

Monitoring Treatment Response in Radiation Therapy: A Scoping Review of Dosimetric, Imaging, and Artificial Intelligence-Based Approaches

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Abstract

Radiation therapy (RT) constitutes a cornerstone of multimodal cancer management; however, systematic monitoring and evaluation of treatment response remain comparatively underemphasized in routine clinical practice. This scoping review synthesizes current techniques and methodologies for monitoring treatment response in external beam radiation therapy (EBRT) and brachytherapy (BT). A systematic literature search was performed across the SAGE, Scopus, PubMed, and Google Scholar databases. Studies were eligible for inclusion if published between 2010 and 2024, written in English, and concerned with treatment response monitoring in radiotherapy or brachytherapy. Two reviewers independently screened and selected studies against the predefined inclusion criteria and review objectives, yielding 21 eligible studies, including two doctoral theses. The findings demonstrate that in vivo dosimetry (IVD) and imaging-based modalities play a central role in assessing treatment response. Conventional imaging techniques, although widely accessible, are largely confined to characterizing anatomical tumor changes, whereas functional magnetic resonance imaging (MRI) techniques, including diffusion-weighted (DW) and dynamic contrast-enhanced (DCE) sequences, additionally capture the physiological and pathological dimensions of treatment response. The growing application of artificial intelligence (AI), encompassing machine learning (ML) and deep learning (DL), in conjunction with radiomics, has demonstrated considerable promise for predicting treatment response and outcome, thereby enabling timely therapeutic adjustment to preserve treatment efficacy. Collectively, current strategies for monitoring treatment response in radiation therapy integrate in vivo dosimetry, imaging, and AI- and radiomics-based predictive modeling; however, further work is required to standardize and clinically validate these approaches across treatment modalities.

Highlights

1. This scoping review synthesizes treatment response monitoring methods in EBRT and brachytherapy.
2. In vivo dosimetry provides a direct, patient-specific measure of delivered radiation dose.
3. Functional MRI techniques capture physiological tumor response beyond conventional anatomic imaging.
4. AI and radiomics show strong promise for predicting and monitoring treatment outcomes.
5. Standardization and clinical validation remain key gaps across current monitoring approaches.

Introduction

Cancer comprises a heterogeneous group of diseases defined by the uncontrolled proliferation of aberrant cells capable of invading adjacent tissue and metastasizing to distant organs. It continues to represent a substantial global health burden and remains among the leading causes of mortality

worldwide. The most recent GLOBOCAN estimates report approximately 20 million new cancer cases and 9.7 million cancer-related deaths worldwide in 2022 [1–6].

Radiation therapy (RT) has been shown to improve clinical outcomes and provide symptomatic palliation in patients with cancer [7]. It has become an indispensable component of comprehensive cancer management, with approximately 50% of all cancer patients receiving radiation therapy at some point during their treatment course [8], albeit with variable degrees of success. Delivery of a therapeutic radiation dose to the tumor is achieved through one of two principal approaches: external beam radiation therapy (EBRT), a non-invasive technique in which the radiation source is positioned outside the body and directed at the target volume, or brachytherapy (BT), also termed internal radiation therapy, which involves the direct placement of radioactive sources within the tumor itself or in the immediately surrounding tissue [4, 9, 10, 11]. Irrespective of whether it is employed as a sole treatment modality or in combination with other therapies, radiation therapy exerts its therapeutic effect by delivering high-energy particles or waves that induce DNA damage in malignant cells, ultimately leading to cell death. The overall effectiveness of radiation therapy, however, can be undermined by limitations in the ability to accurately monitor the treatment process and its impact on the patient's clinical status [4].

Successful radiotherapy requires the delivery of an adequate, precisely targeted radiation dose to the tumor while sparing adjacent normal tissue [11]. Attainment of an optimal therapeutic ratio, that is, maximizing tumor control while minimizing radiation-induced toxicity, depends on accurate delivery of the prescribed dose. All radiotherapy modalities are susceptible to uncertainties and discrepancies between planned and delivered treatment, and such deviations may carry substantial clinical consequences [12]. Consequently, both the delivery process itself and the patient's subsequent response to treatment must be carefully monitored to ensure therapeutic effectiveness. Early differentiation between responders and non-responders during the course of treatment is essential, as it allows for timely modification of the treatment pathway [13]. This scoping review summarizes the principal methods currently used to monitor treatment response in radiation therapy, with a particular focus on dosimetry, imaging, radiomics, and artificial intelligence (AI).

Research questions

As a guide for the review, the following research questions were formulated.

1. What are the current methods used to monitor treatment response in EBRT and BT?
2. What are the current imaging techniques to monitor treatment response in radiation therapy?
3. How effective is in vivo dosimetry in monitoring radiation dose delivery and treatment response?
4. What is the potential of using radiomics and AI-driven models to monitor treatment response?
5. How can these response monitoring methods be optimized for real-time response evaluation in radiation therapy?

6. Are there gaps in the current treatment response monitoring approaches that need to be addressed?
7. What are the current issues relating to the challenges in implementing these methods into clinical practice?

Methodology

A comprehensive literature search was undertaken to identify publications reporting recent techniques and methodological advances in the monitoring of radiation therapy delivery and treatment response in cancer, encompassing dose and dose-rate monitoring, ultrasound (US), computed tomography (CT), magnetic resonance imaging (MRI), artificial intelligence (AI), machine learning (ML), deep learning (DL), and radiomics. The search was limited to peer-reviewed journal articles published between 2010 and 2024, comprising phantom, pre-clinical, and clinical studies addressing treatment response in both EBRT and BT, and was conducted across the SAGE, Scopus, PubMed, and Google Scholar databases. Search terms were applied to the titles and abstracts of full-length articles and included *"cancers"*, *"radiation therapy"*, *"brachytherapy treatment"*, *"treatment response monitoring"*, *"current techniques"*, *"Radiomics"*, *"Machine learning"*, *"Predictive modelling"*, and *"Artificial intelligence"*, together with the compound phrases *"monitoring radiation therapy treatment response"*, *"Radiation therapy treatment response monitoring"*, and *"predicting radiation therapy treatment response"*. The search was restricted to English-language publications within the specified date range (2010–2024). Each identified record was screened independently by two reviewers on the basis of title, abstract, and stated objectives, and records unrelated to radiation therapy treatment response monitoring were excluded. Studies employing chemoradiation in gynecological cancers were retained, whereas studies using chemotherapy alone were excluded.

Results

The literature search yielded a total of 188 records, comprising 28 from PubMed, 55 from SAGE, 34 from Scopus, and 71 from Google Scholar, of which 7 were abstract-only records, and 5 were doctoral theses. Following the removal of 20 duplicate records, 168 references remained for title and abstract screening; of these, 120 were excluded for not meeting the review criteria, leaving 48 studies for full-text eligibility assessment. A further 27 studies were subsequently excluded based on treatment modality, monitoring technique, or inappropriate study outcome, yielding a final total of 21 articles for inclusion in the review. The study identification, screening, and selection process is summarized in the PRISMA flowchart presented in Fig. 1.

Study characteristics

To provide an overview of the evidence base underlying this review, Table 1 summarizes the design, disease site, treatment modality, and monitoring domain of the 21 included studies. Of these, 8 (38%) addressed in vivo dosimetry, 6 (29%) addressed imaging-based response assessment, and 7 (33%)

addressed AI- or radiomics-based predictive modeling. Gynecological and cervical cancers were the most frequently represented disease sites (9/21, 43%), followed by prostate cancer (4/21, 19%); breast, lung, and head and neck cancers were each represented by a single study. Brachytherapy was the treatment modality in 9 of the 21 studies (43%), most of which addressed in vivo dosimetry or AI/radiomics in gynecological cancer, whereas EBRT predominated among the imaging-based studies.

Table 1
Characteristics of the studies included in the review

NO	Author (Year)	Ref.	Monitoring domain	Cancer type	Treatment modality	Study design
1	Belley et al. (2018)	20	In vivo dosimetry	Gynecological cancer	Brachytherapy (HDR)	Prospective clinical trial
2	Peca et al. (2017)	27	In vivo dosimetry	Rectal cancer	EBRT	Prospective clinical
3	Wootton (2014)	28	In vivo dosimetry	Prostate cancer	EBRT (IMRT)	Doctoral thesis
4	Mrcela et al. (2011)	29	In vivo dosimetry	Not specified (phantom)	EBRT (Co-60)	Pre-clinical / phantom + pilot patient
5	Georgi et al. (2024)	23	In vivo dosimetry	Gynecological cancer	Brachytherapy (PDR)	Prospective clinical
6	Jaberi et al. (2022)	24	In vivo dosimetry	Gynecological cancer	Brachytherapy (HDR)	Prospective clinical
7	Muenkel et al. (2021)	25	In vivo dosimetry	Gynecological cancer	Brachytherapy (HDR)	Clinical feasibility study
8	Jamalludin et al. (2020)	26	In vivo dosimetry	Cervical cancer	Brachytherapy (HDR, Co-60)	Phantom study
9	Dong et al. (2024)	44	Imaging	Cervical cancer	Brachytherapy	Clinical (DWI-MRI)
10	Aliotta et al. (2024)	45	Imaging	Head and neck cancer	EBRT	Clinical (multimodality imaging)
11	de Jong et al. (2023)	46	Imaging	Prostate cancer	Radionuclide therapy (223Ra)	Clinical
12	Arteaga-Marrero et al. (2015)	47	Imaging	Not specified	EBRT (animal model)	Pre-clinical / animal study
13	Wang et al. (2015)	48	Imaging	Breast cancer	EBRT (pre-operative)	Clinical
14	Troost et al. (2010)	49	Imaging	Oropharyngeal cancer	EBRT	Clinical
15	Dankulchai et al. (2024)	61	AI / Radiomics	Cervical cancer (LACC)	Brachytherapy	Clinical (radiomics)
16	Ouyang et al. (2023)	62	AI / Radiomics	Rectal cancer	EBRT (neoadjuvant)	Clinical (AI / deep learning)

NO	Author (Year)	Ref.	Monitoring domain	Cancer type	Treatment modality	Study design
17	Lee et al. (2022)	63	AI / Radiomics	Lung cancer	EBRT	Clinical (deep learning)
18	Bellis (2022)	64	AI / Radiomics	Cervical cancer	Brachytherapy	Doctoral thesis
19	Lucia et al. (2021)	65	AI / Radiomics	Cervical cancer (LACC)	EBRT / Brachytherapy	Clinical (radiomics / ML)
20	Wu et al. (2019)	66	AI / Radiomics	Prostate cancer	EBRT (carbon ion)	Clinical (radiomics)
21	Ma et al. (2019)	67	AI / Radiomics	Prostate cancer	EBRT (VMAT)	Clinical (machine learning)

Dosimetric approach to treatment response monitoring

Recent advances in cancer radiation therapy include the incorporation of image guidance and dose calculation algorithms to monitor and precisely deliver the prescribed radiation dose to the tumor [14, 15, 16]. Because any radiotherapy modality is susceptible to errors and uncertainties, deviations may arise between the planned and delivered dose, with potentially substantial clinical consequences [12]. Several approaches exist for monitoring dose and dose-rate accuracy during treatment delivery; one such approach, *in vivo* dosimetry (IVD), has demonstrated considerable potential for therapeutic applications [17]. Numerous *in vivo* techniques are currently employed to monitor and assess radiation dose delivery in radiation therapy. In radiotherapy, IVD refers to the measurement of the radiation dose received by the patient during treatment, typically performed by positioning a detector as close as possible to the target volume or organ at risk for which dose verification is required [17, 18].

A range of detector systems, active, passive, or electronic, can be used to report the cumulative dose following treatment delivery [19, 20]; however, post-delivery dose reporting constrains the available corrective measures, such as adjustment of the dose delivered in subsequent fractions [20]. Real-time dose and dose-rate monitoring, by contrast, permits treatment to be interrupted mid-fraction, thereby offering additional corrective options within the current fraction. *In vivo* dosimetric measurements have been used to determine the radiation dose delivered to organs at risk and to serve as a quality assurance measure [21]. During intrafraction delivery, real-time and online IVD techniques enable treatment to be interrupted to prevent misadministration upon detection of clinically significant discrepancies between the measured and expected dose. In this manner, IVD can be used to monitor and verify that the accuracy of the delivered dose distribution remains within acceptable limits relative to the planned distribution [22]. In dosimetric monitoring, IVD measurements are typically compared against the planned dose to quantify the divergence between planned and delivered dose. Although numerous initiatives and approaches to IVD in radiotherapy and brachytherapy have been reported in phantom

studies, comparatively few of these systems have progressed to routine clinical use. In vivo dosimeters can be broadly classified as real-time detectors, including electronic portal imaging devices (EPIDs), and passive detectors, the latter requiring a defined interval following irradiation before read-out. A summary of reported IVD methods used to monitor radiation dose and dose rate in both EBRT and BT, published between 2010 and 2024, is presented in Table 2.

Table 2
Summary of reported IVD methods used to monitor radiation dose and dose rate

Author /Year	Study design / Disease	Treatment	Monitoring method	Result / Additional info	Dosimeter properties
Georgi et al., (2024) [23]	Prospective GYN cancer	PDR - BT	Time-resolved IVD using Inorganic scintillator detector	The aim was to measure the uncertainty between the planned and delivered dose. 31/32 showed a deviation within the IVD uncertainty (average 9.7%, k = 2) Planned dose calculation uncertainty (1.6%, k = 2)	<i>High light yield, good energy resolution, a high effective atomic number, fast decay time, linear response to radiation, low afterglow, and generally of higher density</i>
Jaberi et al., (2022) [24]	Prospective GYN cancer	BT	microSilica bead TLD	The aim was to verify the rectal and bladder absorbed doses as organs at risk (OARs). Relative difference between TPS and TLD results was – 8.3% ± 19.6% and – 7.2% ± 14.6%	<i>High sensitivity, small size, reusability, tissue equivalence, wide dose range, ability to measure low doses of radiation, and good linearity with dose make them suitable for personal and medical radiation monitoring applications</i>
Muenkel et al. [25]	GYN Cancer	HDR brachytherapy	Plastic scintillation detector	The mean dose difference was – 0.22% ± 5.98% Large deviations were observed when detectors were placed in the area where dose rates were less than 1 cGy/s.	<i>Near water-equivalence, fast response time, high spatial resolution, dose linearity, minimal energy dependence, and resistance to radiation damage make them suitable for accurate dose measurements in various</i>

Author /Year	Study design / Disease	Treatment	Monitoring method	Result / Additional info	Dosimeter properties
					<i>radiation therapy applications.</i>
Jamalludin et al. (2020) [26] (Abstract)	Phantom study	Co-60 HDR intracavitary BT	MOSFET (MOSkin) and Diode (PTW 9112)	To evaluate the dose divergence between the planned and the IVD dose Percentage dose differences (%) $2.22 \pm 0.07\%$ for PTW9112 and $2.5 \pm 0.07\%$ for MOSkin (44.4% (8/18) sessions) RP3 measured was lower than the planned doses in all sessions. Reported uncertainty 5.2% (k = 1) and 6.6% (k = 1) for the detector and TPS, respectively	<i>Small size, high sensitivity, direct reading capability, and the ability to store the post-radiation signal permanently, making them useful for various radiation therapy applications</i>
Balley et al., (2018) [20]	Prospective	Intracavitary HDR - BT	nanoFOD / TLD	The aim was to measure the real-time dose rate during HDR-BT Median ratio: nanoFOD/TPS = 1.00 (IQR 0.94–1.02) TLD/TPS = 1.01 (IQR 0.98–1.04) Dose measurements	<i>Small size, high spatial resolution, immunity to electromagnetic interference, real-time response, and ability to perform in vivo measurements, making them ideal for applications like brachytherapy</i>

Author /Year	Study design / Disease	Treatment	Monitoring method	Result / Additional info	Dosimeter properties
				nanoFOD (63% within 5% of TPS measurement) TLD (70% within 5% of TPS measurement)	
Peca et al., (2017) [27]	Prospective Rectal cancer	Radiotherapy on a belly board device	EPID	The aim was to detect dose delivery discrepancies. proved The measurements were sensitive to dose discrepancies and detected discordances in 7 patients	<i>Dose linearity, field size dependence, energy dependence, spatial resolution, image quality, and the ability to measure dose profiles. They are mostly useful for validating dose delivery in radiation therapy treatments</i>
Wootton L. S. (2014) [28] [Thesis]	Thesis	IMRT	PSD	The mean difference between the measured and expected dose was – 0.4% ±2.8% Mean differences for individual patient were ranged from -3.3% to 3.3%	
Mrcela et al., 2011 [29] (Abstract)	Pre-clinical / phantom/pilot patient study	Co-60 beam EBRT	OSL	The aim was to investigate an OSL dosimeter for IVD Reading uncertainty 0.6% (single irradiation) and 1.6% (repeated irradiation)	<i>High sensitivity, wide dose range linearity, good energy dependence, reusability, and the ability to be read out multiple times without losing stored radiation information, making them</i>

Author /Year	Study design / Disease	Treatment	Monitoring method	Result / Additional info	Dosimeter properties
				Reproducibility 1.6% (single irradiation) and 3.5% (repeated irradiation) Measured entrance dose and the expected dose difference were $0.8\% \pm 2.5\%$	<i>suitable for a variety of radiation monitoring applications</i>

Dosimeters for real-time IVD

As a direct measure of the dose delivered to patients during radiation therapy, in vivo dosimetry holds considerable potential for ensuring safe and effective treatment. Detectors currently used for real-time measurement include diodes, metal-oxide-semiconductor field-effect transistors (MOSFETs), plastic scintillation detectors (PSDs), and electronic portal imaging devices (EPIDs). These real-time dosimeters are capable of measuring the total radiation dose delivered during a treatment session, as well as time-resolved (4D) intrafraction dose or dose rate. In one study, EPID-based IVD was employed to detect dose delivery variations during rectal cancer radiotherapy [27]; portal images were combined with the planning CT to reconstruct the delivered dose at the isocenter depth, and the reconstruction algorithm proved sensitive to dose discrepancies, detecting discordance in seven of ten patients. The authors concluded that EPID-based dosimetric response monitoring can support quality assurance, including assessment of equipment performance and process quality. In a related doctoral thesis, Wootton similarly employed a PSD for in vivo dosimetry of the rectal wall in five patients undergoing IMRT for prostate cancer, reporting a modest difference between measured and expected dose, with mean differences for individual patients ranging from -3.3% to 3.3% [28]. Across radiation therapy more broadly, IVD measurements have been performed using a range of active, real-time dosimeters; diode and MOSFET detectors in particular have shown promising results in providing online dose read-out [27, 28]. These studies, which employed a MOSkin (MOSFET-based) detector and a PTW 9112 diode detector, confirmed the feasibility of integrating such detectors for rectal dose IVD during cervical HDR intracavitary BT.

Dosimeters for passive in vivo dosimetry

Unlike active detectors, passive detectors, including thermoluminescent dosimeters (TLDs), optically stimulated luminescent dosimeters (OSLDs), radiophotoluminescent dosimeters (RPLDs), implantable MOSFET detectors, and radiographic or radiochromic films, do not yield an immediate measurement, instead requiring a predetermined interval, ranging from minutes to hours, before read-out [18]. Whereas

film dosimeters provide two-dimensional dose information, TLDs, OSLDs, RPLDs, and implantable semiconductor detectors are typically employed for point-dose measurement. TLDs are available in powder, chip, rod, or ribbon form and can be reused multiple times, provided they are thermally annealed beforehand to erase the residual signal. Although TLDs possess favorable characteristics for in vivo dosimetry, correction factors must be applied to derive the absorbed dose from the raw TLD reading [30, 31]. In a study evaluating the feasibility of an IVD protocol for patient-specific quality assurance, a silica-bead TLD was used for three-dimensional absorbed-dose verification within the rectum and bladder of gynecologic cancer patients; the relative difference between the TPS-calculated and TLD-measured absorbed dose was $-8.3\% \pm 19.6\%$ for the rectum and $-7.2\% \pm 14.6\%$ for the bladder, indicating reasonably good agreement between the calculated and measured doses [24].

Optically stimulated luminescence (OSL) represents one of the more contemporary optical techniques for the detection and measurement of ionizing radiation [32]. OSL is applied across a range of fields, including medical, environmental, and personal dosimetry, and has been used to measure organ doses in IVD to help characterize the radiation risk-to-benefit ratio. OSL dosimeters have recently been recommended for dosimetry applications owing to their favorable dosimetric properties, including stable sensitivity [33]. Scintillation materials constitute a class of luminescent materials that absorb ionizing radiation and re-emit low-energy photons [34], encompassing applications such as the nanoscintillator-based fiber-optic dosimeter (nanoFOD) and organic and plastic scintillation detectors. In one clinical trial, two TLDs were affixed to the vaginal cylinder alongside a nanoFOD to monitor real-time dose rate during HDR-BT; comparison of the cumulative dose per fraction across the nanoFOD, TLD, and TPS demonstrated reasonable agreement, with a reported uncertainty of 13.9% [20]. Georgi et al. evaluated the accuracy of a multi-channel vaginal cylinder fitted with an organic scintillation detector for in vivo dosimetry during pulsed-dose-rate brachytherapy; IVD data obtained from 24 patients treated with multi-channel-cylinder PDR brachytherapy for gynecological cancers showed a deviation of only 5.9% [23]. Using a total of 75 measurements (48 fractions) acquired from 14 patients undergoing HDR brachytherapy with a multichannel cylinder, Venezia applicator, or Syed-Neblett template, Muenkel et al. described a new in vivo dose-measurement system employing a plastic scintillation detector (PSD) for gynecological HDR brachytherapy, an FDA-approved PSD system (OARtrac) compatible with various applicators for in vivo dose measurement in gynecologic patients. The reported mean dose difference was $-0.22\% \pm 5.98\%$, with the largest deviation from the expected value reaching 26%; notably, larger deviations were observed when detectors were positioned in regions where dose rates fell below 1 cGy/s [25].

Overview of Imaging in Radiation Therapy

Several treatment options are available for patients with cancer, among which radiation therapy occupies a prominent place [35]. Imaging plays a substantial role throughout the course of RT, from initial tumor detection and disease extent evaluation through to the monitoring of treatment response. Cancers treated predominantly with radiotherapy, such as cervical cancer, typically exhibit considerable tumor

regression during the course of treatment [36]. The incorporation of soft-tissue imaging into RT can enhance treatment effectiveness and clinical outcomes, contributing to improved local control and reduced toxicity [37–40]. This section reviews the principal imaging modalities used to monitor treatment response, namely ultrasound, computed tomography (CT), MRI, PET/CT, and PET/MRI; the functional application and additional characteristics of each modality are summarized in Table 3.

Table 3
Summary of functional application for US, CT, MRI, PET-CT, and PET-MRI

Imaging	Description
Ultrasound	• Primary modality to evaluate women with pelvic symptoms • Advantages: widespread availability, feasibility, cost effectiveness and without radiation hazards. • Techniques: include transvaginal, transabdominal, or transperineal approach or combination. • Limitations include a skilled operator, a limited field of view, and low contrast resolution
CT	• Relatively more available compared to MRI and other hybrid imaging modalities • Has a shorter image acquisition time • Multiplanar reconstructed images are obtained within a shorter time • CT has a wider field of view and higher spatial resolution • Less operator dependent • Requires intravenous contrast for evaluation of common gynecologic cancers • Has poor soft tissue contrast • CT scan can be readily useful in the detection of tumoral extension to any adjacent organ
MRI	• Best for local delineation of most gynecological malignancies • It has a higher soft tissue contrast and resolution compared to CT • Does not expose the patients to ionizing radiation compared to CT
PET-CT	• High specificity, low sensitivity in delineating primary gynecologic malignancies • Ability to incorporate the anatomical data (CT) and the metabolic information (functional PET) • Well-established in preoperative staging, monitoring therapy response, and detecting recurrence in gynecological malignancies.
PET-MRI	• Best for evaluating gynecological malignancies • It combines the functional and quantitative metabolic data of PET with the high-resolution anatomic and functional imaging properties of MRI

Imaging approaches for assessing tumor response

Recent advances in imaging, including functional MRI and hybrid imaging techniques, have substantially improved both lesion characterization and the evaluation of tumor response to treatment [35]. Although the literature search identified numerous studies addressing treatment response monitoring in radiation therapy, relatively few were directly relevant to the aims of this review and were therefore subjected to detailed analysis. Imaging methods nonetheless continue to offer considerable potential for monitoring treatment response in cancer radiation therapy [43]. The diverse imaging modalities used to monitor tumor response to radiation therapy are summarized in Table 4.

Table 4
Summary of Imaging for assessing tumor response

Author	Disease	Treatment modality	Imaging technique	Result and Conclusion
Dong et al., (2024) [44]	Cervical cancer	Brachytherapy	DWI – MRI For a complete metabolic response	- 62% of patients achieved CMR - 90th percentile ADC ($p < 0.001$) and HR-CTV size ($p < 0.003$) - Clinical DWI-MRI stratifies CMR patients with bulky cervical cancer
Aliotta et al., (2024) [45]		RT	CT, MRI, PET	A significant correlation was observed - For baseline SUV_{mean} ($p < 0.001$), $CT-HU_{mean}$ ($p < 0.001$) - For DW-MRI, D_{mean} ($p < 0.001$) FDG – PET SUV exhibits a significant correlation with volume regression
de Jong et al., (2023) [46]	Prostate cancer	Radionuclide therapy (^{223}Ra)	PET/CT	- For ^{68}Ga -PSMA PET/CT TTV_{bone} at baseline was lower in good responders than in poor responders ^{68}Ga -PSMA response of TTV_{bone} showed interpatient heterogeneity
A – Marrero et al., (2015) [47]	Animal study	RT	PET/CT, DCE-US	The SUV_{max} values and mean SUV for ^{18}F -FMISO were decreased after treatment
Wang et al. (2015) [48]	Breast cancer	Pre-operative EBRT	fMRI (DFI-MRI and DCE-MRI)	- Initial results after RT - For PTV, ($P < 0.006$), CTV ($P < 0.006$) - V_e increased in PTV ($p < 0.05$) and CTV ($p < 0.05$) There was a linear correlation between

Author	Disease	Treatment modality	Imaging technique	Result and Conclusion
				treatment dose and observed changes in parameters
Troost et al., (2010) [49]	Oropharyngeal tumor	RT	PET/CT	¹⁸ F-FLT PET/CT were taken before and twice during treatment - GTV decreased - SUV _{max} and SUV _{mean} were decreased

Conventional versus functional imaging approaches in treatment response monitoring

Conventional imaging modalities (CT, MRI, and US) play a major role in the assessment of tumor response to therapy, although they are increasingly also used to evaluate treatment-related changes in normal tissue [50]. For conventional CT, tumor response is most commonly assessed according to the two-dimensional Response Evaluation Criteria in Solid Tumors (RECIST) [51], which can be summarized as a *complete response*, defined as disappearance of all target lesions; a *partial response*, defined as a reduction of 30% or more in the sum of the longest diameters of target lesions relative to baseline; and *progressive disease*, defined as an increase of 20% or more in the sum of the longest diameters of target lesions relative to the smallest sum recorded since treatment began, or the appearance of new lesions. Within the conventional imaging framework, volume regression during RT can serve as a predictor of patient-specific treatment response, with progressive tumor shrinkage over the course of therapy indicating a favorable outcome [45, 52]. Functional and metabolic imaging techniques, by contrast, integrate pathological, physiological, and morphological information to provide earlier predictors of treatment response, enabling detection of microscopic changes in the tumor microenvironment and tissue cytoarchitecture through observed alterations in perfusion, oxygenation, and metabolism [53]. Functional imaging techniques, including dynamic contrast-enhanced (DCE)-MRI and diffusion-weighted (DW)-MRI, are generally regarded as superior to conventional anatomic imaging for treatment response assessment, since they capture physiological, morphological, and metabolic information at an earlier stage of treatment [54]. Morphological approaches to tumor response assessment encompass measurement of tumor size, evaluation of tumor enhancement and attenuation, and tumor texture analysis. Aliotta et al. acquired pre-treatment multimodality imaging metrics from PET/CT together with intra-treatment MRI (at weeks 1, 2, and 3) to identify metrics from PET, MRI, and CT capable of predicting rapid tumor regression during RT. PET standard uptake value (SUV), CT Hounsfield unit (HU), and non-Gaussian intravoxel incoherent motion DW-MRI metrics were computed, with the correlated volume changes demonstrating significant volume loss for the baseline FDG SUV_{mean} (Spearman, $\rho = 0.46$, $p < 0.001$), CT HU_{mean} ($\rho = 0.38$, $p < 0.001$), and the DW-MRI diffusion coefficient, D_{mean} ($\rho = 0.39$, $p < 0.001$). PET/CT data can thus be quantified and processed to provide accurate, reliable anatomic information

regarding tumor shrinkage, growth, or disease progression [53]. Nonetheless, important constraints remain when tumor response is assessed using conventional response criteria alone. In a study employing functional MRI (DWI and DCE) [48], the initial area under the concentration curve (iAUC) and related quantitative parameters demonstrated a significant pre- to post-treatment change in PTV, GTV, and CTV following radiotherapy. In a further study, Dong et al. similarly reported that DWI analysis, via the apparent diffusion coefficient (ADC), could meaningfully distinguish patients achieving a complete metabolic response (CMR) from those who did not [44].

Hybrid imaging approaches to treatment response monitoring (PET Imaging)

Numerous studies have reported that contrast agents, including ^{18}F -FMISO, ^{18}F -FLT, and ^{68}Ga -PSMA, represent promising PET tracers for imaging tumor cell proliferation, tumor staging, and treatment response evaluation in solid tumors when used in conjunction with CT, MRI, or US [45–49]. Troost et al. demonstrated, in ten patients with oropharyngeal cancer, that ^{18}F -FLT PET is well suited to early response assessment [49]. de Jong et al. similarly reported that ^{68}Ga -PSMA PET/CT could distinguish good from poor responders to ^{223}Ra radionuclide therapy, outperforming conventional bone scintigraphy in this regard [46]. In an animal study designed to assess the effect of radiation treatment on tumor vasculature and on hypoxia- and choline-related metabolism, functional parameters (SUV_{mean} and SUV_{max}) were derived from PET/CT (^{18}F -FMISO and ^{18}F -FCH) together with DCE-US acquired at day 0 and day 3, to characterize the relationship between metabolic and microvascular parameters reflecting the tumor microenvironment. In the context of treatment response monitoring, the findings suggested that this multimodal imaging approach, combining PET/CT and DCE-US, holds valuable diagnostic and prognostic potential for early, non-invasive evaluation of radiation therapy response [47].

Predictive Modeling Approach to Treatment Response Monitoring [AI and Radiomics]

In recent years, predictive modeling has emerged as a transformative approach for enhancing outcomes in radiation therapy. Predictive modeling employs advanced statistical techniques and algorithms to analyze large datasets, encompassing patient demographics, tumor characteristics, and historical treatment responses, in order to predict how individual patients will respond to radiation therapy [55]. At the forefront of this innovation are radiomics and artificial intelligence (AI) methodologies, which leverage machine learning and deep learning techniques to extract meaningful patterns from complex imaging data [56, 57]. Radiomics, a method for extracting quantitative features from medical images, enables identification of patterns and characteristics not discernible to the naked eye [58]; such features can be used to inform personalized cancer treatment, whereby treatment strategies are tailored to the individual characteristics of each patient and their tumor [58]. By analyzing radiomic features, clinicians may predict the likelihood of treatment success, recurrence, or metastasis. Radiomics thus plays a crucial role in evaluating treatment response by providing quantifiable imaging features that can be tracked longitudinally, offering insight into tumor characteristics and their evolution in response to

therapy that extends beyond the limitations of traditional size-based assessments such as RECIST [60]. The integration of AI methodologies, including machine and deep learning, further enhances the predictive capacity of radiomic analyses by enabling efficient processing of complex datasets. A summary of studies examining AI and radiomics for predicting treatment outcome and response is presented in Table 5.

Table 5
Summary of studies on AI and radiomics for predicting treatment outcome and response

Year	Author	Approach	Study description
2024	Donkulchai et al [61]	MRI Radiomics for LACC BT	• Radiomics features were extracted from GTV and pre-treatment T2-weighted MRI from ninety cervical cancer patients, to investigate the predictive value of the radiomics for the clinical outcome of the RT treatment. • The analysis of the radiomic features showed a correlation with the loco-regional recurrence (LRR).
2023	Ouyang et al [62]	AI models for MRI rectal cancer	• Baseline MRI and clinical data from 89 patients (training cohort) and 29 patients (testing cohort) with locally advanced rectal cancer • Logistic regression (LR) and deep learning (DL) models were developed to predict the pathological response. • Two groups were defined as pathological complete response (pCR) and non-pCR. • The LR AUC values for pCR were 0.853 and 0.866 and 0.829 and 0.838 for DL, showing no significant difference between the two models.
2022	Lee et al. [63]	AI (DL for lung cancer)	• A deep learning algorithm was developed for predicting weekly anatomical changes of the lung tumor and the esophagus during radiotherapy. • Seq2Seq started with the CT of the primary tumor and the esophagus on the planning CT to predict their geometry every week during the RT. • The report confirmed that the weekly predictions using the planning CT were more accurate in estimating the tumor evolution ($p < 0.0001$; two-tailed t-test).
2022	Bellis, R (Thesis) [64]	ML algorithms in cervix BT	• Twelve ML algorithms were tested and validated using 1183 radiomic features extracted from 20 patients from T1, T2 and DW – MRI images. • The report shows that the random forest algorithm achieved an accuracy of 93%. • Other ML methods showed a reported accuracy of up to 85%.
2021	Lucia et al [65]	Machine Learning	• Comparative study for predicting the radiation toxicity of LACC during RT • Based on the DVH parameter and radiomics approach to dose maps at the voxel level • Ninety-one radiomics features were extracted for the rectum, bladder and vaginal dose distribution • Predictive performance of the logistic Normal Tissue Complication Probability (NTCP) model on clinical data,

Year	Author	Approach	Study description
			DVH and radiomics. • Predictive performance of NTCP based on radiomics was higher than that of clinical and DVH data • The AUC was found to be 0.51/0.57 (clinical) to 0.58/0.72 (clinical + DVH) and 0.82/0.89 (clinical + DVH + radiomics) • Dosimetric radiomics is promising for NTCP modeling in RT
2019	Wu et al. [66]	MRI radiomics for prostate tumor	• Radiomics features were extracted from T2-weighted images and apparent diffusion coefficient (ADC) maps. The extracted features from T2-weighted images and ADC maps show a great robustness in quantifying the tumor characteristics of prostate cancer and high accuracy in predicting individual response to radiotherapy
2019	Ma et al. [67]	Machine Learning	• A machine learning model was built using a support vector regression (SVR) approach • A database containing volumetric modulated arc therapy (VMAT) plans of 63 prostate cancer patients was used. • A correlative relationship between the OAR DVH of the PTV-only plan (model input) and the corresponding DVH of the clinical treatment plan (CTP) (model output) was then established with the 53 training cases. • The prediction model was tested by the validation cohort of ten cases. • The framework is capable of predicting DVHs for VMAT planning

Findings from the seven studies identified to assess the feasibility of radiomics and artificial intelligence in predicting treatment response in cancer indicate that machine learning and deep learning approaches, in conjunction with radiomics, hold considerable promise for predicting cancer therapy outcomes [61–67]. In cancer radiation therapy, artificial intelligence (AI) can be applied to monitor treatment response by extracting radiomic features from imaging data to automatically detect changes in tumor size and shape over time, thereby enabling a more precise assessment of treatment effectiveness and allowing clinicians to make timely adjustments to treatment plans where indicated, with the potential to improve patient outcomes [68].

The reviewed studies identified four principal ways in which AI models can effectively monitor the response of cancer to radiation therapy. These are: **1) automated tumor segmentation**, whereby AI systems precisely delineate tumor margins on medical images, a capability that is essential for determining tumor volume and tracking its evolution throughout therapy; **2) radiomics analysis**, whereby AI models

extract quantitative imaging features (radiomic features) that may correlate with tumor regression or progression following radiation therapy, yielding insights that extend beyond visual interpretation alone; **3) predictive modeling**, whereby AI models analyze large datasets comprising patient information and imaging data to estimate the probability of an individual patient’s response to radiation therapy, thereby supporting individualized treatment regimens and the early detection of potential complications or delivery-related uncertainties; and **4) adaptive radiation therapy**, whereby AI models are used to track and adjust radiation dose delivery in real time during the treatment course, informed by changes in tumor position and anatomy observed on imaging acquired during treatment, thereby improving dose distribution and reducing harm to healthy tissue [61–67]. In a further study, radiomic features extracted from DVH data were used to predict radiation toxicity following cervical cancer radiotherapy [65].

Evidence gap mapping

To identify areas requiring further research, the 21 included studies were cross-tabulated by monitoring domain (*in vivo dosimetry, imaging, and AI/radiomics*) and disease site, as presented in Table 6. This mapping highlights several underexplored combinations. No included study evaluated in vivo dosimetry in breast, lung, or head and neck cancer, despite imaging- and AI-based studies existing for these sites. Conversely, no imaging-based response monitoring study was identified for rectal cancer, although both in vivo dosimetry and AI/radiomics approaches have been investigated in this disease. AI/radiomics-based predictive modeling was concentrated in gynecological/cervical and prostate cancer, with no AI/radiomics studies identified for breast or head and neck cancer. Most notably, no included study integrated real-time in vivo dosimetry with AI- or radiomics-based predictive modeling within a single monitoring framework; the only study to combine dosimetric and radiomic data did so using planned dose-volume histogram (DVH) data rather than measured in vivo dose [65]. This represents a key opportunity for future research, namely the development of integrated monitoring frameworks that combine measured dose, multimodal imaging, and AI-based predictive analytics within a single, validated pipeline, as outlined in the conceptual framework presented in Fig. 2.

Table 6
Evidence gap matrix

Monitoring domain	Gynecological / cervical	Prostate	Rectal	Breast	Lung	Head and neck	Not specified / animal
In vivo dosimetry	5	1	1	—	—	—	1
Imaging	1	1	—	1	—	2	1
AI / Radiomics	3	2	1	—	1	—	—

Number of included studies (n = 21) cross-tabulated by monitoring domain and disease site. Shaded red cells (—) indicate disease site combinations not represented among the included studies.

Challenges and future directions

Radiation therapy remains a mainstay in the comprehensive management of cancer, and with more than half of all cancer patients receiving it at some point in their care, ongoing efforts continue to focus on optimizing both its efficacy and safety profile. The capacity to accurately evaluate treatment response is critical for guiding clinical decision-making and improving patient outcomes; nevertheless, accurate evaluation of treatment response to radiation therapy remains a persistent challenge. Current anatomical imaging techniques for treatment response monitoring, such as RECIST, are limited in their ability to fully capture the multifaceted nature of treatment response, particularly in light of emerging therapeutic approaches [61]. Traditional size-based approaches are often inadequate, as they fail to capture changes in tumor biology and function that precede morphological alteration. Recent advances in functional and molecular imaging have shown considerable promise in providing a more comprehensive and nuanced assessment of tumor response, with functional modalities such as PET and MRI offering a richer picture of treatment response by incorporating metabolic, vascular, and microstructural information [70]. In many low- and middle-income settings, however, access to PET scanners and advanced MRI techniques remains limited, giving rise to several interrelated challenges: constraints in cancer diagnostics and staging, restricted treatment planning and monitoring capacity, diminished scope for tailored or personalized treatment approaches, and an elevated risk of poor clinical outcomes. Addressing these challenges will require further investigation of the more widely available CT and MRI modalities for treatment response evaluation, incorporating AI and radiomics to complement conventional anatomic assessment, with a view to determining whether an optimal combination of CT and MRI imaging, radiomics, and artificial intelligence can reliably predict the relationship between delivered radiation dose and the anatomic changes observed in individual patients' tumors in response to therapy. Although ongoing efforts are directed toward developing robust, reproducible, and clinically relevant radiomic models capable of guiding personalized treatment strategies and improving patient outcomes, further research is needed to establish standardized protocols and validate the clinical utility of these advanced treatment response monitoring systems across different cancer types, treatment modalities, and imaging techniques.

Discussion

This review set out to address the research questions outlined above, and the retrieved literature offers several insights in this regard. At present, the most common approach to assessing treatment response in patients undergoing external beam radiation therapy or brachytherapy remains clinical examination combined with imaging studies such as CT or PET [45]. In prostate cancer specifically, MRI has also emerged as an important modality for evaluating treatment response and detecting recurrence following radiation therapy, given its capacity to provide detailed information on tumor size, location, and characteristics, as well as on the changes that occur in response to treatment [71]. A further technique under active investigation is radiomics, which involves the extraction and analysis of quantitative imaging features from standard modalities such as CT, MRI, and PET/CT to predict and evaluate tumor

response to therapy. Numerous studies have demonstrated the potential of radiomics for assessing response to both external beam radiation therapy and brachytherapy across a range of cancer types, including non-small cell lung cancer and prostate cancer. Artificial intelligence and machine learning techniques are likewise being explored for the development of more sophisticated predictive and assessment models based on radiomic data; for instance, radiomic features extracted from pre-treatment PET/CT scans have been used to predict early response to radiation therapy in patients with non-small cell lung cancer [66, 72].

With respect to in vivo dosimetry, current research suggests that IVD can serve as an effective tool for monitoring radiation dose delivery and treatment response in cancer patients. A key advantage of IVD lies in its capacity to measure the actual radiation dose received by the patient, rather than relying solely on calculated or planned doses, a distinction that becomes particularly important when the delivered dose deviates from the planned dose due to anatomical change, patient positioning, or other factors. Given that radiation therapy delivery constitutes a complex, multi-stage process spanning consultation, treatment, and follow-up, accurate monitoring of both the delivered dose and the patient's treatment response is essential for optimizing outcomes and minimizing toxicity. Artificial intelligence and machine learning algorithms have emerged as promising tools for enabling real-time evaluation and streamlining various aspects of the radiation therapy workflow. Optimizing current treatment-response monitoring methods for real-time application, however, requires addressing several limiting factors, including the inherent subjectivity of imaging interpretation and the variability and lack of harmonized systems for data acquisition and analysis, both of which have constrained the clinical implementation of these quantitative methods. Quantitative imaging biomarkers have emerged as a more objective means of addressing this gap.

Beyond the scope of this review, several other treatment response monitoring approaches merit mention, including radiogenomics, which seeks to identify imaging biomarkers correlated with underlying tumor molecular profiles. Although all of these approaches to monitoring radiation therapy treatment response show considerable promise, gaps remain in their clinical implementation, owing largely to the complexity of integrating disparate data modalities.

To consolidate the findings of this review, Fig. 2 presents a conceptual framework for treatment response monitoring in radiation therapy. Within this framework, radiation delivery via EBRT or BT is monitored through three complementary domains: in vivo dosimetry, which provides a direct, patient-specific measure of the radiation dose actually delivered; imaging, spanning conventional, functional, and hybrid modalities, which captures anatomic, physiological, and metabolic indicators of tumor response; and AI- and radiomics-based predictive modeling, which extracts and analyzes quantitative imaging features to forecast treatment outcome. Rather than functioning in isolation, these three domains converge into an integrated treatment response assessment that synthesizes dosimetric, anatomic, and biological data. This integrated assessment, in turn, informs clinical decision-making and, where indicated, supports adaptive radiation therapy aimed at improving local control and reducing treatment-related toxicity. The framework also incorporates a feedback pathway, whereby insights

gained from treatment response monitoring inform and refine subsequent radiation delivery, underscoring the iterative, closed-loop nature of modern response-adapted radiotherapy.

Limitations

This review is not without limitations. Restricting the search to English-language publications may have excluded relevant studies reported in other languages, and the relatively modest number of included studies ($n = 21$), spanning a heterogeneous range of treatment modalities, monitoring techniques, and cancer types, precluded any quantitative synthesis or meta-analysis. The included literature also consisted predominantly of small, single-center studies and phantom-based investigations, with comparatively few large-scale clinical trials, a factor that constrains the generalizability of the reported findings to routine clinical practice.

Conclusion

Collectively, this scoping review indicates that treatment response in radiation therapy can be monitored through a combination of in vivo dosimetry, conventional and functional imaging, and emerging radiomics- and AI-based predictive modeling. Whereas in vivo dosimetry provides a direct, patient-specific measure of delivered dose, imaging approaches, particularly functional MRI techniques, offer complementary insight into the physiological and pathological dimensions of tumor response. Radiomics- and AI-driven models extend this capability further still, enabling earlier and more objective prediction of treatment outcome and supporting timely clinical decision-making. Nonetheless, the clinical translation of these methods remains constrained by a lack of standardization, the inherent subjectivity of imaging interpretation, and the absence of harmonized protocols across treatment centers. Future research should prioritize the prospective validation of radiomic and AI-based models, the development of standardized in vivo dosimetry protocols for both EBRT and BT, and the integration of multimodal data to support real-time, individualized assessment of treatment response in radiation oncology.

Declarations

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Conflicts of interest/Competing interests

There is no conflict to declare.

Ethics approval

Not applicable.

Consent to participate

Not applicable.

Consent for publication

Not applicable.

Availability of data and material

Not applicable.

Code availability

Not applicable.

Authors' contributions

Emmanuel Amponsah conceived and designed the study, developed the methodology, carried out the investigation and data curation, and wrote the original draft, which he subsequently revised and edited. Eric Clement Kotei Addison validated the results and provided project supervision. Christiana Subaar contributed to validation and supervision and reviewed and edited the manuscript. Olivia Christos and Joseph Adom contributed to the development of the methodology and reviewed and edited the manuscript. Edward Gyasi and Philip Owusu Manteaw contributed to the interpretation of radiological data and to the revision of the manuscript. All authors read and approved the final manuscript.

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Figures

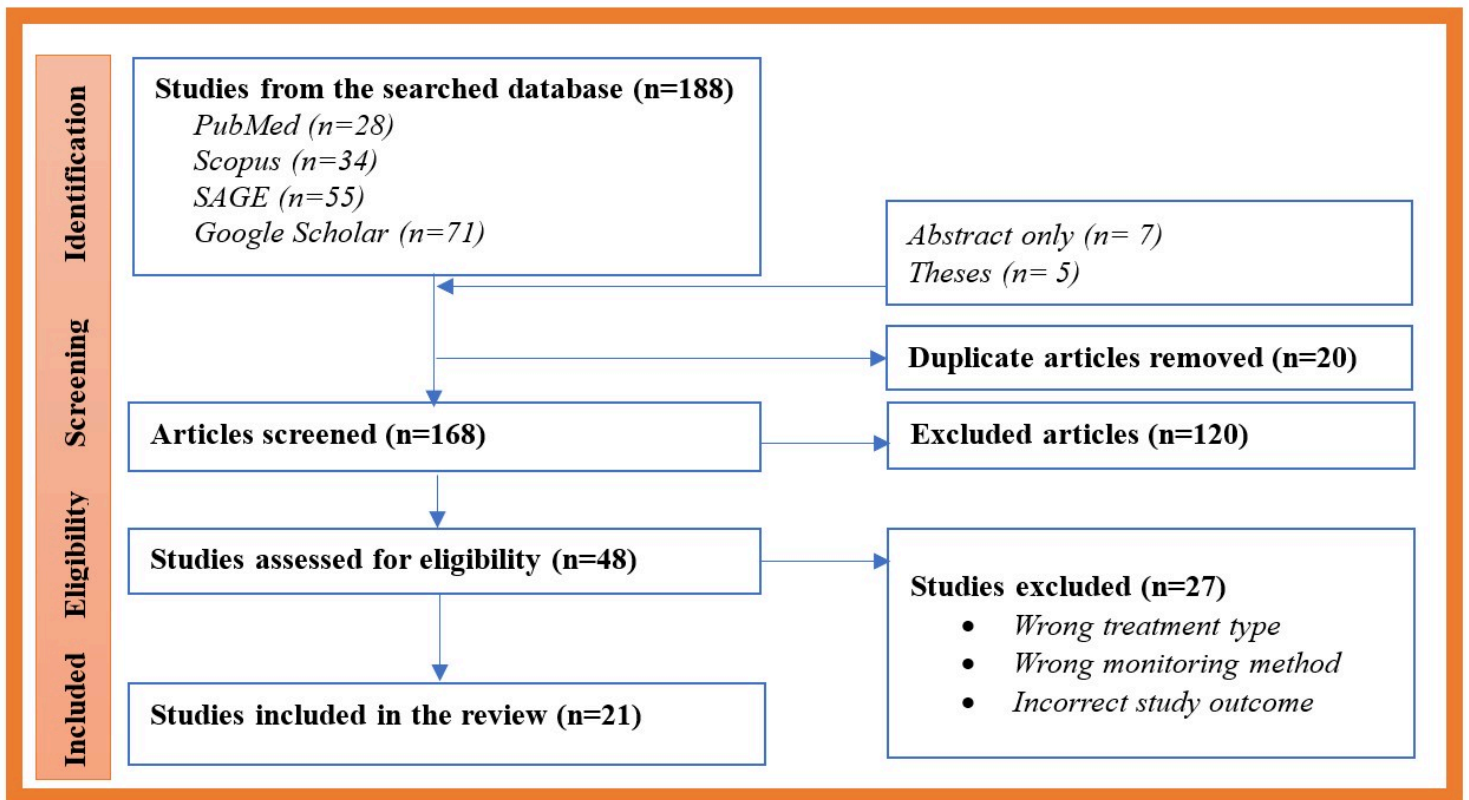


Figure 1

PRISMA flowchart for study identification, screening and selection

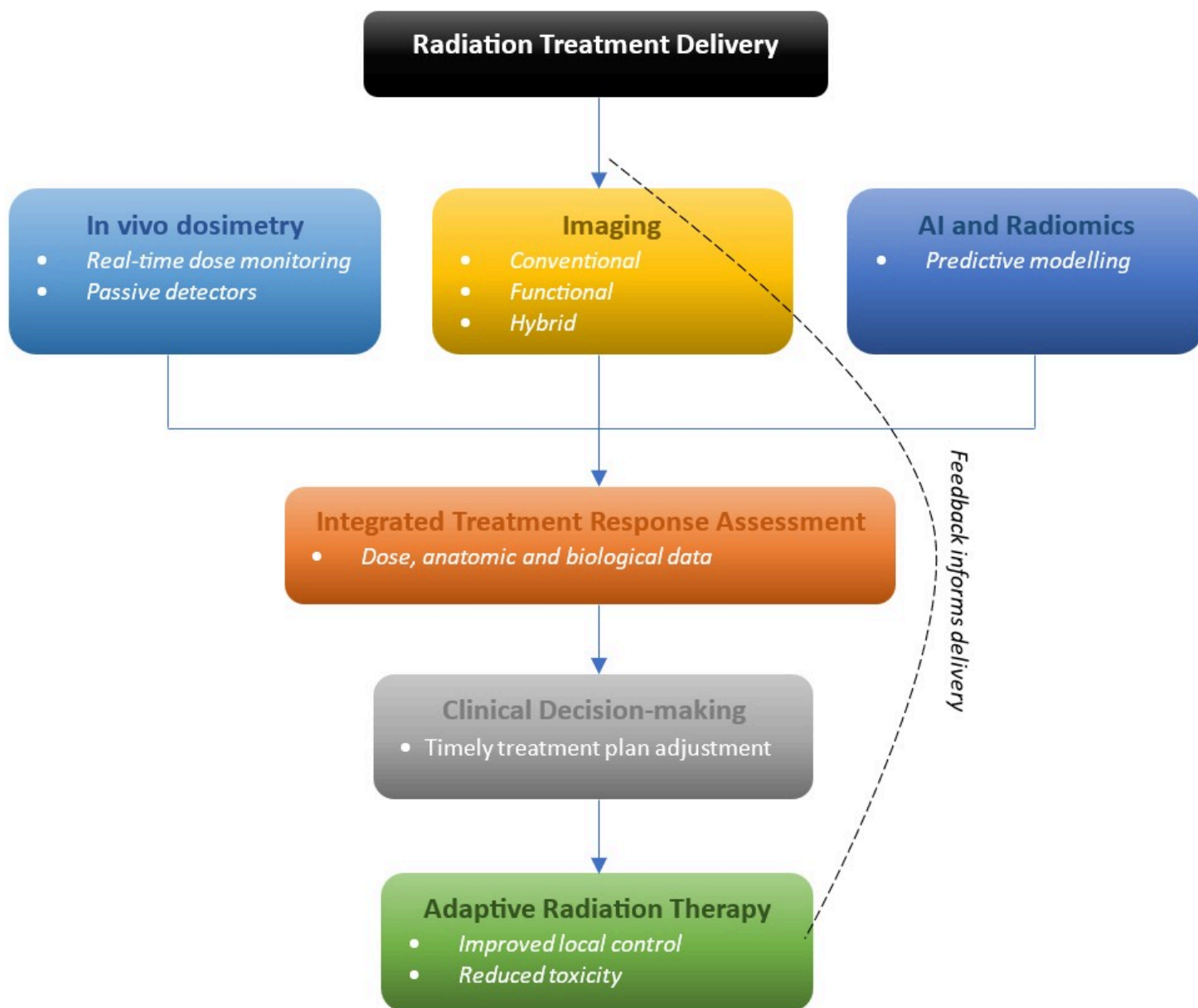


Figure 2

Conceptual framework for treatment response monitoring in radiation therapy. Radiation delivery (EBRT/BT) is monitored through three complementary domains—in vivo dosimetry, imaging, and AI/radiomics-based predictive modeling—which converge into an integrated treatment response assessment. This assessment informs clinical decision-making and, where indicated, adaptive radiation therapy, with feedback to delivery supporting real-time correction.