prove that changing treatment on the basis of the prediction will improve outcome. Prospective clinical validation is therefore essential.

Clinical Impact: Benefits, Limitations, and Implementation Challenges

Potential benefits

The most immediate potential benefit of AI is workflow efficiency. Automated contouring, selected planning tasks, image analysis, and quality-control processes can reduce repetitive manual work, particularly in high-volume departments [34,39]. AI may also improve reproducibility by providing a standardized starting point for contouring and planning. KBP and automated planning can reduce variation related to planner experience and may facilitate consistent treatment quality [62,63].

A second potential benefit is personalization. By combining anatomy, dosimetry, imaging phenotype, clinical characteristics, and biological information, predictive models may help identify patients at higher risk of toxicity or treatment failure and support individualized therapeutic strategies.

Limitations and safety

The principal limitations are data quality, representativeness, bias, overfitting, and limited generalizability. A model trained on a particular patient population, scanner, acquisition protocol, or institutional practice may perform less well when transferred to another environment. Medical datasets may also be incomplete, heterogeneous, and inconsistently annotated. These problems are especially relevant to radiomics, where acquisition and reconstruction parameters can substantially alter extracted features [71,76].

Interpretability is another challenge. Complex DL models may behave as “black boxes,” making it difficult for clinicians to understand why a particular output was generated. Explainable AI may improve transparency, but explanation alone does not establish correctness. Continuous quality assurance, external validation, monitoring for performance drift, and clearly defined escalation procedures are therefore required.

Ethical and organizational considerations are equally important. Health data must be appropriately anonymized or pseudonymized and governed securely. Responsibility for clinical decisions must remain explicit. AI should support, rather than obscure, professional accountability. Staff must also be trained to understand the strengths and failure modes of the systems they use [51,55].

Future Perspectives

The next stage of AI development in radiation oncology is likely to involve increasingly integrated and multimodal workflows rather than isolated automation of individual tasks. Future systems may connect imaging, segmentation, treatment planning, quality assurance, adaptive decision-making, and outcome prediction within a single workflow while retaining human supervision.

Generative AI and large multimodal models may facilitate synthesis of information from medical records, imaging, dosimetry, pathology, and molecular data. Their potential is substantial, but oncology applications require particularly rigorous evaluation because plausible but incorrect outputs could directly affect patient care.

The decisive evidence for clinical adoption will come from prospective and multicenter studies evaluating outcomes that matter to patients and services: safety, treatment quality, toxicity, tumor control, survival, quality of life, workflow efficiency, and cost-effectiveness. The goal should not be automation for its own sake. If AI reduces repetitive work, the time saved represents a clinical resource that can be reinvested in patient communication, shared decision-making, education, research, innovation, and continuous improvement.

Conclusion

Artificial intelligence is becoming an important component of modern radiation oncology, with applications spanning image analysis, automated contouring, treatment planning, adaptive radiotherapy, radiomics, and predictive modeling. Machine learning and deep learning can process complex datasets and automate selected tasks, potentially improving efficiency and reproducibility while supporting more individualized treatment.

Nevertheless, technical performance should not be mistaken for clinical effectiveness. Data quality, algorithmic bias, external generalizability, reproducibility, interpretability, privacy, cybersecurity, and medical responsibility remain major barriers to widespread implementation. Human validation remains essential, particularly for target definition, treatment planning, and adaptive decisions.

The future of radiation oncology is therefore more likely to involve collaboration between clinicians and AI than replacement of clinicians by AI. The key question is not only what AI can do instead of the physician, but what it can enable the physician to do better. If technology genuinely releases clinical time, its greatest value may ultimately be measured by how much of that time is returned to the patient.

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