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Review

Digital twin applications in radiology and radiotherapy: Applications, challenges, and future perspectives

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ABSTRACT

Digital twin technology has emerged as a transformative innovation in healthcare, offering virtual replicas of physical entities at patient-level, equipment-level, and departmental-level that enable real-time monitoring, prediction, and optimisation. This narrative review synthesizes current evidence on digital twin maturity and clinical translation in radiology and radiotherapy. A comprehensive literature search was conducted across PubMed, Scopus, IEEE Xplore, and Web of Science databases for peer-reviewed articles published from 2018 onwards. The review reveals that digital twin applications in radiology remain predominantly experimental, with equipment-focused implementations (predictive maintenance, workflow optimization) showing greater maturity than patient-level applications. In radiology, emerging applications include personalised imaging protocol optimisation, predictive equipment maintenance, dose management, and workflow enhancement. In contrast, radiotherapy demonstrates more advanced patient-level digital twin integration, facilitating individualised treatment planning, real-time dose adaptation, treatment response prediction, and quality assurance. DT-aligned adaptive radiotherapy report improved local/locoregional control in the low-teens to ~18% relative range, alongside clinically meaningful toxicity-risk reductions in selected endpoints, while maintaining lower radiation dose to organs. Key benefits include improved patient outcomes, reduced radiation exposure, enhanced treatment precision, and optimised resource utilisation. However, critical gaps persist in standardized validation frameworks, interoperability standards, and regulatory guidance. Implementation faces challenges including data integration complexity, computational requirements, regulatory uncertainties, and domain-specific barriers differing between radiology and radiotherapy contexts. Successful clinical translation requires addressing technical infrastructure gaps, establishing evidence-based validation protocols, and developing reimbursement mechanisms that recognize digital twin value. Digital twin technology demonstrates substantial potential for advancing precision medicine in imaging and radiation oncology.

1. Introduction

The healthcare industry stands at the cusp of a technological revolution driven by advances in artificial intelligence, computational modelling, and data analytics. Among these innovations, digital twin technology has emerged as a paradigm-shifting concept that promises to transform how medical professionals approach diagnosis, treatment planning, and patient care [1]. Digital twins represent virtual replicas of

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physical entities, whether individual patients, medical equipment, or entire healthcare systems, that continuously synchronise with their real-world counterparts through real-time data exchange [2–6]. This bidirectional flow of information enables predictive analytics, scenario testing, and optimisation strategies that were previously impossible in traditional healthcare delivery models [7].

Crucially, digital twin technology operates across multiple hierarchical scales in healthcare settings. At the patient level, digital twins create personalized virtual representations integrating anatomical, physiological, and pathological information. At the equipment level, they monitor imaging system performance and predict maintenance needs. At the departmental or systems level, they model entire clinical workflows, resource allocation patterns, and operational efficiency [8]. This multi-scale capability distinguishes digital twins from traditional decision support systems, enabling simultaneous optimization across individual patient care and healthcare delivery infrastructure. Understanding these distinct scales is essential for comprehending the varied applications described throughout this review, particularly in radiology where system-level implementations currently predominate over patient-level applications.

In the context of diagnostic radiology, digital twin technology offers both patient-specific and system-level opportunities for personalisation and precision [8]. Radiology departments generate vast amounts of imaging data daily, yet much of this information remains underutilised beyond immediate diagnostic purposes. At the patient level, digital twins can harness this wealth of data to create comprehensive virtual patient models that integrate anatomical, physiological, and pathological information. These models serve as living repositories that evolve with each scan, laboratory result, and clinical observation, providing clinicians with a holistic view of patient health trajectories. At the equipment and departmental levels, digital twins enable simulation of different imaging protocols, prediction of equipment failures, optimization of workflow efficiency, and management of radiation dose across populations [8]. However, the field of digital twins in diagnostic radiology remains relatively immature compared to radiotherapy, with most validated applications focusing on operational optimization rather than patient-specific diagnostic enhancement. Current implementations predominantly address equipment maintenance and departmental workflow, while patient-level applications for protocol personalization and radiomics-driven prediction remain largely experimental.

Radiotherapy, with its inherent reliance on precise dose calculations and anatomical targeting, presents an ideal domain for digital twin implementation [9]. Traditional radiotherapy planning involves creating static treatment plans based on single time-point imaging, often failing to account for anatomical changes during treatment courses or individual variations in tumour response. Digital twin technology addresses these limitations by enabling dynamic treatment adaptation based on continuous monitoring of patient-specific parameters [10]. The integration of real-time imaging data, biological markers, and treatment response indicators into virtual patient models allows radiation oncologists to adjust treatment strategies proactively, potentially improving outcomes while minimising toxicity [11]. The radiotherapy field has achieved greater maturity in patient-level digital twin applications compared to diagnostic radiology, with several validated implementations demonstrating measurable clinical benefits in adaptive treatment delivery and outcome prediction.

The convergence of digital twin technology with advanced imaging modalities, artificial intelligence algorithms, and high-performance computing infrastructure creates new possibilities for enhancing both diagnostic and therapeutic aspects of cancer care [12]. In radiology, digital twins can optimise imaging protocols to individual patient characteristics, predict equipment failures before they occur, manage radiation dose exposure across patient lifetimes, and streamline departmental workflows [13–16]. In radiotherapy, these virtual models enable treatment plan optimisation through in silico testing, real-time monitoring of dose delivery accuracy, prediction of normal tissue complications, and personalised adaptation of treatment schedules based on individual tumour biology and patient tolerance [17,18].

Despite growing interest, the existing literature on digital twins in imaging and radiation oncology remains fragmented. Prior reviews have either focused narrowly on a single domain, such as radiotherapy planning or radiology workflow, or have addressed digital twins broadly across all of healthcare without distinguishing implementation maturity, evidence quality, or domain-specific barriers. As a result, clinicians and healthcare administrators lack a coherent, comparative understanding of which digital twin applications are ready for clinical deployment, which remain experimental, and how to sequence investments strategically across imaging and radiation services.

This review makes four specific contributions to address that gap. First, it introduces a dual-domain maturity classification framework that explicitly stratifies digital twin applications by implementation scale (patient-level, equipment-level, system-level) and validation status (experimental, pilot, early clinical adoption, validated), applied consistently across both radiology and radiotherapy. Second, it provides the first systematic comparative analysis of digital twin maturity between these two domains, revealing a clinically important asymmetry: radiotherapy has achieved greater patient-level digital twin maturity, while radiology's more mature implementations are concentrated at the system and equipment level. Third, it critically contextualises reported outcomes, including adaptive radiotherapy control rates and radiology efficiency gains, within their evidence limitations, distinguishing robust validated findings from promising but unconfirmed results. Fourth, it formalises a four-stage translational roadmap to guide institutions from infrastructure readiness through to scaled clinical deployment, with domain-specific guidance for radiology versus radiotherapy contexts.

The objectives of this review are therefore: 1) to introduce and apply a dual-domain maturity classification framework stratifying digital twin applications by scale and validation status; 2) to evaluate current applications across patient-level, equipment-level, and system-level implementations in both diagnostic radiology and therapeutic radiation oncology; 3) to provide the first comparative maturity analysis between these two domains and characterise the structural asymmetry in their digital twin development trajectories; 4) to critically assess the strength and generalisability of reported clinical benefits; 5) to identify domain-specific barriers to adoption; and 6) to propose a four-stage translational roadmap and recommendations for standardisation, validation, and clinical scaling. As illustrated in Fig. 1, the digital twin workflow integrates patient data into a computational model capable of simulating radiological and therapeutic outcomes.

2. Methodology

This narrative review employed a systematic approach to literature search and selection while maintaining the interpretive flexibility characteristic of narrative reviews. Unlike systematic reviews that aim for comprehensive inclusion of all available evidence with quantitative syntheses, narrative reviews prioritize thematic analyses and interpretive syntheses to contextualize findings within broader conceptual frameworks. The review was specifically designed to support construction of the dual-domain maturity classification framework, which required collecting not only outcome data but also information about validation status, implementation scale, and domain-specific barriers, dimensions not captured by standard systematic review protocols.

2.1. Search strategy

A comprehensive literature search was conducted across four major electronic databases: PubMed, Scopus, IEEE Xplore, and Web of Science. The search covered publications from January 2018 onwards, capturing the period during which digital twin applications in medical imaging and radiation therapy gained substantial research attention. The search strategy combined terms related to digital twin technology with

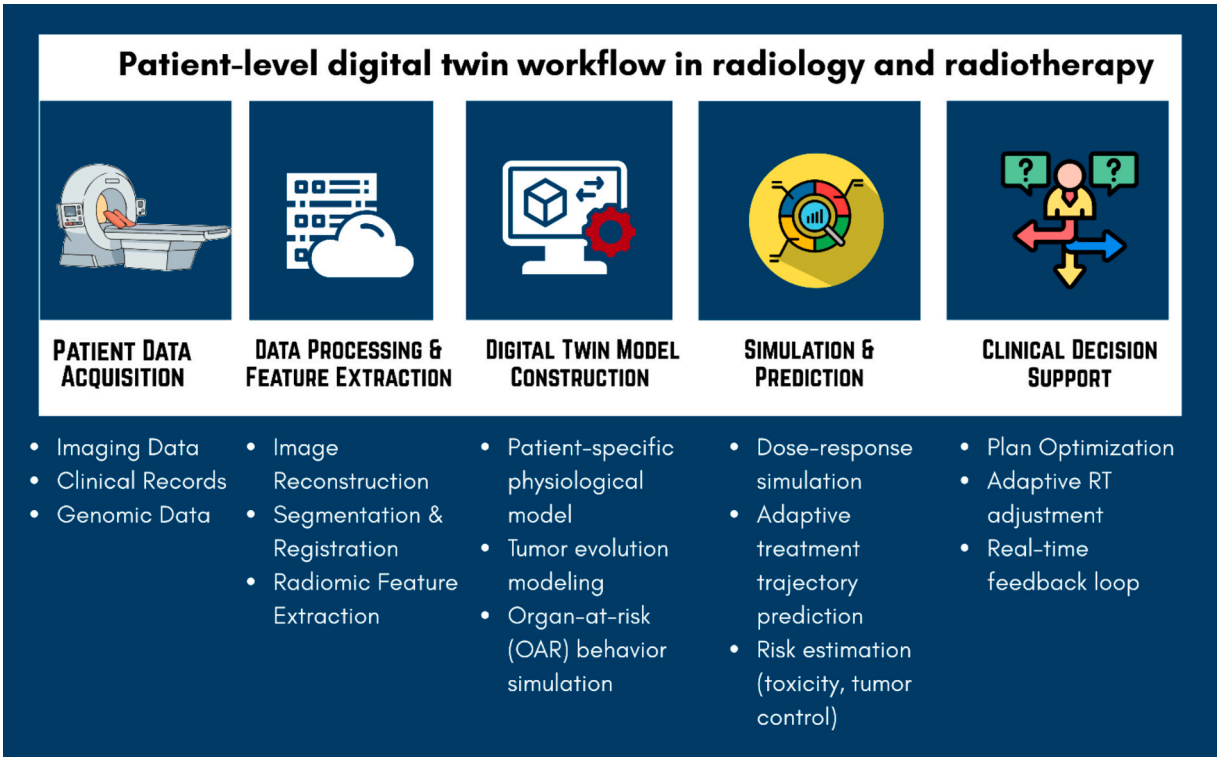

Fig. 1. Patient-level digital twin workflow in radiology and radiotherapy. End-to-end workflow illustrating how multimodal patient data are processed, integrated, and modeled to enable individualized simulation, dose prediction, adaptive treatment planning, and real-time clinical decision support.

radiology and radiotherapy specific terminology. Primary search terms included "digital twin," "digital replica," "virtual patient," "in silico model," combined with "radiology," "radiotherapy," "radiation therapy," "radiation oncology," "medical imaging," "computed tomography," "magnetic resonance imaging," and "treatment planning." The search strategy intentionally emphasized computed tomography, magnetic resonance imaging, and radiotherapy applications, as preliminary scoping indicated these modalities generated the majority of digital twin literature. However, the search also included terms for ultrasound, conventional radiography, and nuclear medicine to ensure comprehensive coverage of all imaging modalities. The predominance of CT, MRI, and radiotherapy in the final selection reflects the current state of digital twin research rather than search exclusions. Boolean operators were used to create comprehensive search strings adapted to each database's specific syntax requirements.

2.2. Selection criteria

Articles were included if they described digital twin applications, implementations, or frameworks relevant to radiology or radiotherapy practice. Eligible study types included original research articles, clinical trials, pilot studies, technical development papers, and review articles that provided substantial insights into clinical applications. Articles were required to be published in English and available in full text format. Exclusion criteria eliminated conference abstracts without full papers, editorials, commentaries without substantial technical content, and studies focusing exclusively on other medical specialties without relevance to imaging or radiation therapy.

2.3. Data extraction and synthesis

Selected articles were reviewed systematically to extract information about digital twin architectures, clinical applications, implementation scale (patient-level, equipment-level, or system-level), maturity level (experimental, pilot, early clinical adoption, or validated), implementation strategies, reported outcomes, and identified challenges. These four maturity categories were defined a priori to enable consistent classification across both domains: experimental denotes proof-of-concept or simulation studies without clinical validation; pilot denotes small-scale clinical feasibility studies; early clinical adoption denotes implementations with single-centre or limited multi-centre validation; and validated denotes applications with regulatory acceptance, multi-institutional evidence, or prospective trial support. Data extraction focused on understanding the technological components of digital twin systems, the clinical contexts in which they were applied, the methods used for validation, the quality and reproducibility of reported outcomes, and the benefits or limitations observed. The synthesis process involved thematic analysis to identify common applications, recurring challenges, and emerging trends across different studies, with particular attention to characterising the maturity asymmetry between radiology and radiotherapy.

2.4. Quality assessment

While formal quality scoring was not applied in accordance with narrative review methodology, articles were evaluated for methodological rigour, clarity of reporting, and relevance to clinical practice. Particular attention was given to distinguishing between experimental proof-of-concept studies and validated clinical implementations, assessing whether reported outcomes included appropriate context regarding study populations, conditions, and limitations. The review prioritised peer-reviewed publications from established journals and conferences, though relevant preprints and technical reports were considered when they contributed unique insights not available elsewhere.

3. Applications in radiology

This section examines digital twin applications across diagnostic radiology practice, classified using the dual-domain maturity framework

introduced in Section 2, and organised into four main categories: personalised imaging protocol optimisation, predictive equipment maintenance, cumulative dose management, and workflow optimisation. A key finding of this classification is that no radiology application currently achieves the 'validated' tier at the patient level; all patient-level radiology applications remain experimental or at pilot stage, whereas equipment maintenance and workflow optimisation reach early clinical adoption in some settings. Table 1 provides a comprehensive summary of these applications with associated benefits and implementation requirements, while Fig. 2 illustrates the conceptual framework of digital twin technology in diagnostic imaging. It is important to note that radiology applications remain predominantly at the experimental or pilot implementation stage, with system-level applications (equipment maintenance, workflow optimization) demonstrating greater maturity than patient-level applications (protocol personalization, radiomics prediction). The numerical ranges provided in Table 1 reflect heterogeneous study conditions and should be interpreted with appropriate consideration of evidence quality and generalizability limitations, as discussed in subsequent subsections.

3.1. Personalised imaging protocol optimisation

Digital twin technology enables personalised optimisation of imaging protocols based on individual patient characteristics, clinical indications, and image quality requirements. Traditional imaging protocols apply standardised parameters across patient populations, potentially delivering excessive radiation doses to some patients while producing suboptimal image quality for others [19]. Digital twins incorporate patient-specific factors including body habitus, clinical history, previous imaging studies, and diagnostic questions to simulate different protocol configurations before actual scanning [8,19,20].

Virtual patient models, including computational phantoms used in virtual imaging trials, can be used to predict how acquisition and reconstruction choices (for example tube voltage, tube current, pitch, gantry rotation time, and reconstruction settings) influence image quality metrics and radiation dose [21,22]. These predictions can then support protocol selection aimed at achieving task-appropriate diagnostic image quality at the lowest reasonably achievable dose under optimisation (ALARA) principles [22]. In practice, dose reduction magnitudes vary by scanner, body region, and clinical task, but single-centre clinical implementations of protocol/reconstruction optimisation commonly report reductions in the ~20–30% range while maintaining or improving diagnostic image quality, with some CT applications reporting reductions approaching or exceeding 40% when deep learning reconstruction is used [23,24]. Evidence quality remains mixed because many "digital twins" or virtual-trial implementations are still presented as methodological or proof-of-concept frameworks, and radiology DT reviews continue to highlight validation and deployment challenges. The magnitude of achievable dose reduction varies substantially depending on patient population (paediatric vs adult), body region, clinical indication, and baseline protocol parameters. Paediatric imaging particularly benefits from personalisation because children have heightened radiation sensitivity and wide variation in size that requires careful parameter adjustment, although large-scale multi-site validation remains limited [22].

Advanced applications propose incorporating radiomics-driven prediction, where DT-type systems use quantitative features extracted from prior images to inform personalised decisions, potentially including protocol tailoring for specific tissue characteristics or suspected findings. Radiomics extracts quantitative descriptors from medical images, including intensity-based statistics, shape measures, and texture patterns that may correlate with disease states or treatment response [25]. In principle, radiomics outputs could be integrated into protocol optimisation by identifying patients whose imaging phenotypes might benefit from modified acquisition parameters, but these applications remain highly experimental because radiomic features can be sensitive to acquisition and reconstruction differences, limiting reproducibility and generalisability across scanners and institutions.

3.2. Predictive equipment maintenance

Equipment-focused digital twins monitor imaging system performance in real-time, predicting maintenance needs before failures occur [9]. Modern imaging equipment generates extensive operational data including tube temperatures, detector performance metrics, mechanical positioning accuracy, and image quality indicators. DT systems analyse these data streams to identify patterns indicating incipient failures or performance degradation.

DT-enabled predictive maintenance models use real-world operating data to estimate remaining useful life, anticipate likely failure modes, and support condition-based replacement planning rather than relying only on fixed manufacturer intervals. By shifting maintenance from reactive or calendar-based schedules to predictive interventions, these approaches are intended to reduce unplanned downtime, improve asset availability, and better target maintenance resources and budgets [26].

In radiology equipment, published evidence includes a European evaluation of GE's OnWatch remote monitoring across 136 CT installations, reporting an average 32% reduction in unplanned downtime rate, alongside reduced time-to-service and fewer disruptions following implementation [27]. In addition, commercial "digital twin" service

Table 1
Digital Twin Applications in Radiology.

Application Area	Specific Functions	Key Benefits	Implementation Requirements	Maturity Level	Evidence Context
Protocol Optimisation [13,32,70]	Patient-specific parameter selection; Image quality prediction; Dose estimation; Alternative protocol comparison	44.8% reduction in average patient waiting time; 14.5% increase in scanner utilization; diagnostic quality; Reduced repeat scans; Enhanced patient safety	Patient anatomical models; Image quality metrics database; Dose calculation algorithms; Protocol library	Early adoption	Reported in single-center CT/MRI studies with limited validation; varies by patient population and clinical indication
Equipment Maintenance [33,91]	Real-time performance monitoring; Failure prediction; Maintenance scheduling; Parts replacement planning	reduction in downtime; cost savings; Extended equipment life; Improved reliability	Sensor integration; Historical failure database; Predictive algorithms; Maintenance management system	Pilot/Early adoption	Based on limited implementations; generalizability depends on equipment age and institutional context
Dose Management [13,92]	Lifetime heath monitoring such as dose tracking; Organ-specific calculations; Risk assessment; Alternative modality suggestions	Informed clinical decisions; Reduced cumulative exposure by 20–35% less dose errors; Optimised imaging utilisation; Enhanced patient counselling	Dose registry; Patient identification system; Risk models; Decision support interface	Pilot/Early adoption	Requires longitudinal data infrastructure; limited multi-institutional validation
Workflow Optimisation [32,33,93]	Patient flow simulation; Resource allocation; Bottleneck identification; Schedule optimization	efficiency gains; Reduced waiting times and treatment cost; Improved resource utilisation; Enhanced patient experience	Process mapping; Real-time tracking; Simulation software; Integration with scheduling systems	Pilot/Early adoption	Varies by department size, case mix, and baseline efficiency; most evidence from simulation studies

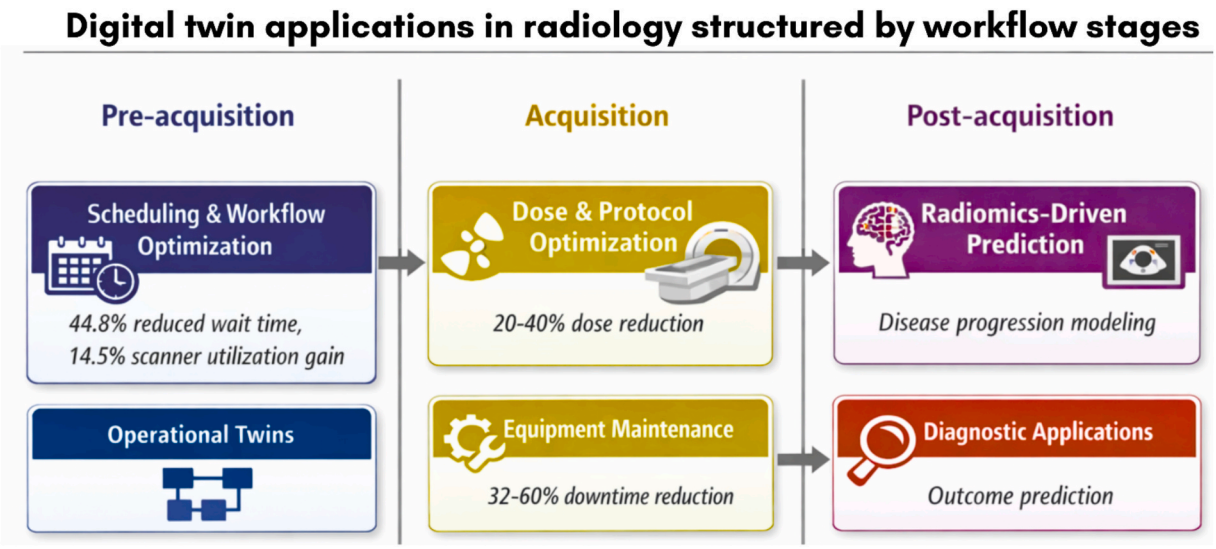

Fig. 2. Digital twin applications in radiology structured by workflow stages (pre-acquisition, acquisition, post-acquisition). The diagram illustrates operational twins for scheduling and workflow optimization (pre-acquisition), dose/protocol optimization and equipment maintenance (acquisition), and radiomics-driven prediction with diagnostic applications (post-acquisition), demonstrating the progression of digital twin technology across the radiology imaging workflow.

offerings report large estimated uptime gains in specific modalities; for example, GE's OnWatch Predict measurable impact on the efficiency and reliability of MRI services resulting in an estimated ~60% reduction in unplanned downtime (vendor-reported metrics with stated caveats that results may vary) [28].

Overall, equipment maintenance is one of the more operationally mature DT applications in imaging because multiple vendors now market predictive and proactive service platforms for installed fleets. However, generalizability across institutions, manufacturers, and operating environments still requires broader independent validation, and the field continues to note gaps in standardized performance metrics and evaluation frameworks for DT-driven predictive maintenance.

3.3. Cumulative dose management

Patient-focused digital twins track cumulative radiation exposure across all imaging studies throughout patient lifetimes, enabling informed risk–benefit decisions for subsequent examinations. Medical imaging contributes substantially to population radiation exposure, with some patients undergoing multiple computed tomography examinations raising concerns about cumulative effects. Lifetime (cumulative) dose tracking remains difficult to implement at scale because patients often receive imaging across multiple providers, historical dose records are incomplete, and dose data are not consistently captured in interoperable formats. Although standards such as the DICOM Radiation Dose Structured Report (RDSR) exist to record dose information, cross-site aggregation still depends on consistent implementation and harmonised procedure naming and data workflows, so many solutions work best inside single health systems rather than across fragmented care pathways [29]. Risk interpretation is also challenging. Professional guidance cautions against using prior exam dose, including cumulative effective dose, to decide whether a new imaging exam is justified, and ICRP guidance emphasises that dose limits do not apply to medical exposures, with the focus instead on justification and optimization [30]. Despite these limitations, cumulative dose management continues to attract growing regulatory and professional attention, including EU requirements to record and report patient exposure information as part of radiological procedure documentation and broader international guidance encouraging patient exposure monitoring to support optimisation.

3.4. Workflow and resource optimisation

Departmental DTs model entire radiology workflows including patient scheduling, equipment allocation, staff deployment, and reporting processes. These system-level models simulate patient flow through imaging departments, identifying bottlenecks, optimising schedules, and predicting resource needs based on examination volumes and types [16,18]. Scenario testing evaluates different operational strategies before implementation, reducing trial-and-error approaches that disrupt clinical operations.

Applications include optimising CT room utilisation by predicting examination durations based on clinical indications and patient factors, balancing radiologist workloads by distributing studies according to complexity and subspecialty expertise, and predicting staffing requirements for varying patient volumes throughout days and weeks [16,18]. Reported efficiency gains are mostly drawn from simulation studies, short pilots, or vendor case studies rather than sustained multisite deployments. For example, a radiology workflow digital twin case study (Mater Private Hospital) reported improved throughput and access metrics, including CT utilisation increasing by 26% and MRI utilisation increasing by 32%, alongside shorter waiting times (13 min for CT and 25 min for MRI) [31]. Similarly, a study by Silva-Aravena et al. [32] demonstrated how a DT-based model outperforms baseline performance by achieving a 14.5% increase in MRI machine utilization and a 44.8% reduction in the average patient waiting time. At the same time, the size of any efficiency improvement depends strongly on baseline departmental organisation, case-mix complexity, and pre-existing optimisation, and evidence remains largely single-centre or context-specific, limiting generalisability. Implementing workflow digital twins also requires substantial upfront work in process mapping, data integration/interoperability, and organisational change management, and reviews of DT deployments in healthcare and radiology consistently identify validation frameworks and operational adoption as ongoing gaps [33].

4. Applications in radiotherapy

This section examines digital twin applications across the radiotherapy treatment continuum, classified using the same dual-domain maturity framework applied to radiology in Section 3, enabling direct cross-domain comparison. Unlike diagnostic radiology where system-level applications predominate at higher maturity, radiotherapy

demonstrates a structurally different maturity profile: patient-level applications, including adaptive treatment delivery and quality assurance, have achieved validated or early clinical adoption status, representing the domain's greatest digital twin maturity. Table 2 provides a comprehensive overview of applications across treatment phases, including the maturity level and evidence quality for each application category. The numerical outcomes reported reflect heterogeneous study conditions, patient populations, and treatment techniques, requiring appropriate contextualization as discussed in subsequent subsections.

4.1. Individualised treatment planning

Digital twin technology transforms radiotherapy treatment planning from a single time-point process to a continuous optimisation system. Traditional planning creates static treatment plans based on initial imaging, assuming anatomical stability throughout treatment courses lasting weeks to months. However, tumours shrink, patients lose weight, and internal anatomy shifts during treatment, potentially compromising dose delivery accuracy.

Patient DTs continuously update anatomical models using daily cone-beam computed tomography imaging acquired for treatment positioning. These updated models enable re-optimisation of treatment plans when anatomical changes exceed predefined thresholds, ensuring continued target coverage and normal tissue sparing. The virtual model simulates different beam arrangements, dose distributions, and fractionation schedules before selecting optimal configurations for individual patients based on tumour characteristics, anatomical constraints, and predicted normal tissue tolerances [34].

Advanced applications incorporate biological modelling predicting how individual tumours respond to radiation based on imaging characteristics, molecular profiles, and treatment histories. These predictions inform decisions about dose escalation for radioresistant tumours or hypofractionation for radiosensitive lesions [13,35]. DTs also facilitate personalised treatment schedules accommodating patient preferences, tolerance of side effects, and logistical constraints while maintaining therapeutic efficacy [36]. These patient-level planning applications represent areas of relatively mature digital twin implementation in radiotherapy, with multiple institutions reporting clinical deployment, though standardization of biological models and validation frameworks remains incomplete [34].

4.2. Real-time adaptive radiotherapy

Adaptive radiotherapy leverages DT to modify treatment delivery based on real-time monitoring during individual treatment fractions [36]. Real-time adaptive radiotherapy updates targeting and/or replans during the treatment session to maintain accurate dose delivery despite day-to-day or intrafraction variation in patient setup, breathing motion, and anatomy [37]. It is particularly valuable for moving targets such as lung and liver tumours, where respiratory motion introduces substantial positional uncertainty and motion-management strategies (tracking, gating, or online adaptation) can reduce that uncertainty [38,39].

This is among the more clinically mature DT-aligned applications because multiple commercial adaptive platforms have regulatory clearances, including Varian Ethos (FDA 510(k)) and MR-guided systems such as Elekta Unity (FDA 510(k), CE mark) and MRIdian [40,41]. However, deployment typically requires substantial technical infrastructure, specialized training, and workflow redesign to deliver online adaptation reliably, which can limit accessibility for smaller centres.

4.3. Treatment response prediction

DTs integrate multimodal data to predict individual patient responses to radiotherapy before treatment initiation [36]. Predictive models incorporate clinical factors including tumour stage, location, and histology; imaging features extracted through radiomics analysis; genomic and molecular biomarkers; and patient characteristics including age, comorbidities, and performance status. Machine learning algorithms trained on large datasets identify patterns correlating with treatment outcomes including tumour control, survival, and toxicity risks [36,42].

In lung cancer, DT-style treatment response prediction is being developed as a multimodal modelling problem, where a patient-specific model is continuously updated using tumour genomics (for example EGFR alterations), imaging-derived features, and knowledge of resistance biology. One important building block is radiogenomics, where quantitative CT image signatures are trained to predict EGFR mutation status non-invasively, enabling more informed targeting and monitoring strategies when tissue sampling is limited [43]. Complementing this, early “response phenotype” work showed that pretreatment radiomic features can help stratify patients into groups more likely to be sensitive vs resistant to EGFR tyrosine kinase inhibitors such as gefitinib, suggesting that imaging can contribute to predicting who will benefit from targeted therapy [44]. More explicitly aligned with the DT concept are

Table 2
Digital Twin-aligned Applications Across the Radiotherapy Treatment Continuum.

Treatment Phase	Digital Twin Functions	Clinical Impact	Technical Components	Maturity Level	Evidence Context
Initial Planning [36]	Anatomical model creation; Dose distribution simulation; Plan optimisation; Normal tissue complication prediction	Improved target coverage; Reduced toxicity risk; Enhanced plan quality; Personalised dose prescriptions	Imaging integration; Dose calculation engine; Optimisation algorithms; Biological models	Early clinical adoption	Multiple single-center validations; standardization needed
Pre-Treatment Verification [94]	Plan delivery simulation; Equipment performance prediction; Error detection; Safety checks	Reduced treatment errors; Enhanced quality assurance; Improved patient safety; Regulatory compliance	Machine performance models; Plan analysis algorithms; Historical error database; Alert generation system	Validated	Regulatory accepted; widely implemented
Daily Treatment Delivery [74]	Real-time anatomy monitoring; Position verification; Adaptive plan modification; Dose accumulation tracking	Accurate dose delivery; Compensation for anatomical changes; Reduced geographic miss; Maintained plan efficacy	Image-guided radiotherapy integration; Fast reoptimisation algorithms; Dose deformation tools; Decision support	Clinical adoption with ongoing refinement	Multiple prospective studies; varies by anatomical site
Response Monitoring [13]	Tumour response assessment; Toxicity prediction; Outcome forecasting; Treatment modification guidance	Early identification of poor responders; Proactive toxicity management; Optimised treatment duration; Individualised follow-up	Serial imaging analysis; Radiomics extraction; Outcome prediction models; Patient-reported outcomes integration	Experimental to pilot	Predictive accuracy varies; limited prospective validation
Post-Treatment Follow-Up [95]	Recurrence risk prediction; Late toxicity surveillance; Second cancer risk estimation; Outcome analysis	Personalised surveillance schedules; Early recurrence detection; Informed survivorship planning; Continuous learning	Long-term data tracking; Risk stratification models; Population outcomes database; Machine learning algorithms	Experimental	Requires longitudinal data; most evidence retrospective

mechanistic or hybrid models that represent a "virtual patient" and simulate disease trajectories under different therapies. For example, a knowledge-based mechanistic model has been presented as a DT capable of predicting disease progression under gefitinib and exploring alternative treatment scenarios in silico [45]. These approaches are often designed to incorporate known acquired resistance mechanisms (such as secondary mutations and bypass pathway activation) so the model can forecast likely treatment failure modes and, in principle, help evaluate therapy sequencing or switching strategies. While promising, these applications require substantial additional validation before routine clinical deployment.

4.4. Quality assurance and safety

Digital twins enhance radiotherapy quality assurance by continuously monitoring treatment delivery accuracy and predicting potential errors before they affect patients. Treatment-focused digital twins' model linear accelerator performance, beam characteristics, and mechanical positioning accuracy [12]. These models compare intended with actual delivery parameters for each treatment fraction, identifying discrepancies indicating equipment malfunctions, setup errors, or plan implementation problems.

Predictive DT-style safety models can be used before plan approval to evaluate radiotherapy treatment plans and identify configurations associated with higher risk, either by detecting likely plan errors or by estimating complication probability from historical outcome data [46]. These systems can flag plans that exceed normal-tissue dose/volume tolerance guidance using established constraint/NTCP evidence bases (for example QUANTEC and later constraint compilations) [47]. They can also highlight highly complex IMRT/VMAT plans that are more susceptible to delivery deviations or quality assurance (QA) failure, using plan-complexity metrics shown to relate to deliverability and dosimetric sensitivity [48]. This automated review complements human expert evaluation, catching potential problems that might otherwise proceed unnoticed until complications occur. QA is one of the most mature DT-aligned applications in radiotherapy because it routinely uses patient-specific "virtual" verification, such as independent secondary dose/monitor unit calculations, which is a long-standing mainstay of radiotherapy QA providing formal guidance for IMRT/VMAT use [49]. Automated plan-checking software has also been reported as contributing to safer and more consistent external-beam plan review in clinical use, although uptake and performance still vary by site and workflow [50].

4.5. Multi-Institutional learning networks

DT frameworks facilitate creation of federated learning networks where institutions collaboratively improve prediction models without sharing raw patient data. Each institution's digital twin system trains local models using institutional data, then shares only model parameters or predictions with the network. Central algorithms aggregate these distributed learnings to create improved models distributed back to participating sites [51].

This approach overcomes data sharing barriers related to patient privacy, institutional policies, and regulatory requirements while enabling learning from much larger patient cohorts than single institutions can accumulate. Multi-institutional networks have developed improved outcome prediction models, identified rare toxicity patterns, and established evidence for optimal treatment strategies across diverse patient populations and treatment approaches [51]. Federated learning networks are an emerging approach with growing uptake in healthcare, but they still face practical barriers including model and system heterogeneity, data harmonisation, and the need for sustainable participation and incentive structures across institutions [51]. However, the European Health Data and Evidence Network (EHDEN) provides a more matured example of a federated health data network. It has demonstrated scalable harmonisation of real-world data by standardising sources to the OMOP Common Data Model, and the EHDEN portal reports 210 harmonised data sources spanning 30 European countries as of 1 September 2024 [52].

5. Technical infrastructure and implementation

5.1. Data architecture

Successful DT implementation requires robust data architecture supporting integration of heterogeneous information sources. The architecture must accommodate structured data from electronic health records, treatment planning systems, and departmental information systems; imaging data in DICOM format from various modalities; unstructured data from clinical notes and pathology reports; real-time streams from monitoring devices and treatment delivery systems; and external data including genomic testing results and patient-reported outcomes [53].

Data lakes provide flexible storage for diverse data types while maintaining accessibility for analytical processing. Standardised data models ensure consistent representation across sources, facilitating integration and analysis. Application programming interfaces enable bidirectional communication between DT platforms and existing clinical systems without disrupting established workflows [54]. Data governance frameworks establish ownership, access controls, quality standards, and lifecycle management policies [51].

5.2. Computational requirements

DT systems demand substantial computational resources for real-time simulations, complex optimisations, and artificial intelligence model training. Dose calculations for radiotherapy planning require solving radiation transport equations through patient anatomies represented by millions of volume elements [36]. Image quality predictions involve simulating photon interactions through tissue-equivalent models. Machine learning algorithms process high-dimensional datasets containing thousands of variables from hundreds or thousands of patients [55].

Cloud computing platforms provide scalable computational resources matching workload demands without excessive on-premise infrastructure investments. Graphics processing units accelerate specific calculations including Monte Carlo dose simulations and deep learning model training. Edge computing enables low-latency processing for real-time applications including adaptive radiotherapy where treatment decisions must occur within minutes [56]. Hybrid architectures combine on-premise and cloud resources, maintaining sensitive data locally while leveraging cloud capacity for computationally intensive tasks [57].

5.3. Interoperability standards

Interoperability remains a critical challenge for DT implementation across diverse healthcare information technology environments. Existing standards including DICOM for imaging, HL7 FHIR for clinical information exchange, and IHE profiles for workflow integration provide foundations for data exchange. However, gaps persist particularly for novel data types including radiomics features, biological model parameters, and artificial intelligence predictions. DICOM adoption is widespread, but real-world implementation can be inconsistent, and dose reporting and monitoring often depend on correctly interpreting RDSR and harmonising protocol naming across systems, which complicates cumulative dose workflows [58]. HL7 FHIR coverage for imaging is also limited in scope, as the core ImagingStudy resource focuses on describing and retrieving imaging studies rather than capturing imaging-specific clinical context such as contrast reactions or detailed preparation history, and contrast reaction documentation is itself often

inconsistent. In addition, AI outputs (including radiomics features and predictions) are not consistently exchanged in a single, universally implemented format, so integrations frequently revert to proprietary data structures, even though standards pathways exist such as DICOM SR templates (for example TID 1500) and related interoperability guidance [58]. Multi-modality DTs also require robust spatial registration because CT, MR, and PET data commonly need transformation into a unified frame, which adds complexity and can be sensitive to scanner and acquisition differences [59]. Finally, radiotherapy DT integration is constrained by vendor-specific treatment planning system interfaces; even where APIs exist (for example within Eclipse), cross-platform integration and multi-vendor workflows remain challenging and are a recognized interoperability gap in IHE-RO discussions.

Emerging standards specifically addressing digital twin applications include ISO 23247, which defines a DT framework for manufacturing and is increasingly treated as a transferable reference architecture, particularly in healthcare-adjacent DT work that explicitly builds architectures "based on ISO 23247" [60]. In parallel, the FAIR principles (Findable, Accessible, Interoperable, Reusable) provide widely adopted guidance for data stewardship and interoperability practices that directly support DT pipelines that depend on reusable, well-described data assets [61]. Finally, open-source platforms and standards-based APIs are commonly positioned as mechanisms to improve integration across proprietary systems and reduce lock-in. For example, the Apperta "open platform" definition explicitly links common APIs and openness with eliminating vendor lock-in, and a Linux Foundation health data interoperability report similarly states that open source mitigates vendor lock-in risk [62].

6. Clinical benefits and outcomes

This section examines documented clinical benefits across both radiology and radiotherapy implementations, emphasizing shared advantages such as improved outcomes and operational efficiency, while also acknowledging domain-specific differences in implementation maturity and evidence quality. Understanding these commonalities and contrasts is essential for strategic planning of digital twin adoption across imaging and radiation oncology departments.

6.1. Patient outcomes

Reported implementations of DT-enabled workflows in radiology and radiotherapy are increasingly linked to measurable improvements in clinically relevant endpoints, but the strength of evidence is uneven and often context-specific. In radiotherapy, benefits are most directly evidenced through adaptive radiotherapy (ART) paradigms that continuously update patient-specific models and plans using new imaging and anatomy/response information [63]. Across head-and-neck reports, DT-aligned ART demonstrated a 2-year loco-regional control in the 88% to 97% range compared with prior non-adaptive benchmarks around 80% (an approximate + 8 to + 17 percentage-point gain) [64]. Though, these comparisons are largely non-randomized and may be tumor-site and institution dependent. Toxicity reductions are supported both by modeled and observed endpoints. For example, MR-guided online adaptation in high-risk prostate cancer reduced modeled acute GI toxicity risk (ΔNTCP 17.4%) and showed smaller but significant modeled reductions for select urinary endpoints, consistent with the premise of personalized dose optimization and margin reduction [63]. In head and neck, weekly replanning reduced estimated xerostomia risk by ~11% on average (up to 30% in a subgroup), illustrating how adaptation can mitigate organ-at-risk overdose when anatomy changes during treatment [65]. Survival gains have also been reported in selected populations. For instance, in a NSCLC cohort comparing pre-ART vs ART eras reported 2-year overall survival increasing from 43% to 56%, but these results remain observational and vulnerable to confounding (e.g., treatment mix changes) [66]. Importantly, the quality of outcome evidence in radiotherapy still ranges from retrospective cohorts and registries to limited prospective studies, with relatively few randomized comparisons; a phase 3 randomized trial in oropharyngeal cancer did not show a xerostomia benefit of systematic weekly ART versus standard IMRT, underscoring that benefits are not universal and may depend on indication and adaptation strategy [67]. Although these studies have not all been tested within a DT-like workflows domain, it holds promise for its adaptation as it allows continuous update with patient-specific data.

In radiology, patient-outcome benefits are maintained via diagnostic assessment alongside meaningful radiation-dose reduction when protocols and reconstruction are tailored. For example, deep-learning CT reconstruction has enabled > 40% dose reduction in coronary CT angiography while preserving diagnostic assessments (e.g., stenosis and plaque evaluation) [68]. Evidence for improved detection within DT-like workflows is emerging mainly through AI integration: real-world implementation studies report substantial reductions in missed incidental findings such as incidental pulmonary embolism (e.g., missed iPE reduced from 50% to 7.1% in one implementation study), although at least one report noted no short-term mortality change, highlighting the gap between improved detection and proven long-term outcome benefit [69]. Dose estimation and organ targeted radiation have proven to improve patient outcomes by ensuring only necessary doses are given to the right organ/region. For example, DT model was used to estimate radiation dose to radiosensitive organs during CT imaging, achieving errors below 10% for most organs. This performance was substantially better than standard approaches, with recorded reduction in dose errors of 20–35% [13].

Across both domains (radiology and radiotherapy), shared benefits include enhanced personalization through patient-specific modeling, improved safety through predictive checks and adaptation to change, and better-informed clinical decisions via integrated data streams; however, both domains still require validated studies with heterogenous population, especially in areas where outcome evidence is still maturing.

6.2. Operational efficiency and resource utilization

Digital twin applications generate substantial operational benefits beyond direct patient outcomes, with similar efficiency improvements documented across both radiology and radiotherapy settings. Radiology departments implementing workflow optimisation improves through automated processes guided by digital twin predictions, reducing patient waiting time by 44.8% and improved scanner utilization by 14.5% [32]. Reduced unplanned equipment downtime through predictive maintenance strategies increases available scanning time and decreases schedule disruptions affecting patients and referring clinicians. In radiotherapy, DT models combine anatomical imaging such as CT and MRI with functional information from PET, alongside tumour contours and organ-at-risk constraints, to support more personalised and optimised treatment planning [36]. This efficiency enables departments to manage increasing patient volumes without necessarily increasing staffing. QA automation reduces physics time requirements while potentially improving error detection compared with manual review processes [50].

DT-driven optimisation improves utilisation of expensive healthcare resources including imaging equipment, linear accelerators, and specialised personnel. Equipment utilisation rates increase through better scheduling, reduced downtime, and elimination of inefficient practices [32]. Simulation-based training using digital twins reduces demands on clinical equipment for education purposes. Predictive models identifying patients suitable for shorter treatment courses has the potential of reducing machine time requirements, enabling treatment of more patients with existing capacity.

Personnel time shifts from routine tasks increasingly automated through DT systems toward higher-value activities requiring human expertise and judgment. Radiologists spend more time on complex cases

and direct patient consultation rather than routine reporting. Radiation oncologists focus on treatment strategy decisions and patient counselling rather than iterative plan optimisation. This reallocation of skilled professional time potentially improves both efficiency and job satisfaction.

The operational benefits demonstrate considerable consistency across radiology and radiotherapy contexts, suggesting that system-level DT applications (workflow optimization, predictive maintenance, automated quality assurance) may represent the most immediately generalizable implementations. However, realization of these benefits requires substantial upfront investment in data infrastructure, process redesign, and change management that may delay return on investment.

6.3. Transformation of quality improvement paradigms

DTs can shift quality improvement in radiology and radiotherapy from largely retrospective review (audits and incident reporting) toward continuous monitoring, prediction, and earlier intervention, because DT frameworks are designed to mirror real-world processes and update as new data arrive. Compared with traditional incident-learning approaches (for example RO-ILS), DT-enabled monitoring aims to detect deviations earlier and support proactive mitigation.

In radiology, DT-aligned approaches can support continuous quality surveillance across operations and imaging outputs. Quantitative image-quality metrics have been shown to be sensitive to reconstruction-performance changes and can be used to monitor image quality over time, enabling earlier detection of degradation than periodic manual review alone [70]. Dose monitoring initiatives also emphasise population-level tracking of radiation safety metrics and automated dose index monitoring as a basis for identifying protocol drift or abnormal outliers that warrant optimization [71]. Operational DTs, often implemented using discrete-event simulation, can test workflow changes virtually and flag emerging bottlenecks; radiology case implementations report measurable improvements in scanner utilisation and waiting times, though evidence is commonly single-site and context-dependent [31].

In radiotherapy, continuous verification is more directly established through patient-specific delivery monitoring, including EPID-based transit/in-vivo dosimetry and real-time error detection approaches that compare expected versus delivered signals during treatment [72]. Predictive modelling is also used to estimate complication risk (for example NTCP and machine-learning toxicity prediction), creating a pathway for earlier identification of higher-risk patients before toxicity becomes clinically evident, although prospective clinical impact varies by endpoint and implementation. Finally, multi-institutional learning and federated approaches are increasingly explored to update models using real-world outcomes without centralising data, but operational and governance barriers remain non-trivial [51].

7. Challenges and barriers

7.1. Technical challenges

Several technical obstacles impede widespread digital twin adoption in radiology and radiotherapy. Data integration remains complex given heterogeneous formats, inconsistent standards, and legacy systems lacking modern interoperability capabilities. Many institutions store imaging and clinical data in siloed systems with limited communication, requiring substantial integration efforts to create unified digital twin platforms [53]. Image registration algorithms necessary for tracking anatomical changes between scans may fail for patients with substantial weight changes, surgical interventions, or complex anatomical variations [73].

Computational demands strain available resources particularly for real-time on online ART where rapid imaging, re-contouring, and fast re-optimisation must be completed within tight on-table time constraints [74]. While cloud computing offers theoretical scalability, latency and large data-transfer requirements can limit practicality for time-critical clinical workflows because transmission delay increases with the volume of data moved to remote servers, motivating edge/low-latency architectures for real-time healthcare tasks [75]. Validation of complex digital twin models also presents major methodological challenges because DTs can be dynamic systems that evolve with new data, and their many parameters, interactions, and decision points require structured verification and validation before clinical deployment.

7.2. Regulatory and legal issues

Regulatory frameworks for DT technology in healthcare remain underdeveloped. Traditional medical device regulations were designed for static software and hardware products rather than continuously learning systems that evolve through real-world use. Questions persist about when DT systems require regulatory approval, what validation evidence suffices, and how post-market surveillance should monitor performance.

Liability concerns arise when DT predictions influence clinical decisions that result in adverse outcomes. Determining responsibility among technology developers, healthcare institutions, and individual clinicians becomes complex when multiple parties contribute to AI-driven recommendations. Intellectual property issues complicate collaborative development when proprietary algorithms, institutional data, and shared learning networks intersect. Data ownership questions arise when patient data generates insights and models with commercial value. The key moral and ethical question is should companies be allowed to profit from patients' health data?

7.3. Clinical adoption barriers

Clinical DT alongside other AI-enabled platforms adoption faces resistance rooted in workflow disruption, training requirements, and scepticism about added value [76]. Busy clinicians prioritise patient care over learning new technologies unless benefits clearly outweigh implementation burdens, particularly when digital tools add time pressure or technostress [77]. Integration of DT systems into existing workflow will require careful interface design, minimal disruption to established practices, and demonstrable efficiency gains.

Generational differences in technology influence adoption rates, with senior clinicians sometimes more resistant than younger colleagues [78]. However, experience and clinical judgment remain crucial for interpreting digital twin outputs, requiring engagement across career stages. Change management strategies addressing organisational culture, stakeholder concerns, and implementation processes may prove as important as technical capabilities for successful deployment.

7.4. Economic considerations

Economic barriers include substantial upfront investment in enabling infrastructure, software, and implementation support, often paired with uncertainty about return on investment and payback timelines [79]. Healthcare organisations also face competing priorities for limited capital and operational budgets, so DT investments typically require a strong business case and resourcing for implementation and change, not just the technology purchase.

Reimbursement mechanisms frequently do not provide clear, dedicated pathways for advanced digital decision-support, creating misalignment between implementation costs and revenue. This barrier is well described in radiology AI adoption, where reimbursement uncertainty is repeatedly cited as a constraint on routine clinical deployment and scalability [80]. Return-on-investment calculations must therefore incorporate both measurable savings (for example throughput and operational efficiencies) and less easily monetised benefits such as improved outcomes, risk reduction, and reputational effects, necessary for a well robust socioeconomic and cost-effectiveness assessment. Long

implementation timelines and learning curves can delay benefit realisation, as health IT transitions commonly require extended workflow optimisation and sustained training beyond go-live. Finally, ongoing maintenance, updates, and support represent recurring costs that persist after initial deployment, a pattern consistently emphasised in digital health costing frameworks and health-system digitisation analyses [81].

7.5. Domain-specific implementation challenges

While radiology and radiotherapy share many common technical and organizational barriers to digital twin adoption, important domain-specific challenges differentiate implementation approaches. In radiology, a key challenge is the heterogeneous mix of scanners and IT systems across vendors, which often requires bespoke integrations and increases operational maintenance burden when DT or AI components are embedded into PACS/RIS workflows [58]. High throughput environments also limit the practical time available for DT-enhanced protocol optimisation during routine operations. In addition, the value proposition for patient-level DT applications can be harder to quantify (beyond intermediate endpoints such as dose or workflow), and governance questions around responsibility and oversight for AI-driven imaging decisions remain an implementation friction point in practice [82].

In radiotherapy, challenges differ in kind and intensity. Treatment courses extend over weeks, creating ongoing computational and workflow demands for repeated DT updates and adaptation decisions, particularly in online ART where multiple professional roles may need to be present at treatment delivery. Safety requirements are stringent, so DT-enabled decision support typically requires extensive verification and validation prior to routine clinical use. Data constraints are also more pronounced: radiotherapy AI/ML development is widely described as being limited by access to sufficiently large, well-curated datasets and the logistics of aggregating data across specialised systems, compared with the larger volumes typical of diagnostic imaging [83]. Interoperability across treatment planning, management, and delivery platforms remains a persistent challenge, with vendor participation and profile adoption highlighted as ongoing limitations in IHE-RO efforts [84].

These differences imply that DT implementation strategies should be tailored to the domain and local workflow: radiology often prioritises system-level DT use cases (operations, maintenance, dose monitoring) that add value with minimal disruption, whereas radiotherapy more often targets patient-level DT applications where the extended treatment timeline can justify the complexity of continuous updating and validation.

8. Future directions

8.1. Emerging technologies

Several emerging technologies are likely to strengthen DT capabilities over the next few years. Quantum computing is widely discussed as a future enabler for complex molecular simulations in medicine, which could eventually support more detailed modelling of radiation-biology interactions, although current systems remain far from routine clinical radiobiology use [85]. Advanced sensors, including wearables and implantables, are also central to the DT roadmap because they can supply high-frequency physiological data streams that continuously update patient-specific models [53]. Photon-counting CT is another relevant technology because it provides intrinsic spectral information and is designed to improve dose efficiency and tissue differentiation compared with conventional CT, supporting richer and potentially lower-dose imaging inputs for patient modelling [86].

Artificial intelligence is evolving rapidly, with transformer architectures and foundation models demonstrating broad multi-modal capability; these approaches can, in principle, reduce dependence on large, labelled datasets for each task by leveraging pretraining and transfer, which is particularly relevant for rare conditions and atypical presentations. Though, real-world health-system validation remains an active concern. Federated learning and related privacy-preserving computation methods are increasingly positioned as practical mechanisms for multi-institutional model development without centralising sensitive patient data, while acknowledging new privacy/security considerations in the federated setting [51]. Finally, blockchain is frequently proposed to provide tamper-evident logging and auditability for healthcare data access and decisions, offering transparent audit trails that may strengthen accountability and trust in DT-supported workflows [87].

8.2. Integration with precision medicine

DTs naturally align with precision medicine initiatives aiming to tailor treatments to individual patient characteristics. Integration of genomic, proteomic, and metabolomic data into digital twin models will enable prediction of treatment responses based on molecular tumour characteristics and patient biology. Pharmacokinetic and pharmacodynamic models incorporated into digital twins can optimise combined modality treatments integrating radiation with systemic therapies.

Circulating biomarkers monitored throughout treatment provide real-time indicators of tumour response, enabling early treatment modifications for patients not responding optimally. Integration of patient-reported outcomes into DT models will ensure treatments align with individual preferences and quality of life priorities. This holistic approach transcends traditional disease-focused care by considering the complete patient experience and individualised definitions of successful outcomes.

8.3. Digital twins in interventional radiology (IR)

Beyond diagnostic imaging and radiotherapy, DT approaches are being developed for interventional radiology, where imaging is tightly coupled to therapy. Pre-procedurally, DTs can support patient-specific planning by simulating access routes, catheter or needle trajectories, and device positioning using individualized anatomy and biophysical assumptions. Examples include DT computational models for image-guided thermal ablation planning and DT frameworks for intra-arterial liver therapies that optimise catheter configuration and injection parameters [88]. These systems have the capabilities as a mechanism to improve procedural preparedness and training, although outcome evidence in IR-specific settings is still developing.

Intra-procedurally, real-time DT concepts emphasize integrating live guidance imaging with pre-procedural models to improve visualization of targets, critical anatomy, and instrument location. Multimodality guidance and fusion approaches commonly used in IR (for example combining pre-procedural 3D datasets with intra-procedural fluoroscopy, cone-beam CT, or ultrasound) illustrate the technical foundation that DT platforms aim to unify into a single, continuously updated representation [89]. DT-enabled monitoring is also proposed as a pathway toward earlier identification of evolving procedural risks; related work shows that AI can detect certain acute adverse events in angiographic sequences (such as perforation detection on DSA), which aligns with DT goals of earlier warning even though such systems are not yet broadly established as DT products in routine IR practice [90].

Post-procedurally, DT frameworks are commonly framed as a way to track response, estimate likelihood of re-intervention, and tailor surveillance schedules by updating patient-specific models with outcomes and follow-up imaging. This fits with wider healthcare DT roadmaps that emphasize longitudinal updating and learning from real-world data, but robust IR-specific clinical validation across sites remains limited. Implementation in IR distinct challenges, including the need for very low-latency computation in time-critical steps, integration across diverse imaging/navigation technologies, and rigorous validation in high-stakes contexts where errors can have immediate consequences.

8.4. A four-stage translational roadmap for clinical implementation

Building on the maturity classification and barrier analysis presented throughout this review, we propose a structured four-stage translational roadmap to guide healthcare institutions in sequencing digital twin investments across radiology and radiotherapy. This roadmap is designed to be domain-sensitive, recognising the different maturity profiles identified in this review.

Stage 1: Infrastructure Readiness (Foundational): Institutions should begin by auditing data integration capabilities, interoperability standards (DICOM, HL7 FHIR), computational infrastructure, and data governance frameworks. Priority actions include establishing dose registries, electronic health record integration, and data lake architectures. This stage applies equally to both domains and is a prerequisite for all subsequent stages.

Stage 2: Pilot Validation (Domain-Prioritised): Institutions should prioritise pilot implementations in the domain with greatest maturity relative to their existing infrastructure. For most institutions, this means beginning with system-level applications: equipment predictive maintenance and workflow optimisation in radiology, and quality assurance automation in radiotherapy. Patient-level applications should be piloted selectively, beginning with adaptive radiotherapy platforms that hold existing regulatory clearances (e.g., MR-linac systems), rather than experimental radiology protocol personalisation.

Stage 3: Regulatory Alignment and Evidence Generation: Institutions implementing novel patient-level digital twin applications should engage proactively with regulatory frameworks, including MHRA guidance in the UK and FDA Software as a Medical Device pathways in the US. Prospective outcome data collection should be embedded into pilot implementations to generate the multi-institutional evidence base currently lacking, particularly for radiology patient-level applications.

Stage 4: Scaled Clinical Deployment and Continuous Learning: Mature implementations should be scaled with formal change management programmes, clinician training, and reimbursement advocacy. Multi-institutional federated learning networks should be established to continuously update predictive models without centralising sensitive patient data. Performance monitoring against pre-defined quality metrics should be ongoing, with formal re-evaluation against the maturity classification at defined intervals.

This roadmap does not prescribe a single universal trajectory; the appropriate entry point and sequencing will depend on institutional readiness, patient population, and available resources. However, the maturity asymmetry identified in this review suggests that radiotherapy departments are generally better positioned to begin at Stage 2 or 3, while most radiology departments should begin at Stage 1 or early Stage 2 for patient-level applications.

8.5. Standardisation and validation

Establishing standards for DT development, validation, and implementation represents a critical need for the field. Standardised architectures, data models, and interfaces will facilitate interoperability and reduce duplicative development efforts across institutions and vendors. Validation frameworks specifying required evidence, testing methods, and performance metrics will support regulatory review and clinical confidence. Reporting standards for digital twin studies will improve transparency and enable comparison across implementations.

Professional societies, standards organisations, and regulatory agencies must collaborate to develop consensus guidelines balancing innovation with patient safety. Open-source reference implementations can establish baselines for functionality and performance while encouraging customisation for local needs. Validation studies should employ rigorous methodologies including prospective trials comparing DT-guided care with standard approaches across diverse patient populations and institutional settings.

9. Limitations of the review

This narrative review has several limitations that warrant acknowledgement. The interpretive nature of narrative reviews introduces potential selection bias as article inclusion depended on authors' judgments about relevance and quality rather than strictly predefined systematic criteria. While efforts were made to comprehensively cover the field, some relevant publications may have been inadvertently excluded particularly from grey literature sources or non-English publications. The rapid evolution of digital twin technology means recent developments may not be fully captured given publication lags between research conduct and article availability.

Heterogeneity in terminology and conceptual frameworks across included studies complicated synthesis and comparison. Some authors described technologies as digital twins that others might classify differently, creating ambiguity about what constitutes true digital twin implementation versus related technologies. Variation in implementation details, clinical contexts, and outcome measures across studies limited ability to draw definitive conclusions about optimal approaches. Many included studies represented early-stage implementations, pilot projects, or proof-of-concept demonstrations rather than mature clinical deployments, potentially overestimating benefits and underestimating challenges of routine implementation.

Publication bias likely affects the literature with successful implementations more likely to be reported than neutral or negative experiences. Limited long-term outcome data restricts understanding of sustained benefits and late complications potentially associated with digital twin-guided care. Economic analyses were sparse and often institution-specific, limiting generalisability about cost-effectiveness. The review could not perform formal quality assessment or *meta*-analysis typical of systematic reviews, reducing capacity to objectively evaluate evidence strength.

Finally, the rapidly changing regulatory landscape and evolving technical capabilities mean findings may become outdated as new guidance emerges and technologies mature. These limitations suggest findings should be interpreted cautiously, recognising gaps in current evidence and the need for ongoing research as the field develops.

10. Conclusion

Digital twin technology represents a transformative innovation with substantial potential for advancing radiology and radiotherapy practices. This review's primary contribution is the introduction of a dual-domain maturity classification framework that stratifies digital twin applications by implementation scale and validation status, applied comparatively across diagnostic radiology and therapeutic radiation oncology for the first time. This framework reveals a clinically important structural asymmetry: radiotherapy has achieved validated patient-level digital twin integration with measurable outcome benefits, while radiology's maturity is concentrated at the system and equipment level, with patient-level applications remaining largely experimental.

Demonstrated benefits include improved patient outcomes, reduced radiation exposure, enhanced treatment precision, and optimised resource utilisation. The technology aligns naturally with precision medicine initiatives while supporting operational efficiency in resource-constrained healthcare environments. The clinical relevance of this analysis is direct: procurement, governance, and patient safety decisions in both domains should be guided by maturity evidence rather than aspirational claims.

However, realising this potential requires addressing significant technical, regulatory, and operational challenges. Data integration complexity, computational demands, lack of standardised validation frameworks, interoperability limitations, and workflow integration difficulties create substantial implementation barriers. Domain-specific barriers differ meaningfully between radiology and radiotherapy contexts, reinforcing the need for domain-tailored implementation

strategies rather than one-size-fits-all approaches.

To bridge the gap between current evidence and clinical reality, this review formalises a four-stage translational roadmap, spanning infrastructure readiness, pilot validation, regulatory alignment, and scaled clinical deployment, providing institutions with an actionable sequence for digital twin investment that is calibrated to the maturity evidence presented throughout the review.

The convergence of digital twin technology with artificial intelligence, advanced imaging, and precision medicine creates unprecedented opportunities for personalised, data-driven cancer care. This review provides the conceptual framework, comparative evidence synthesis, and practical roadmap needed to translate that opportunity into patient benefit, while maintaining the rigour required to distinguish what is ready for clinical use from what remains promising but unproven.

CRediT authorship contribution statement

David B. Olawade: Writing – review & editing, Writing – original draft, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. **Oluwatosin Akinro:** Writing – review & editing, Writing – original draft, Validation, Methodology, Investigation. **Emmanuel O. Oisakede:** Writing – review & editing, Writing – original draft, Methodology, Investigation. **Oluwakemi Jumoke Bello:** Writing – review & editing, Writing – original draft, Methodology, Investigation. **Claret Chinenyenwa Analikwu:** Writing – review & editing, Writing – original draft, Methodology, Investigation. **Eghosasere Egbon:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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