Recent Trends of Artificial Intelligence in Radiation Oncology: A Narrative Review of Prospective Studies

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Abstract

In the past several decades, the delivery of radiation therapy has become increasingly intricate and precise. Such advancements were observed in conjunction with abundant multimodal data available for analysis; these include sophisticated diagnostic imaging, electronic health records, and digital pathology. The impact of artificial intelligence (AI) has become more prominent as numerous prior and ongoing prospective studies aim to integrate it into clinical care in radiation oncology. This review article provides an overview of such prospective studies and examines the role of AI in radiation therapy. By providing an understanding of recent trends in AI, we hope to contribute to improved patient outcomes and precision medicine in radiation oncology.

Keywords: AI, machine learning, deep learning, radiomics, large language model, multimodal

Introduction

Radiation therapy has progressed significantly over the past decades through such advances as stereotactic body radiation therapy (SBRT) for lung cancer[1-3] and oligometastatic cancer,[4-6] proton therapy for leptomeningeal metastasis,[7] magnetic resonance imaging (MRI)-guided SBRT for prostate cancer,[8] MRI-guided adaptive radiation therapy for pancreatic cancer,[9] and adaptive radiation therapy for head and neck cancer.[10] In addition, precision medicine has evolved to improve patient selection for various treatment approaches, including prostate-specific membrane antigen (PSMA) positron emission tomography (PET) for prostate cancer,[11,12] F-fluoromisonidazole PET for head and neck cancer, [13,14] gallium DOTATATE PET for meningioma,[15,16] 21-gene recurrence scores for breast cancer,[17,18] osimertinib after definitive chemoradiation for stage III epidermal growth factor receptor (EGFR)-mutant non-small cell lung cancer,[19] and chimeric antigen receptor T-cell therapy.[12]

With such advancements in precision medicine, cancer genetics, and imaging modalities leading to abundant multimodal data available for health care professionals to interpret, artificial intelligence (AI) has emerged to leverage such data.[20] For example, AI-based algorithms have greatly improved early diagnosis of breast cancer,[21] pancreatic cancer,[22] lung cancer,[23] and skin cancer.[24] Furthermore, generative AI has been shown to answer questions with more empathy than humans[25] and to assist with medical documentation.[26] In radiation

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oncology, several AI-related studies have emerged to minimize unplanned hospitalization[27] and detect extranodal extension (ENE) in head and neck cancer.[28,29] Since then, numerous reviews have summarized the role of AI in radiation oncology.[30-33] However, none have focused on prospective studies incorporating AI into practice. In this review, we aimed to highlight the overview of recent trends in the application of AI in radiation oncology based on prior and ongoing prospective studies.

Methods

To identify relevant prospective studies on AI trends in radiation oncology, a literature search was conducted of the following electronic databases: PubMed, Medline, and Google Scholar. The following keywords were used: "radiation," "radiation oncology," and "artificial intelligence." The search was limited to publications ranging from January 2002 to December 2024 and excluded retrospective studies, systematic reviews, case reports, conference abstracts, and expert opinion articles. Additional filters included utilizing only English language-written articles. Article titles and abstracts were then reviewed after initial screening, followed by full-text review prior to finalizing study inclusion.

Current clinical trials were searched utilizing the ClinicalTrials.gov website with the following keywords: "cancer," "artificial intelligence," and "radiation." Studies that were completed or active (recruiting or not) were included, while those that were suspended or withdrawn were excluded. Trials were further categorized based on type, with only interventional studies included with no specific date range.

When evaluating prospective studies or clinical trials, two reviewers determined the eligibility of such studies for inclusion.

Results

Of 4469 articles found through our literature search, 234 were initially identified as prospective studies. After reviewing abstracts and full texts to confirm their eligibility, 30 studies met our criteria, as shown in **Table 1**.

AI in Prostate Cancer

AI has been investigated extensively to improve outcomes of patients with prostate cancer. In earlier years, because of substantial interobserver disagreements in Gleason grade among pathologists,[61,62] AI-assisted digital pathology algorithms based on whole-slide images of hematoxylin and eosin-stained tissues were developed to improve reproducibility in determining Gleason grade,[63] which were recognized by Food and Drug Administration and other regulatory agencies.[63]

Beyond assessment of Gleason grades, the role of digital pathology has been investigated in radiation oncology. Esteva et al. initially leveraged five NRG Oncology phase III randomized clinical trials (NRG/RTOG 9202, 9413, 9910, 0126, and 9408) that included patients with localized prostate cancer who received radiation with or without androgen-deprivation therapy (ADT).[56] Self-supervised, prognostic, and multimodal AI architecture was developed based on clinical variables (age, Gleason primary and secondary grades, T stage, and baseline PSA) from over 5600 patients and imaging features from over 16 000 histopathology slides.[56] Across all endpoints, AI outperformed the National Comprehensive Cancer Network (NCCN) risk-stratification tool by 9.2%-14.6% for relative improvements in area under the receiver operating characteristic curve (AUC).[56]

With its early success, digital pathology was further investigated for its predictive ability. Spratt et al. utilized four NRG Oncology phase III clinical trials (NRG/RTOG 9202, 9413, 9910, 0126) to develop a similar multimodal AI architecture and validated its performance on the NRG/RTOG 9408 dataset.[57] The primary objective of this study was to identify a subgroup of patients who might benefit from adding ADT to radiation.[57] The development cohort comprised over 2000 patients, with the majority having intermediate-risk prostate cancer, while the validation cohort consisted of over 1500 patients, with more than half having intermediate-risk prostate cancer.[57] Over a third of patients in the validation cohort were classified as predictive model-positive, demonstrating an absolute improvement of 10% by adding ADT for distant metastasis-free survival and prostate-cancer-specific survival at 15 years.[57] However, no differential treatment benefits were identified between predictive model subgroups for metastasis-free survival and overall survival.[57] Spratt et al. performed a separate analysis using six NRG Oncology clinical trials (NRG/RTOG 9202, 9408, 9413, 9910, 9902, 0521), validating the multimodal AI algorithm as prognostic for distant metastasis and prostate cancer-specific mortality among patients with high-risk prostate cancer.[59] Subsequently, the NCCN Guideline for prostate cancer included ArteraAI Prostate as the first AI-based tool with prognostic and predictive benefits from ADT

Table 1. Prior prospective studies

AUTHORS	YEAR	DISEASE SITE	PROSPECTIVE DATA	DATA TYPES	MAIN FINDINGS
Zeleznik et al.[34]	2021	Breast	Not available	CT scan	With deep learning assistance, heart segmentation time was significantly reduced. Expert accuracy was comparable with deep learning-only segmentations.
Ma et al.[35]	2023	Breast	ClinicalTrials.gov ID: NCT05609058	CT scan	Deep learning model identified the lead wire markers in the CT scan images, and the organ feature based on such markers was correlated with ipsilateral lung V20.
Dembrower et al.[14]	2023	Breast	ScreenTrustCAD	Mammogram	Replacing one radiologist with AI for independent assessment of screening mammograms was non-inferior for cancer detection compared with reading by two radiologists.
Preetha et al.[36]	2021	CNS	CORE, CENTRIC, EORTC 26101	MRI scan	Synthetic postcontrast MRI scan based on pre-contrast MRI scanning using deep learning was feasible with no statistically significant difference in the contrast-enhancing tumor burden when compared to postcontrast MRI scanning.
Tsang et al.[37]	2024	CNS	Not available	CT scan	94% of ML plans and 93% of manual plans were deemed to be clinically acceptable. ML plans were able to give 1 Gy less radiation to the normal brain than the manual plan. ML plans required 45 fewer minutes on average to create compared to manual plans.
George et al.[38]	2024	CNS	ClinicalTrials.gov ID: NCT02336165	MRI scan	First on-treatment MRI features were correlated with overall and progression-free survival, while baseline MRI features were not.
Hong et al.[27]	2020	General	SHIELD-RT	Clinical variables	AI-based algorithm based on routine electronic health record data triaged patients and reduced acute care visits during treatments.
Friesner et al.[39]	2022	General	NCT02649569, NCT03102229, NCT03115398	Daily step counts	Daily step counts using an ML model were correlated with hospitalizations.
Kehayias et al.[40]	2024	General	Not available	CT scan	The integration of Deep Learning On-Demand Assistant, an automated clinical platform to help with auto-segmentations and QA reporting using AI, into radiation oncology clinic workflow was feasible.

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Table 1. continued

AUTHORS	YEAR	DISEASE SITE	PROSPECTIVE DATA	DATA TYPES	MAIN FINDINGS
Natesan et al.[41]	2024	General	SHIELD-RT	Clinical variables	High-risk patients identified by the AI-based algorithm experienced lower total medical costs from twice-weekly evaluations.
Wang et al.[42]	2022	GI	RTOG 0822	CT scan	AI-based algorithm using clinical variables, DVH, and radiomic features predicted pCR.
Wesdorp et al.[43]	2023	GI	CAIRO5	CT scan	A DL autosegmentation model accurately segmented the liver and metastatic lesions.
Fremond et al.[44]	2023	GYN	PORTEC-1, PORTEC-2, PORTEC-3, TransPORTEC	Whole-slide images of H&E slides	A DL model predicted molecular classification.
Walker et al.[45]	2014	Head/Neck	Not available	CT scan	Autosegmentation of organs at risk reduced the amount of time needed for segmentation, but expert oversight is still required for accuracy.
Men et al.[46]	2019	Head/Neck	RTOG 0522	CT scan	AI-based algorithm predicted the incidence of late xerostomia.
Sher et al.[47]	2021	Head/Neck	Not available	Radiation plans	AI-based decision support tool improved the dose metrics for organs at risk.
Osapoetra et al.[48]	2021	Head/Neck	ClinicalTrials.gov ID: NCT03908684	Quantitative ultrasound	AI-based algorithm predicted treatment response of involved lymph nodes.
Mashayekhi et al.[49]	2023	Head/Neck	Not available	Radiation plans	AI-based decision support tool improved uniformity of practice.
Kann et al.[29]	2023	Head/Neck	ECOG/ACRIN 3311	CT scan	AI-based algorithm predicted extranodal extension more effectively than did radiologists.
Sher et al.[50]	2023	Head/Neck	INRT-AIR	CT scan	AI-based algorithm identified involved or suspicious lymph nodes, and there was no solitary elective nodal recurrence at 2 years without elective nodal irradiation.
Nicolae et al.[51]	2020	Prostate	Not available	Ultrasound	AI-based radiation treatment planning reduced the time required for planning and was considered clinically acceptable.
McIntosh et al.[52]	2021	Prostate	Not available	Radiation plans	AI-based radiation treatment planning reduced the time required for planning and was considered clinically acceptable.
Sanders et al.[53]	2022	Prostate	Not available	MRI scan	Autosegmentation of prostate and organs at risk was considered clinically feasible.

Table 1. continued

AUTHORS	YEAR	DISEASE SITE	PROSPECTIVE DATA	DATA TYPES	MAIN FINDINGS
Thomas et al.[54]	2022	Prostate	ClinicalTrials.gov ID: NCT03238170	Radiation plans	AI-based algorithm predicted those who would benefit from rectal spacer placement.
Johnsson et al.[55]	2022	Prostate	OSPREY	PSMA PET/CT	AI-based algorithm identified potential lesions and autosegmented organs.
Esteva et al.[56]	2022	Prostate	NRG/RTOG 9202, 9413, 9910, 0126	Whole slide images of H&E slides	AI-based algorithm risk stratified and identified patients with poor prognoses.
Spratt et al.[57]	2023	Prostate	NRG/RTOG 9202, 9413, 9910, 0126, 9408	Whole slide images of H&E slides	AI-based algorithm predicted patients who would benefit from androgen deprivation therapy.
Ross et al.[58]	2024	Prostate	NRG/RTOG 9902	Whole slide images of H&E slides	AI-based algorithm risk stratified and identified patients with poor prognoses.
Spratt et al.[59]	2024	Prostate	NRG/RTOG 9202, 9408, 9413, 9910, 9902, 0521	Whole slide images of H&E slides	AI-based algorithm risk stratified and identified patients with poor prognoses.
Wong et al.[60]	2020	Prostate/Head Neck/CNS	Not available	CT scan	AI-based algorithm reduced the time required for contouring and autosegmented at-risk organs and target volumes.

Abbreviations: AI, artificial intelligence; CT, computed tomography; CNS, central nervous system; DVH, dose volume histogram; H&E, hematoxylin and eosin; GI; gastrointestinal, GYN, gynaecological; MRI, magnetic resonance imaging; ML, machine learning; PSMA, prostate specific membrane antigen; pCR, pathologic complete response; QA, quality assurance.

among patients with localized prostate cancer.[64]

AI in Head and Neck Cancer

Other malignancies targeted by extensive research in AI are head and neck cancers, especially with respect to radiomics. For example, ENE is a known adverse feature associated with poor locoregional control.[65,66] However, ENE identification has been largely based on pathologic evaluation, since radiographic determination has been inconsistent.[67-69] As a result, 24%-31% of patients with p16+ head and neck cancer receive trimodality therapy.[70,71] To reduce this knowledge gap, Kann et al. developed a deep-learning (DL) algorithm based on 270 patients from a single institution with over 650 lymph nodes segmented.[72] The model predicted ENE and nodal metastasis with an AUC of 0.91 for both endpoints.[72] Based on such early success, Kann et al. utilized validation datasets of 82 patients with 130 lymph nodes segmented from Mount Sinai Hospital and 62 patients with 70 lymph nodes segmented from The Cancer Genome Atlas imaging data through The Cancer Imaging Archive.[28] The DL model predicted ENE with an AUC of 0.84-0.90 on these validation datasets, outperforming diagnostic radiologists and improving interobserver agreement among these radiologists.[28] Owing to the small sample size of p16-positive oropharyngeal cancer in these retrospective datasets,[28] further validation was performed using a multicenter phase II clinical trial, ECOG-ACRIN 3311.[29] The DL model was retrained using three retrospective datasets as mentioned previously, ultimately identifying 178 patients from ECOG-ACRIN 3311 with 313 manually segmented lymph nodes.[29] It had an AUC of 0.86 for the identification of ENE, outperforming four radiologists, with a limitation of node level segmentation required prior to independent testing.[29]

Another evolving paradigm for treatment de-escalation among patients with head and neck cancer is to reduce treatment volume. Several phase II clinical trials and a large retrospective study demonstrated the feasibility of reducing the dose of elective nodal irradiation to 30-40 Gy.[73-75] To omit elective nodal irradiation, colleagues from the University of Texas Southwestern Medical Center evaluated several DL models using 129 patients and over 700 lymph nodes segmented with AUC of 0.88-0.98,[76-78] comparable to the AUC of 0.91 from the study by Kann et al.[72] Subsequently,

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Sher et al. incorporated this model in the prospective phase II INRT-AIR trial.[50] Of 67 patients with nonmetastatic head and neck cancer who underwent definitive radiation or chemoradiation, an average of 31 lymph nodes per patient were evaluated by the DL model, determining that approximately 10% were involved.[50] At a median follow-up of 33 months, overall and progression-free survival at 2 years were favorable at 91% and 82%, respectively.[50] One patient with heavy marijuana use had an out-of-field elective nodal recurrence with concurrent distant metastasis, but the study otherwise found favorable quality of life outcomes with no solitary elective nodal failure.[50]

AI in Supportive Care

In addition to improving oncologic outcomes, another area incorporating AI is the effort to reduce acute care visits, such as emergency department visits and unplanned hospitalizations. Predicting such events has been investigated among patients without a cancer diagnosis.[79-82]

In radiation oncology, Hong et al. initially developed a machine learning (ML) model based on nearly 7000 patients with over 8000 treatment courses at a single institution; this model included variables such as baseline demographics, disease and treatment characteristics, prior acute care visits, laboratory values, and recent vital signs.[83] Internal validation demonstrated an AUC of 0.80 for the ML model in predicting acute care visits.[83] Subsequently, Hong et al. performed the SHIELD-RT single-institution, prospective quality improvement study.[27] This model was utilized to identify high-risk patients, who were defined as having more than a 10% risk of acute care visits, and randomized them to twice-weekly on-treatment visits versus standard of care.[27] Of nearly 1000 treatment courses, 311 were evaluated as high-risk courses, with the majority of patients having gastrointestinal cancer or primary brain cancer.[27] The ML model had a favorable performance with an AUC of 0.82 for triaging patients to high- versus low-risk for acute care visits, and fewer than 3% of low-risk patients had acute care visits.[27] Twice-weekly evaluation led to a reduction from 22% to 12% of acute care visits during radiation therapy, the primary endpoint of this study.[27] Furthermore, a post-hoc economic analysis showed that such a reduction in acute care visits translated to lower health care costs.[41]

Ongoing Clinical Trials

Table 2 consists of a list of ongoing clinical trials that incorporate AI. In particular, a multimodal AI risk-stratification developed by Spratt et al.[57,59] has been incorporated into two such clinical trials. The HypoElect study (ClinicalTrials.gov ID: NCT06582446) is a single-arm phase II clinical trial that consists of patients with NCCN high-risk, multimodal AI high-risk prostate cancer and is evaluating the role of whole-pelvis radiation in five fractions with radiation dose escalation using brachytherapy and two years of ADT. The second study is the (ClinicalTrials.gov ID: NCT06772441), a single-arm, phase II HypoPro clinical trial comprising patients with NCCN high-risk, multimodal AI low-/intermediate-risk prostate cancer and is investigating SBRT in combination with brachytherapy and concurrent ADT. Additionally, while most ongoing clinical trials leverage AI for adaptive radiation therapy (**Table 2**), another noteworthy study is a randomized clinical trial by researchers at the University of Hong Kong (ClinicalTrials.gov ID: NCT06636188). It is the first prospective study incorporating a chatbot, Digi-Coach, to help reduce physical and psychological distress versus usual nursing care among patients with head and neck cancer.

Limitations

Limitations of this study include its utilization only of prospective studies while excluding retrospective studies and other types of journal articles. The rationale for this decision is that several published reviews already incorporate retrospective studies to discuss the role of AI in radiation oncology.[30-33] As a result, however, bias may be introduced toward reporting studies from major cancer centers with access to experts with significant AI technical skills. Subsequently, results from these prospective studies may not be generalizable to or implemented in smaller community cancer centers without access to such AI expertise. For instance, significant barriers hindered implementation of the SHIELD-RT trial process; these included labor-intensive, manual verification of treatment course data for each eligible patient, generating and verifying AI predictions by multiple investigators for each enrolled patient, and manually deploying clinical alerts for treating physicians and enrolled patients to ensure that the intervention was completed on time per protocol.[84] In addition, discussion of commercially available technologies is beyond the scope of this review. These have been comprehensively discussed by NRG Oncology in its summary of the roles of commercial products in adaptive radiation, autosegmentation, treatment planning, and clinical trial development.[85-88] Lastly, despite our efforts to include prospective AI data, we may have inadvertently excluded other relevant studies from

Table 2. Ongoing Prospective Studies

CLINICAL TRIAL	CLINICAL TRIALS.GOV ID	START DATE	ESTIMATED END DATE	STUDY DESIGN	ROLE OF AI	STATUS	DISEASE SITE
Artificial Intelligencel for Prostate Cancer Treatment Planning	NCT04441775	2020	2022	Observational	Improve consistency and quality of radiation treatment plans.	Completed	Prostate
Two Studies for Patients With High Risk Prostate Cancer Testing Less Intense Treatment for Patients With a Low Gene Risk Score and Testing a More Intense Treatment for Patients With a High Gene Risk Score, The PREDICT-RT Trial	NCT04513717	2020	2033	Interventional	Radiation therapy quality assurance using an AI algorithm.	Recruiting	Prostate
ARtificial Intelligence for Gross Tumor Volume Segmentation (ARGOS)	NCT05775068	2021	2024	Observational	Autosegmentation of GTV on CT scan.	Active, not recruiting	Thoracic
Artificial Intelligence in Functional Imaging for Individualized Treatment of Head and Neck Squamous Cell Carcinoma Patients (KIVAL-KHT)	NCT05192655	2021	2026	Observational	Analysis of diagnostic imaging and clinical and histopathological data to predict outcomes.	Recruiting	Head/Neck
AI for Head Neck Cancer Treated With Adaptive RadioTherapy (RadiomicART)	NCT05081531	2021	2024	Interventional	Analysis of diagnostic imaging to predict outcomes and toxicities.	Recruiting	Head/Neck
PostRadiotherapy MRI-based AI System to Predict Radiation Proctitis for Pelvic Cancers	NCT04918992	2021	TBD	Observational	Analysis of post-radiation MRI scan to predict proctitis.	Unknown status	General
Clinical Validation of AI-Assisted Radiotherapy Contouring Software for Thoracic Organs At Risk	NCT05787522	2022	2024	Observational	Autosegmentation of organs at risk on CT scan.	Completed	Thoracic
Simulation-Free Hippocampal-Avoidance Whole Brain Radiotherapy Using Diagnostic MRI-Based and Cone Beam Computed Tomography-Guided On-Table Adaptive Planning in a Novel Ring Gantry Radiotherapy Device	NCT05096286	2022	2022	Interventional	Simulation-free workflow using a semi-automated planning based on AI.	Completed	CNS
The Impact of Radiotherapy on Oligometastatic Cancer	NCT05933876	2022	2037	Observational	Analysis of clinical data, medical images, and biological samples to predict who will benefit from radiation to oligometastatic sites.	Recruiting	General

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Table 2. continued

CLINICAL TRIAL	CLINICAL TRIALS.GOV ID	START DATE	ESTIMATED END DATE	STUDY DESIGN	ROLE OF AI	STATUS	DISEASE SITE
Intensive Symptom Surveillance Guided by Machine Learning-Directed Risk Stratification in Patients With Non-Metastatic Head and Neck Cancer, The INSIGHT Trial	NCT05338905	2022	2027	Interventional	Analysis of clinical data to identify high-risk patients who will benefit from symptom surveillance	Recruiting	Head/Neck
Artificial Intelligence in CNS Radiation Oncology (AI-RAD)	NCT06036394	2023	2028	Observational	Autosegmentation of tumor and organs at risk, use radiomics to predict toxicities and outcomes.	Active, not recruiting	CNS
Stereotactic Body Radiation Therapy Planning With Artificial Intelligence-Directed Dose Recommendation for Treatment of Primary or Metastatic Lung Tumors, RAD-AI Study	NCT05802186	2023	2026	Interventional	AI to guide radiation dose for primary lung cancer and lung metastases.	Recruiting	Thoracic
Adaptive Radiation in Anal Cancer	NCT05838391	2023	2025	Interventional	Adaptive radiation using AI.	Recruiting	GI
Randomized Evaluation of Machine Learning Assisted Radiation Treatment Planning versus Standard Radiation Treatment Planning	NCT05979883	2023	2026	Interventional-Phase III	AI-assisted radiation treatment planning.	Recruiting	Head/Neck
MR-guidance in Chemoradiotherapy for Cervical Cancer (AIM-C1)	NCT06142760	2023	2026	Interventional	Adaptive radiation using AI.	Recruiting	GU
Daily-Adaptive Stereotactic Body Radiation Therapy for Biochemically Recurrent, Radiologic Apparent Prostate Cancer After Radical Prostatectomy	NCT05946824	2023	2028	Interventional-Phase II	Adaptive radiation using AI.	Recruiting	Prostate
Computed Tomography-Guided Stereotactic Adaptive Radiotherapy (CT-STAR) for the Treatment of Central and Ultra-Central Early-Stage Non-Small Cell Lung Cancer	NCT05785845	2023	2026	Interventional	Adaptive radiation using AI.	Recruiting	Thoracic
A Chatbot to Reduce Physical and Psychological Distress of Patients With Head and Neck Cancer Undergoing Radiotherapy	NCT06636188	2024	2027	Interventional	AI-based patient navigator chatbot to reduce physical and psychological distress.	Active, not recruiting	Head/Neck

Table 2. continued

CLINICAL TRIAL	CLINICAL TRIALS.GOV ID	START DATE	ESTIMATED END DATE	STUDY DESIGN	ROLE OF AI	STATUS	DISEASE SITE
Glioma Adaptive Radiotherapy With Development of an Artificial Intelligence Workflow (GLADIATOR)	NCT06492486	2024	2028	Interventional-Phase II	Adaptive radiation using AI.	Not yet recruiting	CNS
AI as an Aid for Weekly Symptom Intake in Radiotherapy	NCT06525181	2024	2024	Interventional	Medical documentation for on-treatment visits to improve accuracy and efficiency.	Not yet recruiting	General
A phase II Clinical Trial of Artificial Intelligence-assisted One-stop Radiotherapy for Breast Cancer After Breast-conserving Surgery (BC-AIO)	NCT06686459	2024	2027	Interventional-Phase II	Autosegmentation and radiation treatment planning.	Not yet recruiting	Breast
Evaluation of a Novel Auto Segmentation Algorithm for Normal Structure Delineation in Radiation Treatment Planning	NCT06200116	2024	2026	Observational	Autosegmentation.	Recruiting	General
Online Adaptive Radiotherapy for Nasopharyngeal Carcinoma (OART)	NCT06516133	2024	2030	Phase III Clinical Trial	Adaptive radiation using AI.	Recruiting	Head/Neck
One Fraction Simulation-Free Treatment With CT-Guided Stereotactic Adaptive Radiotherapy for Patients With Oligometastatic and Primary Lung Tumors (ONE STOP)	NCT06236516	2024	2025	Phase III Clinical Trial	Adaptive radiation using AI.	Recruiting	Thoracic
Artificial Intelligence to Personalize Prostate Cancer Treatment (the HypoElect Trial) (HypoElect)	NCT06582446	2024	2027	Interventional-Phase II	Patient selection and risk stratification.	Recruiting	Prostate
Artificial Intelligence Driven Personalisation of Radiotherapy and Concomitant Androgen Deprivation Therapy for Prostate Cancer Patients (the HypoPro Trial) (HypoPro)	NCT06772441	2024	2027	Interventional	Patient selection and risk stratification.	Recruiting	Prostate
RAdiotherapy With FDG-PET Guided Dose-PAINTing Compared With Standard Radiotherapy for Primary Head and Neck Cancer-3 (RADPAINT-3)	NCT06297902	2024	2030	Interventional	Analysis of blood samples to predict tumor response and toxicities.	Recruiting	Head/Neck

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Table 2. continued

CLINICAL TRIAL	CLINICAL TRIALS.GOV ID	START DATE	ESTIMATED END DATE	STUDY DESIGN	ROLE OF AI	STATUS	DISEASE SITE
Artificial Intelligence-Guided Radiotherapy Planning for Glioblastoma (ARTPLAN-GLIO)	NCT06657027	2025	2027	Observational	Analysis of MRI scans to evaluate the extent of tumor infiltration.	Not yet recruiting	CNS
Locally Optimised Contouring With AI Technology for Radiotherapy (LOCATOR)	NCT06546592	2025	2029	Interventional	Autosegmentation.	Not yet recruiting	General

Abbreviations: AI, artificial intelligence; CT, computed tomography; GTV, gross tumor volume; MRI, magnetic resonance imaging.

our review. Further studies are warranted to capture the growing complexity of AI and its impact in radiation oncology.

Conclusion

Radiation oncology is poised to be influenced substantially by AI in the coming decades. Emerging AI tools will streamline radiation treatment planning and adaptive radiation, guide treatment recommendations by improving patient selection based on digital pathology and radiomics, and tailor supportive care to reduce acute care visits. As a result, such efforts will translate to further progress in radiation oncology and patient outcomes.

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