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Systematic Review

Exploring digital twinning in MRI: A systematic review of current applications, barriers, and future opportunities

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ABSTRACT

Introduction: Digital twinning (DT) – the development of dynamic virtual replicas bidirectionally linked to their real-world counterparts – has the potential to enhance diagnostic precision, optimise interventions, and support patient-specific care, yet its impact within the magnetic resonance imaging (MRI) domain remains underexplored. This study systematically reviews how DT is being applied to MRI, maps current applications and outlines priorities to accelerate safe and sustainable implementation.

Methods: Five electronic databases were searched for original articles published between January 2020 and June 2025 that explicitly described a DT implementation within MRI. Screening and data extraction followed Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidance. Two academic MRI radiographers independently screened records and extracted study-level data. A mixed qualitative-quantitative synthesis and thematic content analysis were used to identify principal application domains.

Results: After duplicate removal and full-text assessment, 51 studies met inclusion criteria. Over half of the included articles related to two main DT-MRI categories: (1) cardiac prediction, treatment and imaging; and (2) cancer diagnosis and therapy optimisation. Six themes emerged: (1) diagnosis, treatment planning and monitoring (63%); (2) hardware, protocol and infrastructure (20%); (3) safety and quality assurance (5.5%); (4) operational efficiency and cost (5.5%); (5) training and education (3%); and (6) energy and environmental sustainability (3%).

Conclusions: Digital twinning shows substantial promise for personalised diagnosis, treatment planning and facility-level optimisation in MRI, particularly within cardiology and oncology. Radiography-centred opportunities such as models for improving training, safety and operational applications remain understudied.

Implications for practice: The review identified the need for medical imaging departments to prioritise the development of training simulations, safety-validation pilots and operational integration initiatives, supported by interoperability and governance measures, to expand the scope and effective use of digital twinning within MRI practice.

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Introduction

Magnetic Resonance Imaging (MRI) is a medical imaging modality extensively used in healthcare because of its superior soft tissue contrast and lack of potentially harmful ionising radiation.[1] MRI clinical use has grown significantly worldwide, over the past few decades, in view of its diagnostic accuracy and the increasing complexity of clinical care.[2] For example, in the United Kingdom (UK), the National Health Service (NHS) performed over 2.5 million MRI scans in 2024, marking a 10.3% increase from the previous year.[3] This trend extends to other countries, such as the United States, where it has been estimated that the number of MRI examinations performed each year has reached a peak of around 40 million.[4] A similar increase has been noted in MRI referrals in recent years. Nonetheless, this upward trend in MRI demand, combined with the current workforce shortages affecting the radiology sector, has contributed to long waiting lists, as well as delays in imaging, diagnostic results and potential treatments across many countries. For instance, in the UK, 16.3% of patients recently waited more than six weeks for an MRI, well above the NHS target of just 1%.[5]

Some established technologies have demonstrated promising results to tackle this growing healthcare complexity. Among these, Digital Twinning (DT) has emerged as a particularly valuable addition to healthcare ecosystems.[6–9] A digital twin consists of a dynamic virtual replica of a physical object that evolves via real-time data integration and advanced analytics. Unlike static computer models, digital twins can be considered bidirectionally linked to their real-world counterparts through continuous data streams and simulation capabilities. Current examples include "anatomical twins" used for pre-surgical planning and "operational twins" utilised to predict equipment component failure before it occurs.[10] By consolidating patient data from electronic health records, wearables, and medical devices such as MRI scanners, DT offers a comprehensive, multimodal perspective of individual health. Beyond diagnosis and treatment, DT facilitates predictive healthcare, offering a quantitative understanding of any potential "patient trajectories". This makes DT an important enabler of future precision medicine, with the potential to make personalised care a standard practice.[11]

The integration of DT with advanced imaging modalities, including MRI, has already shown significant potential to enhance diagnostic precision, optimise interventions, and support patient-specific care.[12] However, it remains unclear whether DT can also improve areas that are more closely tied to MRI clinical operations such as training radiographers to effectively operate scanners, enabling MRI safety decisions and practices, boosting operational efficiency, supporting patient-centred care driven adaptations or reducing equipment's environmental impact. These aspects are increasingly critical considering the fast growth in MRI utilisation.

A systematic review of published studies on DT applications in MRI was, thus, conducted exploring their use across the field, highlighting methodological limitations and gaps, and proposing future directions to guide clinical adoption and technological advancement. The research question was formulated in line with the PIO framework, a common adaptation of PICO for evidence synthesis.[13] From a PIO perspective, patients undergoing MRI examinations and practitioners utilising MRI equipment represent the "(P)articipants" of our research question; the "(I)ntervention" consists of DT technology; while the "(O)utcome" is shedding light on current applications, barriers, and future opportunities of DT usage within the MRI field.

Materials and methods

Design

Reporting of this systematic review's findings aligns with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) Statement. A review protocol was registered with PROSPERO (registration number: CRD420251207768).[14]

Search strategy

An extensive literature search was performed across five different electronic databases, including PubMed, Google Scholar, arXiv, Scopus and Web of Science, using multiple combinations of Medical Subject Heading (MeSH) terms, keywords, and free text strings. Search terms encompassed "digital twinning", "digital twin", "virtual twin", "magnetic resonance imaging", "MRI", and "MR imaging", which were logically combined with the Boolean operators "AND" and "OR" to ensure retrieving the most pertinent articles. The full search strategy, along with the PRISMA checklist, is provided in the Supplementary Material.

Criteria for study selection

Inclusion and exclusion criteria were defined based on the objectives outlined in the introduction section. The inclusion process was implemented with some restrictions, to include only articles published in English. Google Scholar search was limited to the first 100 entries to avoid any possible quality bias related to later entries. Although the review prioritised peer-reviewed literature, arXiv was searched to capture emerging DT-MRI applications. Because of the rapid progress of studies in this field and the contemporary relevance of the topic, all the searches were limited within a narrow period of five years, from January 2020 to June 2025. Source of evidence in the form of reviews, editorials, theses, conference abstracts (unless a full peer-reviewed version was available), and any work not explicitly defining the DT-MRI relationship or focusing solely on one of these two technologies were excluded from this investigation. A DT was additionally required to exhibit explicit linkage to a physical patient, device, environment or system; dynamic updating or calibration using real-world data; and the capacity to support simulation, prediction, or optimisation beyond static modelling. Studies limited to static anatomical reconstructions, single-pass simulations, or non-updating computational models were excluded unless they explicitly fulfilled the DT criteria outlined above.

Data extraction and analysis

All the identified records were imported into RefWorks for further review and analysis. No machine-assisted screening tools were used; only RefWorks deduplication was applied. Two independent reviewers – both academic MRI radiographers with over ten years of experience in the MRI field – initially screened titles, abstracts and then full text in order to assess articles' eligibility against the agreed inclusion and exclusion criteria. Any disagreements, if present, were then resolved by a third researcher, an academic MRI radiographer with over twenty years of experience in MRI research. Full-text review enabled key data to be extracted from each study, including authors, country, year of publication, specific focus (e.g., DT for cardiac disease prediction and treatment

optimisation), nature of the DT-MRI relationship (e.g., MRI is the primary data source used to construct the DT) and study outcomes (e.g. personalised atrial DTs, built from late gadolinium enhancement (LGE) MRI data, can better predict the occurrence of iatrogenic atrial tachycardia after ablation for persistent atrial fibrillation). The extracted data were ultimately stored into an extraction matrix (Supplementary File 2). A content analysis was performed on NVIVO, relying on a hybrid inductive-deductive coding approach.[15] The coding process was undertaken independently by two reviewers with domain expertise in MRI, followed by iterative consensus discussions to resolve discrepancies. An initial codebook was developed deductively from the review objectives, and relevant prior literature, and inductively refined through open coding of an initial subset of 20% of included studies. The final codebook was subsequently applied, independently, to the full set of included articles. Where appropriate, codes were grouped into categories and then aggregated into themes through iterative team discussions. Qualitative synthesis was used to interpret recurring concepts and to construct thematic narratives. Reflexivity was actively considered throughout the analytic process, with regular team discussions used to challenge assumptions and mitigate the influence of professional preconceptions on interpretation. A word cloud was generated, with textual data undergoing standard preprocessing on NVivo.[16] Near-synonyms and morphological variants were consolidated to avoid artificial fragmentation of terms (e.g., "tumour/tumor" or "modelling/modeling"). Quantitative summaries (e.g., counts and percentages of studies within categories, themes, country distributions and study designs) were used to characterise the evidence base.[15]

Risk of bias assessment

Risk of bias was assessed using the Critical Appraisal Skills Programme (CASP) tool, with checklist types specifically chosen to match the design of each study.[17] The CASP checklists utilised included those for diagnostic, clinical prediction, and cohort studies, as well as randomised controlled trials. Design-specific checklists target the key bias domains for each methodology, including selection bias, confounding, blinding, and spectrum bias. This approach was adopted to obtain more valid domain judgements and to improve transparency during results reporting. Each study was independently reviewed and ultimately classified as having a low, moderate or high risk of bias.

Results

Study selection

A total of 284 records were identified through electronic database searches, with 126 studies promptly removed as duplicates. Upon screening of titles, abstracts, and full texts, 107 additional records were excluded: 34 were identified as reviews; 14 were articles not published in peer-reviewed sources; 10 were conference papers; 8 failed to clearly state the nature of the DT-MRI relationship and 41 focused on a single technology only (either DT or MRI only). This resulted in a total of 51 suitable articles to be included in the review (Fig. 1).[18–68]

Characteristics of selected studies

Of the 51 studies included, a significant majority were quantitative observational studies (n = 41). Of these, 5 were cohort studies. Experimental studies comprised 9 articles (including one randomised controlled trial). One study was a clinical pharmacokinetic investigation. A notable number of studies employed computational modelling as a secondary method (n = 8). The publication years range from 2020 to 2025. More than half of the included studies were found to be linked to two specific countries: the United States (n = 15) and the United Kingdom (n = 12). Other studies were conducted in countries within the European Economic Area (EEA) (n = 15), including Germany, France, Italy, Spain, the Netherlands, Norway, Sweden, Denmark, Austria, and Greece. The remaining studies were linked to countries like China (n = 7), India (n = 2), and Iran (n = 1). Some studies were associated with one or more countries as determined from the main author's institutional affiliations (Supplementary File 2).

Quality assessment

Approximately 47% of the studies included in this review were assessed as having a low risk of bias (Supplementary File 2). These studies were found to have an overall high level of methodological quality and, for some of these, an elevated potential for result generalisability. 20% of the studies were characterised by a moderate risk of bias. This was linked to some potential limitations in study design, reporting, or conduct which could ultimately alter the applicability of the findings, despite clearly defined aims and objectives. The remaining 33% were classified as having a high risk of bias, as a result of some tangible limitations on study characteristics (e.g., small sample size), methodological concerns (e.g. lack of blinding, limited reporting of sensitivity and specificity and/or likelihood ratios) and limited external validation, particularly for computational models.

Content analysis

A total of 106 distinct codes were extracted in NVivo by analysing the most frequently occurring terms across the full text of the 51 included articles. These codes were visualised in a word cloud graph to display the predominant concepts and terminology within the DT-MRI available literature (Fig. 2).

Overall, 17 categories were identified from close coding of individual papers, reflecting the specific clinical topics and applications reported in each study. A significant majority of articles (36%) fell under DT-MRI in "cardiac prediction, treatment, and imaging",[19,20,26,28,29,32–34,36,38–40,42,44,48,54,56,61] while 16% addressed DT–MRI in "cancer diagnosis and treatment optimisation" encompassing applications in brain, head and neck, breast, hepatic, and prostate tumour.[21,22,45,47,51,55,59,64] In this context, studies frequently focused on the use of patient-specific cardiac DT models obtained from late gadolinium enhancement and/or cine imaging to either predicting, diagnosing or treating cardiac conditions such as ventricular/atrial tachycardia, ventricular/atrial fibrillation, and arrhythmia,[19,26,28,29,38,44,56] whereas others recurrently explored the adoption of biophysical tumour DT models, built from MR imaging data, aimed at predicting response to neoadjuvant therapy.[22,45,47,51,59]

Further categories comprised DT-MRI in "anatomical modelling" (8%),[23,24,27,57] DT-MRI in "neurological diagnosis and treatment optimisation" (6%),[41,52,66] DT in "MRI scanner management and performance" (6%),[51,65,67] DT-MRI in "haemodynamic analysis" (4%),[31,46] and DT in "MRI image enhancement and processing" (4%).[62,63] Particularly, few engineering and physics studies extended the scope of DT in MRI by investing its use in scanner and sequence design, radiofrequency coil modelling and implant-heating assessments.[37,60,67]

Categories that were more rarely identified and collectively labelled as "Others" accounting for around 20% of the total, included DT-MRI in "neurological functional understanding"[49]; DT-MRI in "temporomandibular disorder treatment

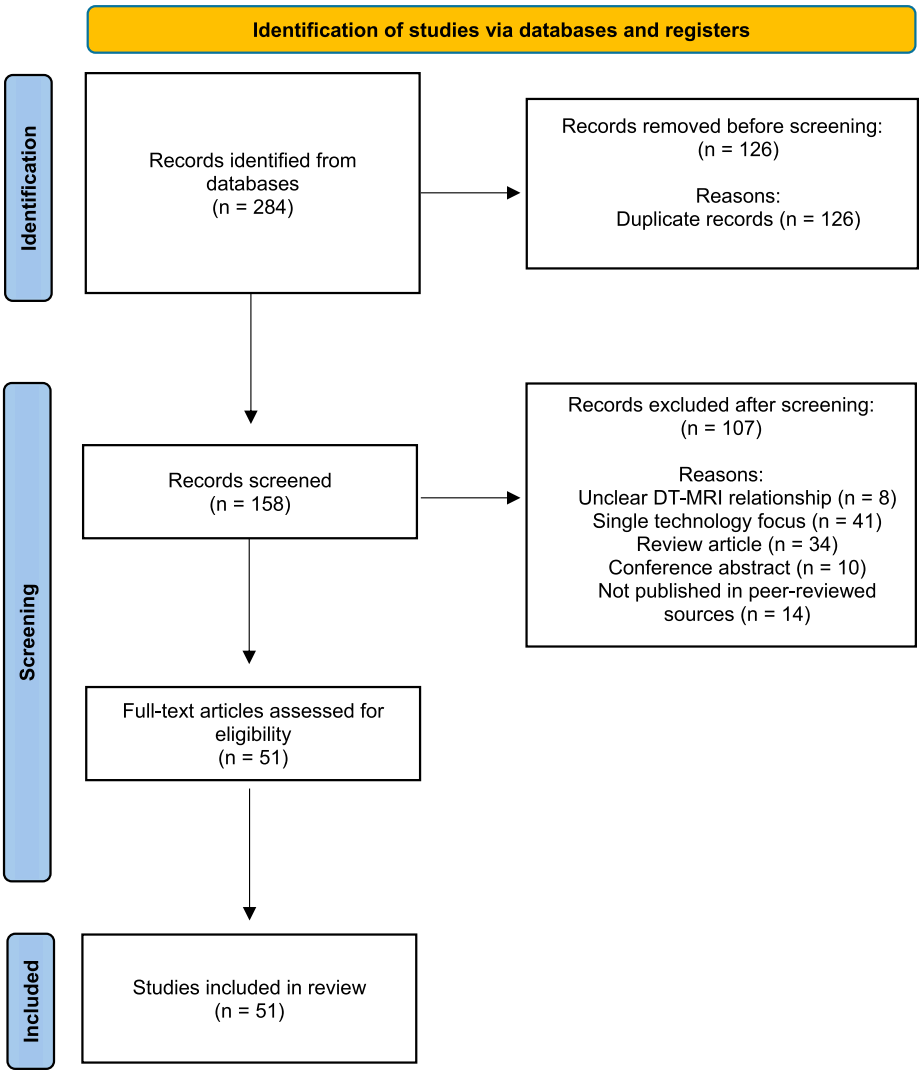

Figure 1. PRISMA flow chart for study selection.

optimisation"[50]; "DT-MRI in "musculoskeletal disease prediction and biomarker identification"[58]; DT-MRI in "hepatic treatment outcome prediction and optimisation"[43]; DT–MRI in "pharmacokinetic prediction"[35]; DT-MRI in "metabolic disease treatment optimisation"[17]; DT in "MRI integration and operation"[25]; "DT in MRI validation"[37]; DT in "MRI in medical education"[68]; and DT in "MRI in equipment training"[53] (Fig. 3).

The identified categories were iteratively grouped into broader clusters based on shared purpose and outcomes, guided by NVivo co-occurrence queries and team consensus, and synthesised into operationally framed themes reflecting cross-cutting functions and translational implications for MRI practice.

Six themes emerged within the DT-MRI nexus investigated in the current literature: 1) Diagnosis, treatment planning and monitoring; 2) Training and education; 3) Safety and quality-assurance; 4) Hardware, protocol and infrastructure; 5) Cost and operational efficiency; 6) Energy and environmental sustainability (Fig. 4).

Of the total studies included in the review, 63% explored the synergy of DTs and MRI for diagnosis, treatment planning and patient monitoring; 20% investigated hardware, protocol or infrastructure innovations enabled by DT-MRI integration; 5.5% examined safety and quality-assurance applications; another 5.5% evaluated cost reduction and operational efficiency; and 3% each addressed training and education or energy and environmental sustainability (Fig. 5). Some articles (n = 12) spanned multiple themes due to their inherently hybrid DT-MRI focus.

DT-MRI relationship

The relationship between DT and MRI has been additionally reported for each paper. A large proportion of the articles screened involved the usage of MRI as the primary data source to build DT models and frameworks (n = 33). Even in far smaller numbers, MRI has also been reported to be the key tool for calibrating, validating and demonstrating the accuracy of DT (n = 7). Other key areas related to the DT-MRI relationship encompassed in this review included: DT to simulate the challenges related to the integration and operation of MRI (n = 3); MRI for measuring and assessing the efficacy of the DT-enabled personalised intervention (n = 2); MRI to provide patient-specific haemodynamic and physiological data that can be incorporated into a personalised DT model (n = 2); DT for validating and demonstrating the accuracy of an MRI sequence (n = 1); DT utilised for MRI image enhancement (n = 1); DT to simulate the functionality of an RF coil (n = 1); DT used to train staff members to operate the MRI scanner (n = 1).

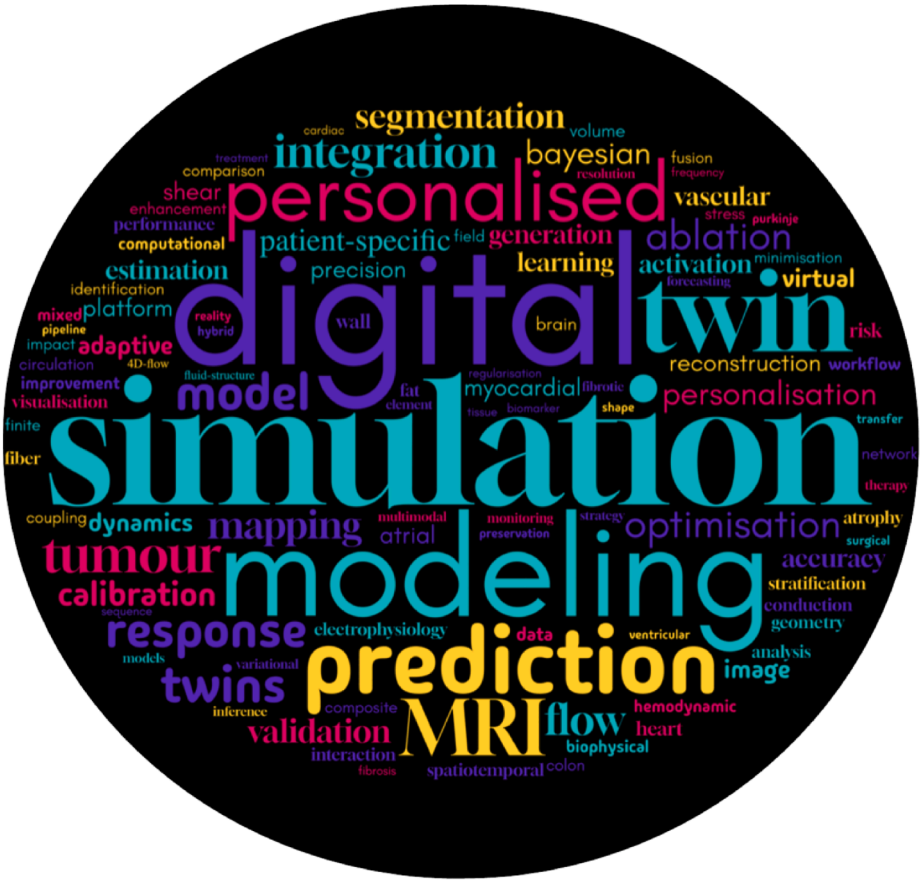

Figure 2. Word size reflects the frequency of use of different terms within the coded dataset across the included studies.

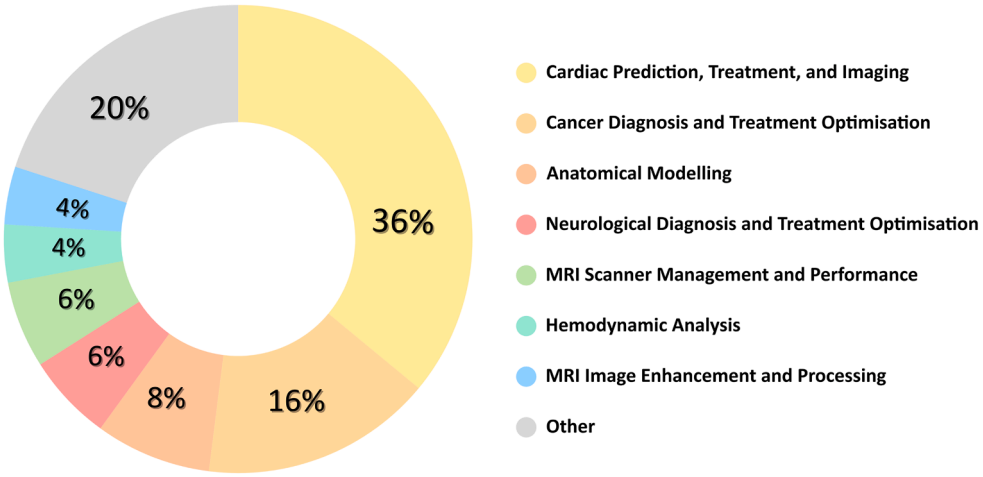

Figure 3. Category breakdown (%) of included articles relating to DT-MRI.

Full results, including author, country, year, study aim, study design, sample size and characteristics, study outcome, DT-MRI relationship, codes, category, theme(s), and risk of bias are summarised in the Supplementary Material (Supplementary File 2).

Discussion

The conducted systematic review combined a comprehensive search and content analysis with a full extraction of study-level data to appraise how DT is being utilised in the MRI field, what barriers are impacting translation, and what opportunities remain underexplored. Fifty-one studies were analysed, and six main themes emerged: diagnosis, treatment planning and monitoring; training and education; safety and quality assurance; hardware, protocol and infrastructure; cost and operational efficiency; and energy and environmental sustainability. Within these themes, three consistent observations stand out; together, these could characterise the field's current state of maturity and direction taken.

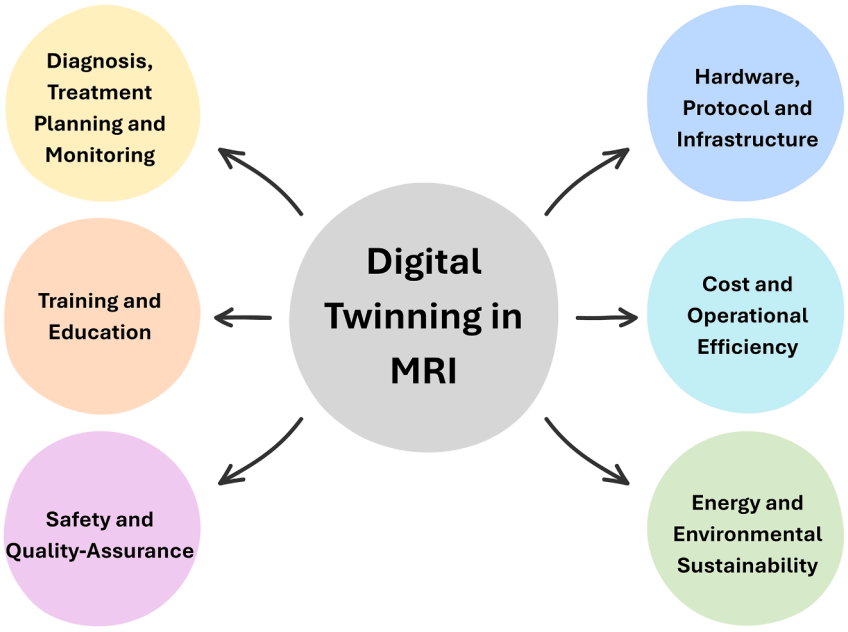

Figure 4. The six identified themes.

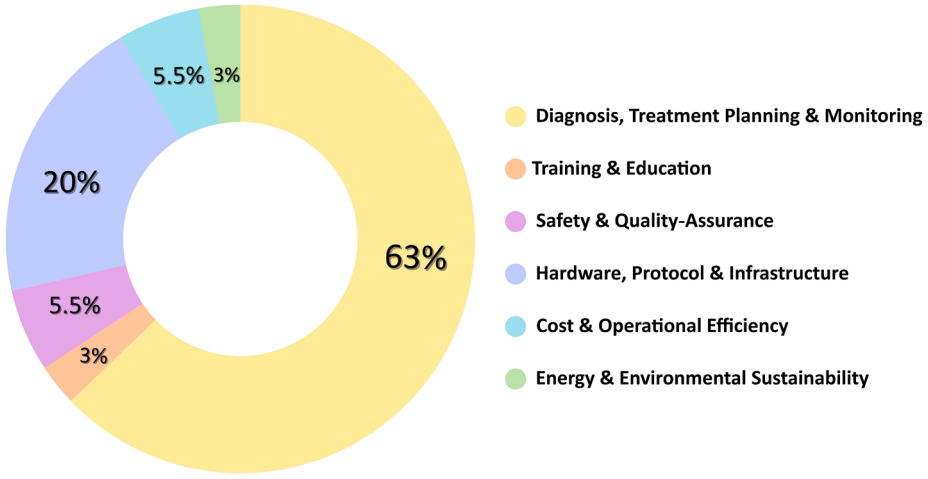

Figure 5. Thematic breakdown (%) of included articles relating to DT-MRI.

First and foremost, the majority of the included studies relied on MRI imaging data as primary source to build patient or device DTs. MRI provides anatomy, physiology or flow information that can be subsequentially utilised to construct, calibrate or validate the DT models. This pattern reflects the value of the unique soft-tissue contrast and multi-parametric capabilities that characterised such an imaging modality, but, simultaneously, it links DT development to the heterogeneous and technical variability in MRI data.

Second, the review reveals that the literature is predominantly composed of quantitative proof-of-concept studies, in silico experiments, and task-based demonstrations that focus on establishing technical feasibility. A significant number of high-quality examples is particularly common in the field of cardiology and oncology. Other studies recurrently investigated the role of DT in relation to the MR scanner features (e.g. protocols and infrastructures) and its main components. These latter investigations illustrate important capabilities and translational potential, but with the caveat of being frequently validated using constrained experimental conditions.

Third, it can be argued that the field is experiencing some significant signs of "expansion" since a growing number of recent larger-cohort, population-scale efforts and prospectively designed validations has been observed in the DT-MRI literature explored. Relevant examples, supporting this trend, include population-level cardiac DT pipelines built on UK Biobank imaging,[34] cohort studies for arrhythmic risk relying on hundreds of participants,[56] and large imaging cohort analyses for osteoarthritis prediction.[58] These efforts admittedly expand the evidence base and cautiously shed light on a potential translation from small, single-centre DT explorations towards more generalisable DT pipelines. Nevertheless, prospective multisite clinical effectiveness trials and comprehensive implementation studies remain, at present, relatively rare within the DT-MRI domain.

Overall, these findings have valuable implications for both practice and education. DTs already have plausible near-term

applications for clinical decision support, education and operations. Cardiac and oncological DTs, based on MRI data, are the most likely to have immediate and clear clinical utility for personalised therapy planning and risk stratification.[69] Such a clinical potential is further expanded by data processing and AI related innovations.[70] In the context of staff training instead, equipment and patient-specific anatomical twins offer high-fidelity simulation which have the potential for improving the skills of key MRI professionals such as radiographers, radiologists and healthcare assistants, thus, supporting key areas like competency assessment, preparedness for adverse events and standardised learning when switched into the adoption of new protocols or devices[53]; yet, comparative studies aimed at evaluating DT-based training against conventional educational approaches are needed to further confirm the value of such applications. From an operational perspective, DTs replicating entire scanners and facilities emerge as key tools for aiding predictive maintenance, improving MRI safety procedures and supporting energy optimisation.[67] However, these applications are strictly bounded on integration with manufacturer data and hospital information systems, which made them, at present, significantly under studied. Finally, scalable DT pipelines created from population imaging cohorts may also have the benefit to long-term facilitate in silico trials and subgroup hypothesis testing that would otherwise be expensive or not feasible.[69]

Barriers to adoption

A number of barriers to adoption exist within the DT-MRI nexus, mainly arising from technical and systemic complexities. Some of the main technical issues encompass the considerable heterogeneity in MRI data (multiple vendors, broad spectrum of pulse sequences, and different magnetic field strengths), the high computational demands for complex simulations, and the need for large, labelled datasets for supervised learning.[9] Further complexity is added by the variability in hardware infrastructure, in particular the adoption of highly efficient GPU clusters compared to consumer-grade systems, which can increase the degree of inconsistency in performance metrics across different studies. Any comparison of reported sensitivity, specificity and accuracy across DT implementations should account for all these discrepancies.[13] Another considerable obstacle is represented by the lack of regulatory and ethical recommendations surrounding the DT-MRI domain. For example, a small number of studies have begun to address operational and equipment challenges, illustrated by DT prototypes for facilities management and predictive maintenance[65] and by DT models enabling teaching platforms for MRI operation[53]; however, because of broader governance, workforce and regulatory issues remaining inadequately examined, the generalisability of these investigations is still significantly limited. Additionally, a clear dependency exists at present on sensitive patient data, which requires clearer governance concerning data privacy and security.[12]

Recommendations

The lack of strong governance emerges to be one of the top priorities to focus on. Although many countries already employ robust ethical review boards and utilise data governance frameworks (e.g., GDPR in Europe, HIPAA in the US) to protect patient data, the dynamic and persistent nature of DT presents unique challenges, particularly in relation to longitudinal data integration, interoperability across platforms, data privacy and cross-institutional data flows.[12,13] Protection for people who have DTs created based on their personal MRI data is paramount. This can be achieved by making sure data is safely stored, and privacy is preserved, while also ensuring that the usage is ethical and transparent at every level.

It must be acknowledged that healthcare data comes from many sources and in many formats, and it can be difficult combining and aligning information into a single DT. Additionally, the lack of homogeneity in clinical environment design and scanner interfaces limits the generalisability and impact of DT to only specific contexts.[14] However, within specific patients or environments the benefits for disease monitoring, treatment optimisation, and professional training can be tremendous. Agreeing on interoperability standards and technical protocols will be essential so different systems, devices, and platforms can share and merge data smoothly.[9] This will also help ensure that DT models and their feasibility are developed free from bias.

There are operator- and patient-specific areas within the DT-MRI domain that may be worth exploring for future work. For example, while DT involves the digital representation of physical objects, they could also replicate human entities in the form of avatars. The use of avatars and interactive virtual patients represents a pragmatic, scalable approach to train large numbers of radiographers in a safe environment, at low cost, while preserving high repeatability and authenticity of interaction.[71,72] Simulations based on these tools offer standardised, reproducible scenarios that enable healthcare professionals to learn in a safe environment and make mistakes without any risk to real patients.[71,73] When combined with patient-specific DT models, avatars could be used to recreate authentic MRI environments and enable rehearsal of device operation, protocol selection and management of patient distress, thereby increasing transferability to clinical practice.[74] In this context, DT has already demonstrated the potential to identify and elaborate different individual's emotions,[75] yet this feature has not yet been exploited from a patient comfort standpoint in MRI. Healthcare settings could rely on DT to build smart diagnostic tools, featuring sensors that track patient's physiology and anticipate any reactions (e.g., claustrophobic panic attack), thus, promoting good quality communication from the radiographer and minimise scan interruptions or repeat rates.

As a final recommendation, with the ever-increasing trend in DT research in healthcare, workforce and pedagogic research should consider defining competencies and curricula for DT literacy, while economic and lifecycle environmental assessments should be routinely incorporated in any validation study.

Limitations

This review has its own methodological limitations. Restricting Google Scholar to the first 100 items may have excluded some grey literature which could have, instead, reinforced the value of the overall work. However, a targeted check beyond the first 100 results did not identify additional eligible studies. Moreover, the author(s) observed the relevance of findings on Google Scholar quickly declined after the first 50 articles, thus supporting confidence in the methodology adopted. A certain extent of heterogeneity also exists across the included study designs, which limited qualitative pooling, and, therefore, some thematic distinctions required interpretative analysis. The qualitative approach adopted was able to recognise these inhomogeneities. Finally, the risk of bias assessment, which included design-specific checklists for each study, revealed that one-third of the studies were characterised by a high risk of bias, particularly because of methodological concerns that may limit our findings' generalisability. This reflects the emerging nature of the field and the varying maturity of the technology and its implementation across different studies and clinical contexts. These factors should be taken into account

when interpreting the strength of cross-theme conclusions and the overall evidence base of this systematic review.

Conclusion

The use of digital twinning in magnetic resonance imaging is a rapidly evolving tool, with growing clinical interest. From this review, it emerges that the strongest, and possibly most extensive evidence to date supports diagnostic and treatment planning applications, with a particular emphasis on cardiology and oncology, where MRI derived digital twins have shown promising results for personalised risk stratification, as well as for diagnosis and therapy optimisation. At the same time, training, safety and operational applications (equipment simulation, implant-safety testing, predictive maintenance and protocol optimisation) represent practical, radiography-centred opportunities that currently remain understudied, yet directly relevant to radiographers, radiologists and healthcare administrators. In order to transition from proof of concept to routine practice, the community must prioritise interoperability standards, prospective multisite validation with clinically meaningful endpoints, frameworks for data privacy, and workforce readiness including defined competencies and digital twinning/simulation focused curricula. Active interactions with key stakeholders such as regulators, manufacturers and patients will be critical to tackle recurrent barriers like governance, ethical and complex economic questions. If these priorities are addressed through coordinated research, open science and co-designed pilot implementations, digital twins have the potential to make MRI services safer, more personalised and more sustainable, and to deliver significant benefits for radiography practice and patient care.

Ethics approval and consent to participate

This review was based on a secondary analysis of existing literature and does not contain any data gathered from human participants or animals. The PRISMA statement for reporting systematic and meta-analysis was followed.

Availability of data

All data generated or analysed during this study are attached to this published article.

Consent for publication

Not applicable.

Author contributions

Conceptualization: J.G., C.M. Data curation: J.G., N.S. Formal analysis: J.G., N.S. Funding acquisition: J.G., C.M. Investigation: J.G., C.M., N.S., K.L.S. Methodology: J.G., C.M., N.S., K.L.S. Project administration: J.G., C.M. Resources: J.G., C.M., N.S., K.L.S., D.S., S.P.S., S.H., S.M.W. Software: J.G., N.S. Supervision: C.M., D.S. Validation: J.G., C.M., N.S., K.L.S., D.S., S.P.S., S.H., S.M.W. Visualization: J.G., C.M., N.S., K.L.S., D.S., S.P.S., S.H., S.M.W. Writing – original draft: J.G. Writing – review and editing: J.G., C.M., N.S., K.L.S., D.S., S.P.S., S.H., S.M.W. All authors read and approved the final manuscript.

Generative AI use

The authors declare that no generative artificial intelligence tools were used in the preparation of this manuscript, including during the writing, analysis, data interpretation, or production of figures or tables.

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Conflicts of interest

The authors declare no conflicts of interest.

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Appendix A. Supplementary data

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