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EDITORIAL

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Artificial Intelligence in radiotherapy: Why radiation therapists must be part of the conversation

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ABSTRACT

Artificial Intelligence (AI) is having a massive impact in the field of radiotherapy with improvements in image registration, automated segmentation, treatment planning, image reconstruction, adaptive radiotherapy and Quality assurance (QA). As these technologies move from the research setting into the real world of clinical practice, the changing role of the radiation therapist (RTT) is something that needs to be thought about. This editorial argues that the RTT should be seen as much more than just the end user of AI technology. They should be seen as active participants in its design, evaluation, validation, implementation and governance. The RTT is the one who is actually providing the patient care and delivering the treatment, so they have the unique clinical and contextual knowledge that algorithmic performance metrics can never capture. AI can, of course, improve efficiency, allow for automation, improve pattern recognition, and standardize workflows. However, the outcome of any AI application is still susceptible to issues such as dataset bias, domain shift, atypical anatomy, workflow differences and clinically inappropriate recommendations. Human oversight, professional judgement, quality assurance and accountability are therefore essential if AI is to be used safely in radiotherapy. The RTT is in the ideal position to be assessing patient positioning, immobilisation, image quality, anatomical changes, treatment verification and the clinical relevance of any AI-generated recommendations at the point of care. This new role will require greater AI literacy to be embedded into RTT education and throughout their careers, with appropriate ongoing professional development in areas such as model validation, uncertainty, failure modes, data security and escalation. The future of radiotherapy is not simply a choice between human and machine. It is about the integration of computational intelligence with clinical judgement to provide safer, more efficient and more patient-focused care. The RTT must be involved in this process from the very beginning of the development of any AI application right through to its clinical implementation.

KEYWORDS

Artificial Intelligence; Radiotherapy; Radiation therapists; Clinical AI literacy; Adaptive radiotherapy; Quality assurance

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Introduction

AI is rapidly moving from the research phase into routine radiotherapy with applications in image registration, treatment planning, image reconstruction, adaptive radiotherapy and QA [1–8]. The radiation therapist (RTT) is the interface between the technology and the patient. They are responsible for immobilisation, imaging, image guidance, treatment verification and delivery and for responding to the individual clinical needs of the patient [9,10]. The implementation must of course preserve human monitoring, accountability and patient safety.

Point of View

AI shouldn't just be sitting alongside RTTs. RTTs need to be in the driver's seat in terms of how AI is going to be used. AI in radiotherapy is never going to be a standalone tool. Its output is going to be part of the whole patient care picture, part of the fabric of what we do in the department, from the equipment through to the imaging, the immobilisation, the planning, the verification and the actual treatment. An algorithm may be very precise, but the RTT is the one who is going to interpret that in the context of that individual patient. The goal isn't to have machines doing the thinking; it's to have a working partnership where the speed and pattern recognition of the AI is combined with the clinical judgement, the patient interaction and the practicality of the RTT.

Explanation and Evidence

Automated image segmentation is among the most established radiotherapy applications of AI. Deep-learning systems can delineate organs at risk (OARs) and targets while reducing contouring time [1–5]. Oktay et al. reported performance comparable to expert segmentation in head-and-neck and prostate datasets, with faster annotation [1]. Cha et al. found that deep-learning auto-segmentation reduced prostate contouring time by a median of approximately 12 minutes; most generated contours required no or only on-centre adjustment. Wong et al. showed that AI-generated contours could be incorporated into workflows at two cancer centres, with feedback from RTTs, dosimetrists and radiation oncologists informing implementation [3]. Shi et al. developed a deep-learning framework for whole-body OAR and tumour delineation, reporting an average Dice similarity coefficient of approximately 0.95 across more than 28,000 cases and near-real-time segmentation for several structures [4]. Wang et al. demonstrated deep-learning auto-segmentation of rectal tumours on MR images [5]. The results support clinician review of machine-generated structures; automated contours remain proposals requiring expert assessment.

AI is also being investigated for dose prediction, treatment-plan generation, achievable dose-volume histogram estimation and optimisation [6–12]. Fan et al. described a method that predicts three-dimensional dose distributions and uses them to generate treatment plans [6]. Kandalan et al. found that

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prostate dose-prediction models trained using one planning approach performed less effectively when transferred to different institutional practices, demonstrating the requirement for adaptation and local validation [7]. Liu et al. developed a model to predict achievable OAR dose-volume histograms for inverse planning, while Bakx et al. evaluated dose-prediction models in breast radiotherapy [8,9]. Lee et al. developed a framework to predict anatomical changes during lung cancer treatment and incorporate them within adaptive planning [12].

AI is extending beyond isolated automation, requiring RTTs to supervise intelligent processes, understand system behaviour and recognise when intervention is necessary. Researchers are investigating automated registration, segmentation, image enhancement, synthetic CT, and adaptive workflows. Yang et al. used deep learning to improve cone-beam CT (CBCT) image quality, addressing a limitation of CBCT-based adaptive workflows [13]. Zhao et al. demonstrated projection synthesis for low-dose CBCT reconstruction, improving image quality and showing potential to reduce imaging dose [14]. Radici et al. evaluated deep-learning CBCT auto-segmentation in prostate adaptive radiotherapy [15]. Personalised deep-learning segmentation for large brain metastases in MR-guided adaptive radiotherapy improved segmentation efficacy and decreased contouring time compared with manual delineation. In image-guided radiotherapy, AI may identify anatomy, register images and propose positional corrections. RTTs must verify positioning, immobilisation, anatomy, image quality, registration and the appropriateness of proposed corrections. Research into online adaptive radiotherapy retains contour review and manual correction while evaluating workflow robustness and reproducibility. AI should therefore function as a capable assistant, not an autonomous clinical decision-maker.

Recent medical workflows reinforce this distinction. In a 2026 left-breast study, only 43% of fully automated plans met all clinical goals, despite reduced planning time. A 2026 prospective prostate evaluation achieved acceptable plans in 86% of patients, with mandatory physician review. Automation does not remove the need for professional verification. Clinical context is critical because AI systems learn from their training data. Unrepresented cases may include unusual anatomy, metallic implants, post-surgical changes or positioning difficulties [7]. Kandalan et al. demonstrated that a prostate dose-estimation model did not transfer reliably between different planning practices, underscoring that performance at one centre cannot be assumed at another. Similarly, studies show that automatically generated contours may need human review and correction [2,3,15]. RTTs should consequently move beyond being end-users and become co-designers of AI-enabled systems. They can define requirements, map workflows, identify failure modes and test usability before implementation. A high Dice coefficient may not guarantee clinical acceptability; a reliable, easily corrected contour may be more useful than a mathematically stronger but impractical output. Clinical usefulness and technical accuracy are related, but not interchangeable.

RTTs may also contribute to AI-supported QA. El Naqa et al. demonstrated machine-learning approaches using electronic portal imaging device data to identify issues such as gantry sag, field shifts and multi-leaf collimator errors. Li et al. investigated machine learning for patient-specific VMAT QA and for predicting and classifying QA outcomes. A multicentre study supported the application of machine-learning-based virtual IMRT QA across institutions. Nevertheless, AI-based QA must complement, not replace, established checks and professional responsibility. Their direct interaction with treatment and imaging systems also helps identify workflow problems algorithms may miss. Adaptive radiotherapy is another area where AI may accelerate assessment of anatomical changes, contour updates, dose calculation, plan adaptation, and treatment delivery [12,15]. Li et al. developed a deep-learning model to track weekly lung-tumour shrinkage on CBCT, supporting the possibility of predictive planning. Lee et al. similarly investigated prediction of lung-cancer anatomical changes for responsive planning [12]. RTTs should review generated contours, verify dose calculations versus the clinical plan, check adapted plans for inadvertent changes, and confirm that AI-detected anatomical variations match the patient's condition. RTTs must escalate unexpected findings and uncertain outputs. Are RTTs prepared for these changes? Marr and Tsang surveyed 74 RTTs: 93.2% wanted to learn more about AI, while 79.7% felt that AI was not yet fully utilised in radiation therapy. A Canadian survey involving radiation oncologists, RTTs, medical physicists and trainees similarly indicated that AI would influence radiation oncology's future. AI education should therefore become part of continuing professional development. Online healthcare AI courses, ESTRO and ASTRO activities, local workshops, and multidisciplinary journal clubs can provide a foundation.

AI education for RTTs doesn't mean that every RTT is going to become a computer scientist. What it does mean is that RTTs need to develop a degree of clinical AI literacy. This would involve understanding the process of model training and model validation; the difference between real-time clinical validation and retrospective review; the nature of error (including error sources, dataset bias, domain shift and uncertainty); and the limitations of AI-generated recommendations. RTTs should be able to identify when human monitoring is required, how to perform the appropriate AI quality checks, how to detect system failure, how to protect data privacy and security and how to deal with a situation where the AI output is at odds with their own clinical judgement. All of this is to underpin safe, reliable and patient-centred practice.

Counterarguments

AI may seem objective, but its reliability is predicated on the quality of the data, the design of the system, rigorous validation, correct implementation and continuous monitoring. There is a potential for error in contouring, registration or treatment planning, and QA systems can be prone to misclassification of atypical cases. Knowledge-based and machine learning approaches have shown promise in planning across a range of diseases and techniques. There are also ongoing advances in AI-driven synthetic CT, MR-only planning, segmentation and automated workflows. Technical performance in itself does not equate to clinical value, as models can fail in novel situations and human-guided systems can be more efficient and assist the expert. The real question is not whether AI will replace RTTs but rather how it can augment the wider radiotherapy team and improve patient care.

Summarize and Suggest Solutions

The RTT role is very likely to move from being about the execution of repetitive tasks to being about the supervision of

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intelligent systems, the management of the atypical and patient communication. The professional value will increasingly lie in perception, judgement, accountability and compassion. The RTT will be the one to interpret the machine output in context, to spot the deviations and to decide whether the recommendations are appropriate for the patient. AI is already having an impact on planning, segmentation, image guidance, adaptive treatment and CBCT. The interest of RTTs in the implications of AI is clear. Radiotherapy education and practice will have to change as a result. RTTs need to be involved in AI development teams, in the clinical testing and in the decisions around the adoption of the technology. Their involvement should start right at the very beginning of the process: identifying the clinical problem, designing the workflow, testing the performance, identifying the failure modes, validating the technology and establishing the standards for safe use. Institutions and societies need to support the education of AI, the multidisciplinary approach, local validation, monitoring and the clear delineation of review responsibilities. AI should not be something that happens to the RTT. It should be something that the RTT helps to shape. The future of radiotherapy won't be determined simply by how intelligent our machines become. It will be determined by how intelligently we combine those machines with the professionals who actually deliver the treatment.

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