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Artificial Intelligence in Radiation Therapy, Imaging and Radiation Protection: A Comprehensive Review

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Abstract

Artificial intelligence (AI) has rapidly evolved from experimental prototypes to clinically relevant tools across radiation therapy, diagnostic imaging, and radiation protection. In radiation therapy, deep learning (DL) enables auto-segmentation, dose prediction, adaptive MR-linac workflows, and data-driven quality assurance, demonstrating measurable efficiency gains and improved consistency. In imaging, AI-based reconstruction techniques reduce CT radiation dose by up to 40–45% while preserving diagnostic accuracy, accelerate MRI acquisition without loss of fidelity, and support PET imaging at significantly reduced counts using transformer-based models. In radiation protection, AI-driven pipelines enable personalized organ dosimetry, real-time staff exposure monitoring, and decision-support systems that enhance safety in interventional suites.

Despite these advances, critical challenges persist, including dataset shift, limited prospective trials, workflow integration barriers, and the need for uncertainty quantification. Regulatory frameworks such as the EU AI Act and FDA pathways, along with ethical guidance from WHO, are shaping deployment toward safe, transparent, and accountable use. This comprehensive review synthesizes current evidence, highlights mature and emerging applications, and outlines limitations and future directions to ensure sustainable and equitable adoption of AI in clinical practice.

Keywords: Artificial Intelligence; Radiotherapy; Deep Learning; DLIR; PET; MRI

1. Introduction

Artificial intelligence (AI)—especially deep learning—now underpins several steps across radiation oncology and medical imaging. For target and organ-at-risk auto-segmentation, systematic reviews document robust performance across disease sites and emphasize site-specific validation and human oversight [2]. In planning, knowledge-based and learned dose-prediction pipelines, catalyzed by the Open KBP benchmark, improve plan consistency and throughput when paired with appropriate optimization and re-validation [6]. Automation is integral to online adaptive workflows on MR-linacs, where consensus reviews and multi-center cohorts report safe, well-tolerated treatment and accelerating on-table contouring and plan adaptation [7–9]. In diagnostic imaging, deep learning image reconstruction (DLIR) for CT enables sizeable dose reductions with preserved diagnostic quality, while foundational reviews clarify differences from iterative reconstruction and implications for reader training [12–13]. For PET, AI-based denoising and learned reconstruction maintain clinically acceptable image quality at substantially reduced counts, including recent transformer-based approaches; open questions include physics-informed modeling and task-based prospective evaluation [14–16]. Open datasets and public challenges such as fastMRI have accelerated learned MRI reconstruction, demonstrating competitive radiologist scoring and reproducible benchmarks that support translation [17–18]. Deployment requires alignment with evolving regulation and ethics: the EU AI Act introduces risk-based obligations for

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high-risk medical AI, the US FDA publicly tracks AI-enabled medical devices, and WHO guidance underscores transparency, accountability, and bias mitigation in health-AI deployments [37–40].

AI methods—particularly deep learning—now underpin several steps in cancer imaging and RT workflows. Clinicians increasingly encounter tools for organ and target auto-segmentation, knowledge-based or learned dose prediction, and adaptive planning on MR-linacs; in diagnostic imaging, DL-based reconstruction has matured across CT, PET, and MRI. At the same time, safe translation depends on robust validation, prospective monitoring, and clarity about uncertainty and data shift. This review provides a concise, clinically oriented map of where AI is reliable today, where benefits are plausible but evidence is evolving, and which regulatory/ethical frameworks govern deployment.

2. Methods

This narrative review emphasizes peer-reviewed studies and authoritative guidance (2019–2025) on AI for RT, imaging, and radiation protection. Representative evidence and resources were selected for recency, methodological quality, clinical relevance, and reproducibility with preference for multi-center studies, reviews/guidelines, and official documents. Two summary tables were constructed to orient readers to mature use-cases and key datasets.

2.1. Radiation Therapy (RT)

2.1.1. Auto-segmentation of targets and organs at risk

Deep learning auto-segmentation (DLAS) has reached clinically useful performance across multiple sites, with systematic reviews reporting strong accuracy for organs at risk (OARs) and improving target delineation. Clinical adoption studies stress the importance of site-specific validation, human oversight, and reporting standards [1–4]. Time savings of ~40–50% and reduced inter-observer variability have been demonstrated in multi-center evaluations of commercial tools [5]. Typical failure modes include small/low-contrast structures, post-operative anatomy, and pediatric cases; structured review by radiation oncologists/physicists remains essential.

2.2. Dose prediction and knowledge-based planning (KBP)

Modern KBP and learned dose-prediction models can accelerate plan generation and improve plan consistency. The OpenKBP initiative established open datasets and a reproducible benchmark to compare pipelines across institutions, demonstrating that high-quality dose predictions can translate into clinically acceptable plans when paired with appropriate optimization [6]. Prospective adoption should include periodic re-validation and guardrails to catch out-of-distribution anatomies.

2.3. Online adaptive RT and MR-linac

Automation (auto-contouring, adaptive re-optimization) is integral to MR-guided RT. Consensus reviews describe AI's role in accelerating contouring and plan adaptation on MR-linacs. A recent multi-center cohort found online adaptive 1.5-T MR-guided RT to be safe and well tolerated with low rates of high-grade acute toxicity [7–9].

2.4. Quality assurance (QA), patient-specific QA (PSQA), and in-vivo dosimetry

Guidelines from professional societies now outline development, validation, and reporting requirements for AI in RT [1]. Uncertainty quantification (UQ) remains underused beyond auto-contouring and should be incorporated into clinical AI tools (e.g., conformal prediction) [10]. For treatment verification, deep learning has been applied to EPID-based in-vivo dosimetry to distinguish plan-specific from generic deviations–aids that can focus physics review on clinically relevant errors [11].

Table 1 Representative AI use-cases and maturity

Domain / Task	Clinical value (typical)	Evidence snapshot	Key refs
RT–Auto-segmentation (OARs/targets)	Time savings, reduced variability	Multi-site evaluations; target contours improving but require review	[1–5]
RT–Dose prediction / KBP	Faster planning; consistency	OpenKBP benchmark and pipelines; external validation needed	[6]
RT–Adaptive MR-linac (AI-assisted)	On-table re-planning; margin reduction potential	Cohort data show safety/tolerability; workflow efficiency improving	[7–9]
RT–PSQA / EPID in-vivo dosimetry	Targets high-impact errors; triage alarms	DL can separate plan-specific vs generic deviations	[11]
CT–DL image reconstruction (DLIR)	Dose reduction while preserving quality	Prospective CCTA study shows ~40% dose reduction; broad review coverage	[12–13]
PET–Low-count/full-dose synthesis	Dose/time reduction	Review + multicenter studies; transformers emerging	[14–16]
MRI–Accelerated reconstruction (fastMRI)	Shorter scans with preserved fidelity	Public benchmarks and challenge results	[17–19]
Protection–Personalized CT organ dose	Prospective optimization; patient-specific risk	ML/cGAN pipelines show accurate, rapid dose estimation	[20–23]

3. Medical Imaging

3.1. CT: Deep-learning image reconstruction (DLIR)

Comprehensive reviews conclude that DLIR can outperform hybrid/iterative reconstruction for noise/artifact suppression. In a prospective CCTA study, DLIR enabled ~43% effective dose reduction without compromising stenosis assessment, plaque composition, or quantitative plaque volume [12]. These gains depend on proper protocoling and vendor implementation; image appearance differs from IR and requires reader familiarization [13].

3.2. PET: Low-count restoration and direct AI reconstruction

AI methods for PET include post-acquisition denoising and learned reconstruction. A recent review and multi-center studies support clinically acceptable image quality at substantially reduced counts, with transformer-based approaches showing promise for whole-body exams [14–16]. Physics-informed models and prospective, task-based reader studies remain priorities.

3.3. MRI: Acceleration and reconstruction

Open datasets and benchmarks (e.g., fastMRI) catalyzed rapid progress in learned MRI reconstruction, enabling higher acceleration factors with competitive radiologist scoring in challenge settings [17–19]. Clinical translation emphasizes data fidelity (esp. for small pathologies), uncertainty estimation, and safeguards against hallucinations.

Table 2 Selected public datasets and resources

Resource	Modality / Focus	Why it matters	Where / Citation
TCIA – The Cancer Imaging Archive	CT/MRI/PET (oncology)	De-identified research-grade collections; reproducible AI studies	cancerimagingarchive.net; Prior et al., Sci Data 2017 [24]
LIDC-IDRI (TCIA)	CT – lung nodules	Reference dataset with multi-reader annotations	Armato et al., Med Phys 2011 [25]
NLST subset (TCIA)	LDCT screening	Screening imaging linked to outcomes; benchmarking	TCIA NLST collection [26]
fastMRI	MRI (k-space + DICOM)	Large raw data for learned reconstruction; public benchmarks	Knoll 2020; Muckley 2021 [17–18]
OpenKBP / OpenKBP-Opt	RT dose prediction/KBP	Open data + reproducible pipelines for plan prediction/optimization	Babier et al., Phys Med Biol 2022 [6]

4. Radiation Protection and Safety

Two trends stand out: (i) AI-assisted, patient-specific organ dosimetry for CT to support protocol optimization and risk communication; and (ii) real-time decision-support for staff protection in interventional suites. Machine-learning and deep networks now estimate organ doses rapidly from routine CT (or even scout views), closely matching Monte Carlo references; recent studies demonstrate feasibility for multi-organ pipelines and near-real-time performance [20–23, 27–28]. In interventional radiology, real-time dosimetry and educational visualization tools can reduce staff exposure and improve shield placement [29–33]. Occupational dose-limit context (e.g., the ICRP's 20 mSv/year lens limit averaged over 5 years) remains critical when designing monitoring dashboards and alerts [34–36].

5. Governance, Regulation, and Reporting

Implementation should align with professional guidance and law. The joint ESTRO–AAPM guideline provides development, clinical validation, and reporting requirements for AI in RT [1]. The EU AI Act introduces risk-based obligations for high-risk medical AI systems, and national regulators increasingly update pathways for AI-enabled medical devices (e.g., the US FDA's public list) [37–39]. Ethics guidance from WHO emphasizes transparency, accountability, data protection, and bias mitigation in health-AI deployments [40].

AI performance can degrade under data drift and out-of-distribution (OOD) inputs; continuous monitoring, re-calibration, and site-specific re-validation are therefore required. Evidence for several tasks remains predominantly retrospective, with limited prospective, task-based reader studies (particularly for PET and accelerated MRI). Privacy-preserving data sharing and federated evaluation, along with clear cost–benefit analyses and lifecycle governance (post-market surveillance), are priorities for safe and equitable translation.

Table 3 Comparative Outcomes of AI vs Conventional Methods

Domain	Task	Conventional Benchmark	AI-Based Performance	Key Refs
CT	Iterative reconstruction	~20–25% dose reduction	~43% with DLIR	[12–13]
RT	Manual contouring	2–3 h, high variability	40–50% faster, reduced variability	[2–5]
PET	Classical denoising	Fails <50% counts	Acceptable at 25–33% counts	[15–16]
MRI	CS/parallel imaging	~2× acceleration	4× acceleration with fidelity	[17–18]

- These data show that AI consistently improves efficiency and dose reduction, yet requires rigorous validation, external benchmarking, and site-specific calibration [6,10].

Abbreviations

- DLIR: Deep-Learning Image Reconstruction

- KBP: Knowledge-Based Planning
- PSQA: Patient-Specific Quality Assurance
- UQ: Uncertainty Quantification
- OOD: Out-of-Distribution
- MR-linac: Magnetic-Resonance Linear Accelerator

6. Conclusion

AI demonstrates quantifiable advantages across modalities. In CT imaging, DLIR enabled ~43% effective dose reduction in coronary CT angiography without loss of diagnostic accuracy, compared with ~20–25% reductions using iterative reconstruction. In RT auto-segmentation, commercial DLAS tools reduced contouring time by 40–50% and decreased inter-observer variability [5], relative to conventional manual workflows that can take several hours per case. In PET imaging, transformer-based models preserved diagnostic quality at only 25–33% of standard counts, while traditional denoising fails below 50% counts. For MRI, fast MRI benchmarks showed 4× acceleration with equivalent radiologist scoring, surpassing parallel/CS techniques that typically reach 2×.

6.1.1. Limitations & Future Work

Key limitations hinder clinical adoption. Dataset shift and generalizability remain major issues, as AI trained on specific scanners or demographics often underperforms elsewhere [10]. Clinical training and workflow adaptation are under-recognized; radiologists and oncologists need education to interpret AI-enhanced images and manage uncertainty [37–40]. Infrastructure and cost barriers—GPU clusters, cybersecurity safeguards, and PACS/RIS interoperability—limit deployment in low-resource centers. Moreover, many published studies remain single-center or retrospective, with inconsistent external validation.

Future research should prioritize federated evaluation and secure data sharing [27–28], task-specific benchmarks tied to clinical outcomes [6], and continuous monitoring pipelines to recalibrate models under drift .Clinical trials must assess not only workflow efficiency but also patient safety, diagnostic accuracy, and cost-effectiveness .

Practical Recommendations

- **Clinicians**
- Adopt AI where it measurably reduces contouring/planning time without compromising plan quality.
- Prefer tools with clear failure modes, uncertainty displays, and rollback to standard workflow.
- Use task-focused reader studies to confirm non-inferior diagnostic performance at intended dose levels.
- **Medical Physicists**
- Integrate AI into QA: independent checks for auto-segmentation, dose prediction, and DL reconstruction.
- Track dataset shifts (scanner, protocol, demographics) and re-validate after software/model updates.
- Implement change control with versioned models, phantom tests, and alerting on drift/outliers.
- **Admins / IT**
- Demand procurement checklists: cybersecurity, audit logs, data retention, and vendor update policies.
- Budget for evidence generation and post-market surveillance, not just licenses.
- Ensure interoperability (DICOM, FHIR) and assign data stewards for traceability.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

References

[1] Hurkmans C, et al. A joint ESTRO and AAPM guideline for development, clinical validation and reporting of AI models in radiation therapy. Radiother Oncol. 2024;197:110345. doi:10.1016/j.radonc.2024.110345.

[2] Isaksson LJ, et al. Automatic segmentation with deep learning in radiotherapy: a review. Cancers. 2023;15(16):4130.

[3] De Biase A, et al. Clinical adoption of deep learning target auto-segmentation in radiotherapy. Br J Radiol: Artificial Intelligence. 2024;1(1):ubae015.

[4] Matoska T, et al. Review of deep learning-based autosegmentation for clinical target volume. Adv Radiat Oncol. 2024;9(6):1014707.

[5] Pang EPP, et al. Multicentre evaluation of deep-learning CT auto-segmentation for head-and-neck. NPJ Digit Med. 2025;8:– (online).

[6] Babier A, et al. OpenKBP-Opt: an international and reproducible evaluation of 76 knowledge-based planning pipelines. Phys Med Biol. 2022;67(18):10.1088/1361-6560/ac8044.

[7] Psoroulas S, et al. MR-linac: role of artificial intelligence and automation. Strahlenther Onkol. 2025;201(3):298–305.

[8] Westerhoff JM, et al. Safety and tolerability of online adaptive high-field MR-guided radiotherapy. JAMA Netw Open. 2024;7(5):e2413322.

[9] MOMENTUM Study Consortium. Selected MR-linac publications summary (2018–2024).

[10] Wahid KA, et al. Artificial intelligence uncertainty quantification in radiotherapy: a scoping review. Radiother Oncol. 2024;–.

[11] Olaciregui-Ruiz I, et al. Deep learning tools to distinguish plan-specific vs generic deviations in EPID-based in-vivo dosimetry. Med Phys. 2024;51(2):854–869.

[12] Benz DC, et al. Radiation dose reduction with deep-learning image reconstruction for CCTA. Eur Radiol. 2022;32(4):2620–2628.

[13] Koetzier LR, et al. Deep learning image reconstruction for CT: technical principles & clinical prospects. Radiology. 2023;306(2):e223604.

[14] Reader AJ, Pan B. AI for PET image reconstruction. Br J Radiol. 2023;96(1150):20230292.

[15] Wang YRJ, et al. AI transformers for radiation dose reduction in serial whole-body PET scans. Radiology: Artificial Intelligence. 2023;5(4):e220246.

[16] Seyyedi N, et al. Deep learning-based techniques for estimating full-dose PET from low-dose scans: a systematic review. BMC Med Imaging. 2024;24:–.

[17] Knoll F, et al. fastMRI: a publicly available raw k-space and DICOM dataset. Radiology: Artificial Intelligence. 2020;2(1):e190007.

[18] Muckley MJ, et al. Results of the 2020 fastMRI challenge for MR image reconstruction. IEEE Trans Med Imaging. 2021;40(9):2306–2317.

[19] fastMRI breast/radial dataset update (NYU CAI2R resource page, 2025).

[20] Tzanis E, Damilakis J. Machine-learning pipeline for multi-organ patient-specific CT dosimetry. Eur Radiol. 2025;35(2):919–928.

[21] Berris T, et al. Real-time personalized CT dosimetry with deep learning. Physica Medica. 2024;–.

[22] Damilakis J. AI-powered personalized patient dosimetry in CT. Br J Radiol: Artificial Intelligence. 2025;2(1):ubaf007.

[23] Shao W, et al. Fast prediction of personalized abdominal organ doses in CT using radiomics + SVR. Sci Rep. 2024;14:–.

[24] Prior F, et al. The public cancer radiology imaging collections of TCIA. Sci Data. 2017;4:170124.

[25] Armato SG III, et al. The LIDC/IDRI thoracic CT database of lung nodules. Med Phys. 2011;38(2):915–931.

[26] TCIA NLST collection (low-dose CT screening).

[27] Imran A-A-Z, et al. Scout-Net: prospective estimation of CT organ doses from scout views. arXiv:2312.15354 (2023).

[28] Fu W, et al. iPhantom: individualized computational phantoms for CT organ dosimetry. arXiv:2008.08730 (2020).

[29] Krompaß K, et al. Real-time dosimetry in interventional radiology. Cardiovasc Intervent Radiol. 2025

[30] Hattori K, et al. Evaluation of a new real-time dosimeter for interventional radiology staff. Sensors. 2023;23(1):512.

[31] Baumann F, et al. Effect of real-time monitoring on staff dose in interventional radiology. Cardiovasc Intervent Radiol. 2015;38:1105–1111.

[32] Fujibuchi T, et al. Visualization/education tools for scatter radiation in fluoroscopy. Information. 2025;16(4):266.

[33] Fujibuchi T. Radiation protection education using virtual reality by visualization of scatter. J Radiol Prot. 2021;41:S317.

[34] ICRP Publication 118. Threshold doses for tissue reactions; lens-of-eye limit statement (2011/2012).

[35] NEA/OECD. Radiation dose limits to the lens of the eye (policy brief). 2021.

[36] ICRP/IAEA. International Basic Safety Standards–lens-of-eye dose limit (20 mSv/y averaged over 5 y).

[37] FDA. Artificial Intelligence (AI)–Enabled Medical Devices List (accessed Jul 2025).

[38] EU Artificial Intelligence Act–Official Journal of the European Union (June 2024).

[39] FDA SaMD guidance updates (general references to AI/ML pathways).

[40] WHO. Ethics and governance of AI for health. 2021.