

Artificial Intelligence in Radiotherapy: From Technical Automation to Assisted Clinical Decision-Making. A Literature Review

Jihane Bouziane ^{1,*}, El Mehdi Sadiki ², Kaoutar Soussy ¹, Samia Khalfi ¹, Wissal Hassani ¹, Fatima Zahraa Farhane ¹, Zenab Alami ¹ and Touria Bouhafa ¹

¹ Department of Radiation Oncology, Hassan II University Hospital, Fez, Morocco.

² Laboratory of Applied Physics, Computer Science and Statistics, Faculty of Sciences Dhar El Mahraz, Sidi Mohamed Ben Abdellah University, Fez, Morocco.

World Journal of Advanced Research and Reviews, 2025, 28(03), 2082-2087

Publication history: Received on 22 November 2025; revised on 27 December 2025; accepted on 30 December 2025

Article DOI: <https://doi.org/10.30574/wjarr.2025.28.3.4312>

Abstract

Artificial intelligence (AI) is transforming the radiotherapy landscape by addressing challenges related to efficiency, standardization, and treatment personalization. This literature review critically synthesizes current and emerging applications of AI across the radiotherapy care continuum. We analyze evidence of its impact on four key areas: automatic segmentation, treatment planning, radiomics for prediction, and quality control. The data demonstrate substantial gains in reproducibility and operational efficiency. However, major obstacles to clinical implementation persist, including the need for robust prospective validation, the lack of transparency in algorithms ("black box" nature), risks of bias, and ethical-legal issues. We conclude that AI is destined to become an indispensable "co-pilot" for the radiation oncologist, but its successful integration will require rigorous validation frameworks, ethical governance, and an evolution of professional skills to prioritize patient safety and benefit.

Keywords: Artificial Intelligence; Deep Learning; Precision Radiotherapy; Radiomics; Treatment Planning; Automatic Segmentation; Quality Control

1. Introduction

Modern radiotherapy relies on a delicate balance between optimal tumor control and minimizing toxicity to healthy tissues. Radiotherapy planning is a complex process where the precise delineation of organs at risk (OAR) is crucial for sparing healthy tissues. This manual contouring step, however, presents significant inter-observer variability [1], a well-documented limitation that introduces uncertainty into dosimetric optimization.

Simultaneously, pressure on services continues to grow. Artificial intelligence (AI), and particularly deep learning, is emerging as a powerful set of tools to address these challenges, with demonstrated potential to automate, optimize, and personalize each link in the treatment chain, as highlighted by recent reviews in the field [2].

The objective of this review is to provide a critical overview of AI applications in radiotherapy, assess the level of evidence associated with each, and discuss the practical and conceptual challenges posed by its adoption in routine clinical practice.

* Corresponding author: Jihane Bouziane

2. Methods

A literature review was conducted to synthesize current evidence on artificial intelligence (AI) applications in radiotherapy. The aim was to identify key trends, assess the maturity of evidence, and highlight persistent challenges to clinical adoption. The review process, summarized in Figure 1, followed a structured approach to ensure a comprehensive and reproducible search.

2.1. Search Strategy

A systematic search was performed across two major biomedical databases: PubMed/MEDLINE and Scopus. The search timeframe encompassed all literature published up to December 2025. To capture the breadth of the field, the search strategy combined key terms and their synonyms using Boolean operators (AND/OR). The core search terms included: "Artificial Intelligence", "Machine Learning", "Deep Learning", "Radiotherapy", "Radiation Oncology", "Treatment Planning", "Radiomics", and "Quality Assurance".

2.2. Study Selection and Eligibility Criteria

The initial pool of records was screened in two stages based on pre-defined eligibility criteria, as detailed below in table 1:

Table 1 Study Selection and Eligibility Criteria

Stage	Inclusion Criteria	Exclusion Criteria
Title/Abstract Screening	<ul style="list-style-type: none"> • English language publications. • Primary focus on AI/ML in a radiotherapy context. 	<ul style="list-style-type: none"> • Studies with no relevance to radiotherapy or AI.
Full-Text Review	<ul style="list-style-type: none"> • Study types: Systematic reviews, meta-analyses, clinical trials, and prospective/retrospective cohort studies. • Studies reporting quantitative outcomes (e.g., Dice score, dosimetric parameters, model accuracy). 	<ul style="list-style-type: none"> • Editorials, letters, opinion pieces. • Studies with insufficient methodological detail or irrelevant outcomes.

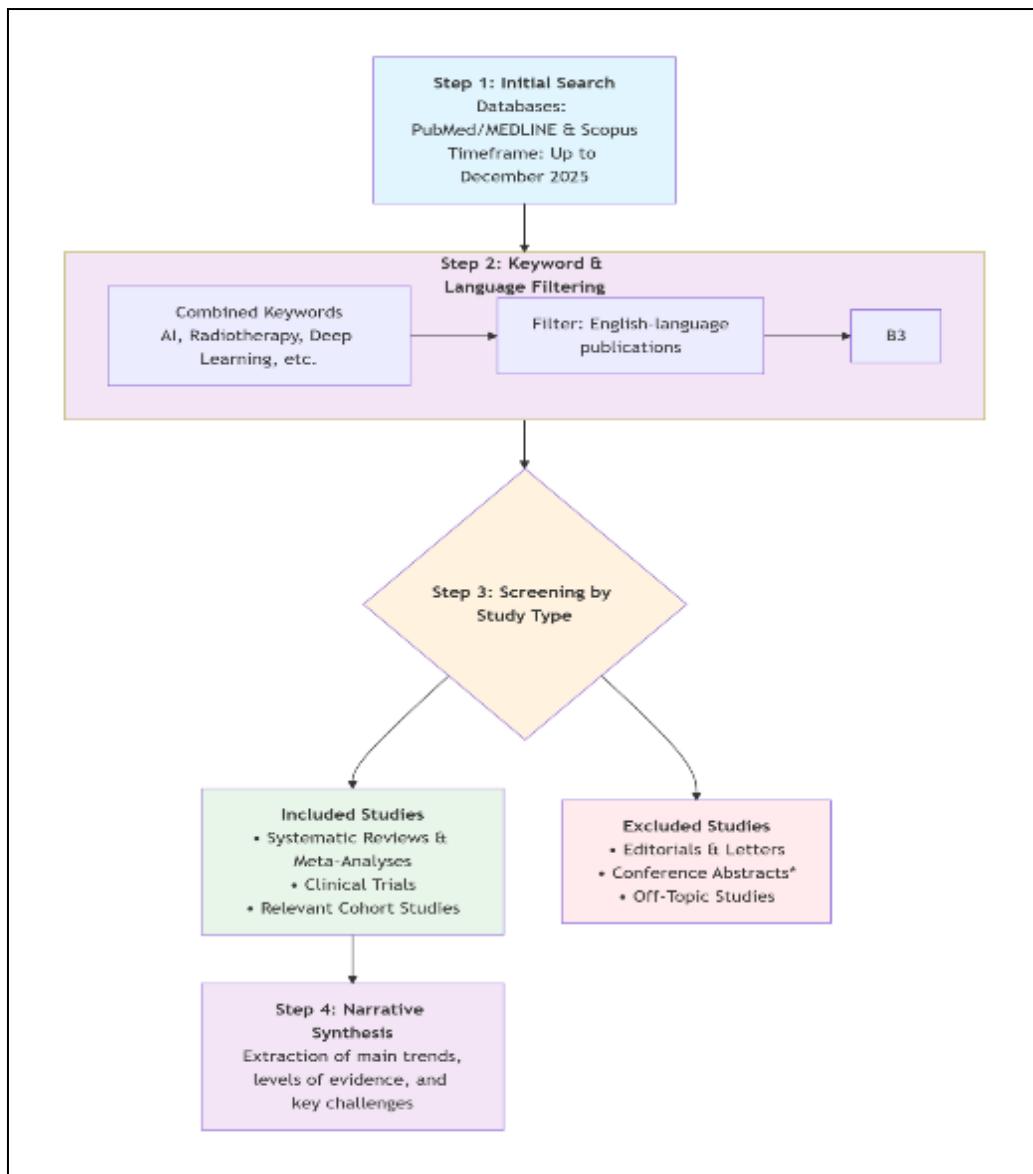


Figure 1 Literature Search Strategy and Study Selection Process

3. Results and Discussion

3.1. Automatic Segmentation:

Freeing Time, Standardizing Quality Manual segmentation of organs at risk (OAR) and target volumes represents a major bottleneck. Deep learning algorithms, particularly U-Net type architectures, have demonstrated exceptional performance for the delineation of standard OARs. Dice similarity scores (DSC) often exceeding 0.90, frequently surpassing inter-expert variability, are reported for structures such as the parotid glands, bladder, or rectum [3].

These algorithms also enable a significant reduction in working time and improve contour consistency, as demonstrated for head and neck OARs where manual contouring time was reduced by 33% and inter-observer variability was significantly decreased [4].

The current challenge is no longer raw performance, but the seamless integration of these tools into the hospital information system (PACS, TPS) for a hybrid workflow where the expert validates and edits the AI's proposals.

3.2. Automated Treatment Planning:

Towards Standardized Dosimetric Excellence Inverse planning for intensity-modulated radiotherapy (IMRT/VMAT) is a complex iterative process. AI, via Knowledge-Based Planning (KBP) or reinforcement learning, now enables the near-instantaneous generation of high-quality plans. Validation studies have confirmed that automated plans were dosimetrically non-inferior, and often superior, to manual plans, with a measurable improvement in target volume dose homogeneity and organ-at-risk sparing, as demonstrated for head and neck cancer [5]. This allows for more advanced optimization of dose constraints, standardization of quality between centers, and redistribution of medical physicists' time towards higher value-added tasks.

3.3. Radiomics and Prediction

The Promise of Personalized Medicine Radiomics extracts hundreds of quantitative features from medical images (CT, MRI, PET). Coupled with AI for analysis, it aims to identify prognostic or predictive signatures. Promising models have been developed to predict complete response after neoadjuvant chemoradiotherapy in locally advanced rectal cancer [6], survival in glioblastoma [7], or the risk of xerostomia and sticky saliva after radiotherapy [8]. However, the "translational gap" remains significant. Issues with feature reproducibility, standardization of image acquisition protocols, and external validation on independent multi-center cohorts are major barriers to routine adoption [9].

3.4. Quality Control and Adaptive Radiotherapy:

AI in Real Time The integration of artificial intelligence (AI) into the radiotherapy workflow is revolutionizing two fundamental aspects: quality assurance and dynamic treatment personalization. For automated quality control (QC), deep learning algorithms aim not only to detect but also to assist and automate the correction of positioning errors. A recent study explored the feasibility of a neural network designed to analyze portal images (PFIs) and digitally reconstructed radiographs (DRRs) to assist this process [10]. This approach illustrates the path towards fully automated assisted correction, reducing the cognitive load on technicians. The impact of AI is even more transformative in the field of real-time adaptive radiotherapy. Here, AI actively participates in dosimetric correction by analyzing the daily anatomy (visualized by CBCT or MRI) via automatic segmentation models, enabling the recalculation of an optimized treatment plan within minutes and its immediate delivery. This capability, validated in demanding clinical settings such as MR-guided stereotactic abdominal radiotherapy, allows for dose adjustment to the changing anatomy at each session, ensuring constant millimeter precision [11, 12]. AI thus operates as the central nervous system of a new generation of radiotherapy, making treatment both smarter, safer, and truly personalized.

The key applications, benefits, and current limitations of AI in radiotherapy are summarized in Table 2.

Table 2 Key Applications of Artificial Intelligence in Modern Radiotherapy: Principles, Benefits, and Current Challenges

Application	Key Principle / Technology	Main Benefits	Current Challenges / Limits
Automatic Segmentation	Deep neural networks (e.g., U-Net)	<ul style="list-style-type: none"> • Time savings ($\geq 33\%$) • Quality standardization (DSC > 0.90) • Reduction of inter-expert variability 	<ul style="list-style-type: none"> • Seamless integration into clinical workflow (PACS, TPS) • Need for expert validation/editing
Automated Treatment Planning	Knowledge-Based Planning (KBP), Reinforcement Learning	<ul style="list-style-type: none"> • Rapid generation of high-quality plans • Inter-center standardization • Dosimetric improvement (homogeneity, OAR sparing) 	<ul style="list-style-type: none"> • Adaptation to complex/atypical cases • Redefining the medical physicist's role
Radiomics and Prediction	Quantitative feature extraction + ML/AI	<ul style="list-style-type: none"> • Promise of personalized medicine • Prognostic/predictive signatures (response, toxicity, survival) 	<ul style="list-style-type: none"> • Translational gap: reproducibility, standardization of acquisition protocols, external validation
Quality Control and Adaptive Radiotherapy	AI for image analysis (PFI, DRR, CBCT, MRI)	<ul style="list-style-type: none"> • Automated error detection/correction • Real-time plan recalibration 	<ul style="list-style-type: none"> • Real-time validation for safety • Complexity of technological and decisional integration

		(millimetric precision) • Reduction of cognitive load	
--	--	--	--

3.5. Challenges and Perspectives:

Beyond Technology The clinical adoption of AI faces substantial challenges:

- Transparency and Trust: The "black box" nature of many deep learning models undermines clinical trust. The development of Explainable AI (XAI) is a research priority [13].
- Bias and Fairness: Algorithms trained on non-representative data can perpetuate or amplify existing biases, as demonstrated by their ability to identify patients' racial origin from standard medical images with high accuracy, a capability even expert clinicians lack. This represents a major risk for any model deployment [14].
- Integration and Medico-Legal Responsibility: Integration into existing clinical workflows is complex. Who is responsible in case of an error? The algorithm developer, the clinician who validated it, or the institution? A clear regulatory framework is needed.
- Impact on the Profession: It is imperative to view AI not as a replacement, but as an amplifier of human expertise. It should free clinicians from repetitive tasks to focus on therapeutic strategy, empathy, and complex decision-making in a multidisciplinary context.

4. Conclusion

Artificial intelligence is no longer a futuristic prospect in radiotherapy; it is a transformational reality in the process of implementation. Its benefits in terms of efficiency, reproducibility, and standardization are demonstrated. The next decade will be decisive for moving beyond technical proofs and establishing robust clinical evidence of its impact on patient outcomes. Success will hinge on a human-centered approach, integrating rigorous validation, ethical governance, and continuous professional training. The ultimate goal is to forge a symbiotic alliance between clinical intuition and computational power to deliver the safest, most precise, and most personalized radiotherapy possible.

Compliance with ethical standards

Acknowledgments

The authors thank colleagues in the Department of Radiation Oncology for helpful discussions.

Disclosure of conflict of interest

The authors declare no competing interests.

Author contributions

All authors contributed to the conception, literature search, analysis, and manuscript drafting.

All authors approved the final manuscript.

Data availability

All data are contained within the article and its references.

References

- [1] Brouwer, Charlotte L et al. "3D Variation in delineation of head and neck organs at risk." *Radiation oncology (London, England)* vol. 7 32. 13 Mar. 2012, doi:10.1186/1748-717X-7-32
- [2] McIntosh, Chris et al. "Clinical integration of machine learning for curative-intent radiation treatment of patients with prostate cancer." *Nature medicine* vol. 27,6 (2021): 999-1005. doi:10.1038/s41591-021-01359-w
- [3] Cardenas, Carlos E et al. "Advances in Auto-Segmentation." *Seminars in radiation oncology* vol. 29,3 (2019): 185-197. doi:10.1016/j.semradonc.2019.02.001

- [4] van der Veen, J et al. "Benefits of deep learning for delineation of organs at risk in head and neck cancer." *Radiotherapy and oncology : journal of the European Society for Therapeutic Radiology and Oncology* vol. 138 (2019): 68-74. doi:10.1016/j.radonc.2019.05.010.
- [5] Tol, Jim P et al. "Evaluation of a knowledge-based planning solution for head and neck cancer." *International journal of radiation oncology, biology, physics* vol. 91,3 (2015): 612-20. doi:10.1016/j.ijrobp.2014.11.014
- [6] Bibault, Jean-Emmanuel et al. "Deep Learning and Radiomics predict complete response after neo-adjuvant chemoradiation for locally advanced rectal cancer." *Scientific reports* vol. 8,1 12611. 22 Aug. 2018, doi:10.1038/s41598-018-30657-6.
- [7] Kickingereder, Philipp et al. "Radiomic Profiling of Glioblastoma: Identifying an Imaging Predictor of Patient Survival with Improved Performance over Established Clinical and Radiologic Risk Models." *Radiology* vol. 280,3 (2016): 880-9. doi:10.1148/radiol.2016160845.
- [8] van Dijk, Lisanne V et al. "CT image biomarkers to improve patient-specific prediction of radiation-induced xerostomia and sticky saliva." *Radiotherapy and oncology : journal of the European Society for Therapeutic Radiology and Oncology* vol. 122,2 (2017): 185-191. doi:10.1016/j.radonc.2016.07.007
- [9] Lambin, Philippe et al. "Radiomics: the bridge between medical imaging and personalized medicine." *Nature reviews. Clinical oncology* vol. 14,12 (2017): 749-762. doi:10.1038/nrclinonc.2017.141
- [10] Muhammed, A et al. "The potential use of deep learning in performing autocorrection of setup errors in patients receiving radiotherapy." *Radiography (London, England : 1995)* vol. 31,2 (2025): 102881. doi:10.1016/j.radi.2025.01.016.
- [11] Bohoudi, O et al. "Fast and robust online adaptive planning in stereotactic MR-guided adaptive radiation therapy (SMART) for pancreatic cancer." *Radiotherapy and oncology : journal of the European Society for Therapeutic Radiology and Oncology* vol. 125,3 (2017): 439-444. doi:10.1016/j.radonc.2017.07.028
- [12] Henke, Lauren E et al. "Phase I Trial of Stereotactic MRI-Guided Online Adaptive Radiation Therapy (SMART) for the Treatment of Oligometastatic Ovarian Cancer." *International journal of radiation oncology, biology, physics* vol. 112,2 (2022): 379-389. doi:10.1016/j.ijrobp.2021.08.033
- [13] Antoniadi, A. M., Du, Y., Guendouz, Y., Wei, L., Mazo, C., Becker, B. A., & Mooney, C. (2021). Current Challenges and Future Opportunities for XAI in Machine Learning-Based Clinical Decision Support Systems: A Systematic Review. *Applied Sciences*, 11(11), 5088. <https://doi.org/10.3390/app11115088>
- [14] Gichoya, Judy Wawira et al. "AI recognition of patient race in medical imaging: a modelling study." *The Lancet. Digital health* vol. 4,6 (2022): e406-e414. doi:10.1016/S2589-7500(22)00063-2