



Review

Is the Healthcare Industry Ready for Digital Twins? Examining the Opportunities and Challenges

Srinivasini Sasitharasarma ¹, Noor H. S. Alani ^{1,*} and Zazli Lily Wisker ²¹ School of Computing, Eastern Institute of Technology, Napier 4142, New Zealand² School of Business, Eastern Institute of Technology, Napier 4142, New Zealand

* Correspondence: nalani@eit.ac.nz

Abstract

Recent advancements in the healthcare sector have reached a pivotal juncture, catalysed by the emergence of Digital Twin (DT) technologies. These innovations facilitate the development of virtual replicas that accurately simulate real-world conditions, thereby transforming traditional approaches to medical analysis, diagnostics, and treatment planning. Although widely successful in manufacturing, the adoption of Digital Twins in healthcare is relatively limited, particularly regarding their impact on clinical efficiency and patient outcomes. This study addresses three primary research questions: (1) How does Digital Twin technology improve individualised patient treatments and care quality? (2) What is the role of Digital Twin technology in accurately predicting patient responses to medical interventions? (3) What are the significant challenges of integrating Digital Twin technology into healthcare? Synthesising findings from 70 peer-reviewed articles, this review identifies critical knowledge gaps and provides practical recommendations for healthcare stakeholders to effectively navigate these challenges. This research proposes a conceptual framework illustrating the lifecycle of Digital Twin implementation in healthcare and outlines essential strategies for successful adoption. It emphasises the importance of robust infrastructure, clear regulatory guidance, and ethical practices to fully leverage the advantages of DT technologies. Nevertheless, this review acknowledges its limitations, including reliance on secondary data and the absence of empirical validation. Future research should focus on practical applications, diverse healthcare contexts, and broader stakeholder perspectives to comprehensively assess real-world impacts.

Keywords: Digital Twin; healthcare; personalised treatment; virtual models; technology advancements; generative AI; digital impacts; patient treatment outcomes and applications; IoT in healthcare



Academic Editor: Jose I. Moreno Novella

Received: 29 June 2025

Revised: 25 July 2025

Accepted: 19 August 2025

Published: 27 August 2025

Citation: Sasitharasarma, S.; Alani, N.H.S.; Wisker, Z.L. Is the Healthcare Industry Ready for Digital Twins? Examining the Opportunities and Challenges. *Future Internet* **2025**, *17*, 386. <https://doi.org/10.3390/fi17090386>

Copyright: © 2025 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

1.1. Background

The healthcare sector, a vital component of the global economy, is rapidly evolving, yet it continues to face significant challenges, including capacity limitations, rising demand, constrained resources, and the pressing need for more advanced healthcare systems [1]. The present analysis of existing sources would optimise demand variations, assisting with patient movement, bed and room deployments, and staff management [1]. The global rise in the ageing population has also increased the occurrence of chronic illnesses, highlighting the necessity for advanced continuing treatment solutions [2]. Thus, the implementation of promising innovative technologies in healthcare frameworks could

enable more effective healthcare communication and integration. Digital Twin technologies are computer-generated virtual models of physical systems that offer synchronised and simulated monitoring and replica functions for practical counterparts in digital contexts [3]. These comprise four core sections, namely, the physical system, stimulated demonstration, a data transformation to DTs from physical objects, and vice versa [4]. The latest sensor and computational innovations have enabled the real-time collection of data and investigation, thereby increasing DTs' empirical applications [5]. By combining digital technologies and physical objects, DT technologies can replicate complicated empirical situations and deliver significant details regarding system efficacy and upcoming circumstances.

The advanced technologies improve disease diagnostics, estimations, and management across diverse areas, including the medical industry, where they support tailored healthcare therapies. According to [6], the Digital Twin concept was derived from aerospace and manufacturing areas, but has newly extended into medical care, presenting advanced opportunities to optimise patient treatments and care. By integrating machine learning (ML), sensors, artificial intelligence (AI), data analytics, and Internet of Things (IoT), these Digital Twins have the capability to transform healthcare settings through complete virtual models, predictive simulations, and optimised illness detection and control management [4]. Digital twin technologies are used in numerous clinical areas, including cardiology, in which they replicate organ operations to enhance medical trials, drug supplies, and targeted treatments [7]. This technology also performs a key role in the critical care area, permitting medical providers to combine massive multidimensional data for optimised personalised care and decision-making [8]. Additionally, the application of DTs for chronic illness management, such as diabetes, is gaining more dominance, though its integration in the health sector remains limited compared to other areas [9].

The DT technology adoption in healthcare highlights a revolutionary shift in patient treatment and healthcare management systems. It gives considerable benefits for functional competence in healthcare structures through facilitating simultaneous views and adaptive controls, like patient movements and staffing [1]. The potential advantage of DTs extends beyond enhancing functional effectiveness to transform tailored medicines, as indicated by their implementation in different clinical areas, as demonstrated by [1]. However, several challenges continue to persist. Combining DT technology with existing medical systems poses significant concerns and challenges, including ethical concerns regarding data confidentiality and confirming that these innovative technologies offer substantial benefits for healthcare structures and patients [6]. As technology progresses rapidly, it is important to perform further studies to completely understand the possible and practical functions of DTs in the healthcare sector. Figure 1 presents a literature-derived visualisation of the Digital Twin healthcare workflow, as investigated across recent studies. It outlines stages from data acquisition and smart monitoring to AI-powered analytics and surgical intervention, illustrating how DTs personalise treatment, enhance diagnostics, and support informed decision-making through real-time virtual representations.

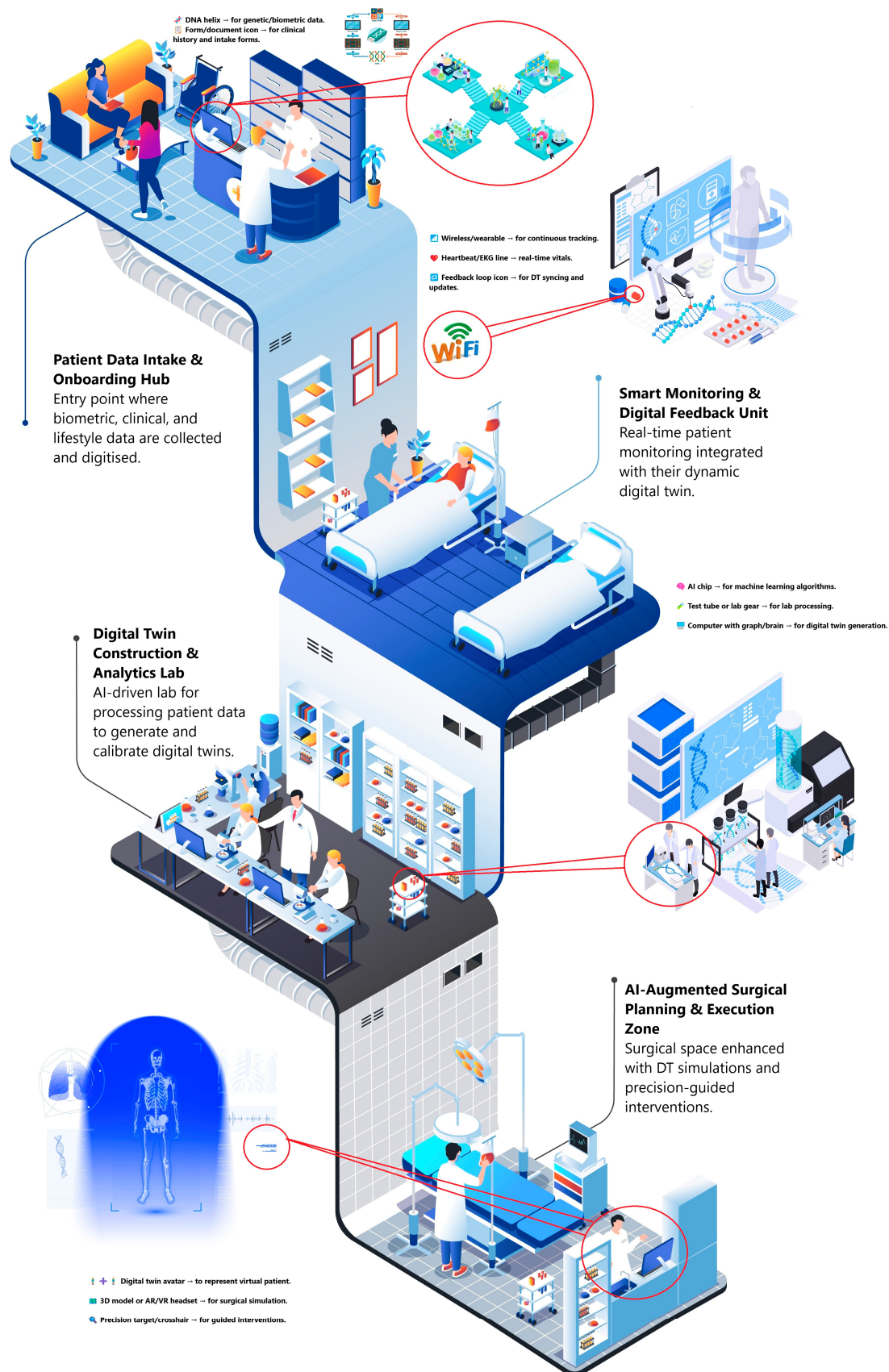


Figure 1. Visual summary of Digital Twin technologies implemented in healthcare. Patient journey from data collection to AI-augmented surgical intervention.

1.2. Research Motivation (Gaps)

Digital Twins offer the promise of personalised healthcare through predictive modelling, real-time patient monitoring, and simulation of treatment pathways. By integrating data from wearables, electronic health records, IoT devices, AI, and machine learning, DTs can mirror physiological states and simulate disease progression [10–12]. These capabilities are particularly relevant in complex care scenarios such as oncology, cardiology, and chronic disease management [7,13,14]. Despite this promise, the actual adoption of DTs in clinical practice remains nascent, and their practical implications for patient outcomes are not yet well understood. Several recent reviews have examined Digital Twin technologies in healthcare, but most focus on technical architectures, domain-specific applications, or speculative benefits [15]. What remains underexplored is a comprehensive synthesis that evaluates how DTs are actually being used to impact clinical outcomes, decision-making, and personalised care across multiple healthcare domains [3,16]. Furthermore, while prior studies acknowledge the challenges of integration, such as data privacy, ethical concerns, and interoperability, there is little synthesis of how these challenges are currently being navigated in practice.

This review addresses this gap by analysing 70 peer-reviewed articles published between 2019 and 2024. It aims to examine the empirical applications of Digital Twins in healthcare, highlight recurring challenges, and propose a conceptual framework for DT implementation. In doing so, we differentiate this review by shifting the focus from speculative potential to grounded insights drawn from diverse clinical domains. The review thus positions itself as both a consolidation of current practical applications and a roadmap for future integration of DTs into real-world healthcare systems. This study addresses three primary research questions:

1. How does Digital Twin technology improve individualised patient treatments and care quality?
2. What is the role of Digital Twin technology in accurately predicting patient responses to medical interventions?
3. What are the significant challenges of integrating Digital Twin technology into healthcare?

This study is significant both theoretically and practically. It provides a comprehensive synthesis of how Digital Twins are currently applied across healthcare domains, moving beyond speculative discussions to focus on real-world impacts. By identifying empirical applications, recurring challenges, and integration risks, this study offers valuable insights for researchers, healthcare practitioners, and managers who seek to adopt DT technologies effectively. The findings also lay a foundation for future research and implementation strategies in personalised medicine and intelligent health systems.

2. Methodology

2.1. Study Design

This study begins by discussing the research methodology used, which is an important component for conducting research studies, thoroughly analysing the adoption of Digital Twins in the healthcare sector, with a significant focus on their capacity to innovate patient treatment decisions and outcomes. This study also examines the suitability of the applied study methodology along with its keywords, search strategy, and inclusion and exclusion criteria for the research [17]. Finally, this section highlights the study's screening and selection approaches that were applied to identify final study articles and investigates the important relevant ethical concerns of this study.

2.2. Integrative Review Method

This study adopts an integrative review approach to synthesise a wide range of literature across diverse yet related topics, providing comprehensive insights into the role of Digital Twins in clinical care [18]. This methodology allows for the integration of findings from studies with varied designs, distinguishing it from systematic reviews, narrative overviews, and meta-analyses [18]. The objective is to collate and analyse research from multiple domains that address similar themes through different theoretical frameworks, methodologies, and perspectives [19]. This approach enables the identification of gaps, recurring challenges, and overlooked opportunities that may not be evident within narrower review designs. The strength of the integrative review method lies in its ability to synthesise diverse insights from various research domains, offering a comprehensive understanding of Digital Twin technologies in healthcare. By drawing on findings from multiple sources and perspectives, this approach supports the identification of gaps, emerging themes, and future research directions [18,19]. It also ensures analytical neutrality by not privileging any single research design, thereby providing a balanced and inclusive synthesis relevant to both theory and practice.

2.3. Key Terms

The literature argues that key terms are significant in successfully searching databases and discovering appropriate studies, as the research terms determined by researchers substantially impact the strength of the findings [18]. To perform extensive research on DTs in the healthcare industry, significant terms were accurately determined for this research assessment. The key research terms comprised: Digital Twin, Personalised treatment, Healthcare, Technology advancements, Patient treatment outcomes, Virtual models, Impacts, and Applications. These keywords were chosen because they represent the core perceptions of DT technologies in the clinical field. For example, “Patient treatment outcomes” and “Personalised treatments” underscore the focus on tailored DT execution, whereas terms such as “Technology improvements” and “Impacts” reflect the improvements and effects of Digital Twins’ implementation in healthcare contexts. The inclusion of these key terms ensured that the search was both comprehensive and focused, allowing for a robust collection of studies relevant to the research questions.

2.4. Search Strategy

A search strategy methodically gathers data from various sources and substantially controls an analysis’s attribute summaries by validating significant findings that are contained within it [20].

The following search strategy was pursued for this research.

- **Resources and databases:** This study primarily utilised ProQuest due to its wide coverage of peer-reviewed journals across healthcare, technology, and interdisciplinary fields relevant to Digital Twin applications. PubMed, Scopus, Web of Science, and ProQuest’s advanced filtering features also supported focused searches aligned with the study’s inclusion criteria. To complement this, Google Scholar was used to broaden the search and capture additional literature, particularly emerging studies, grey literature, and articles that may not be indexed in discipline-specific databases. The combined use of these platforms ensured both depth and breadth in identifying relevant and diverse sources across the Digital Twin and healthcare literature.
- **Using “key terms”:** Affiliated with study concentrations, the key terms applied were “Digital Twin”, “Technology improvements”, “Healthcare”, “Impact”, “Customised treatment”, “Virtual models”, “Patient treatment”, and “Applications”. These were chosen to screen Digital Twin technology’s potential and its implementation in health-

care circumstances, mainly focusing on patients’ treatment outcomes and innovative applications of the technologies.

- Boolean finding operators: These strings were applied to construct the finding sequences and advance the search area as required. The key Boolean search operator used was (“Digital Twins” AND “Healthcare” AND “Patient”).
- Inclusion criteria: Once the early results, articles’ headings, sub-headings, and abstracts were systematically assessed for pertinence to the research topic, the adoption of Digital Twin models in healthcare contexts, individualised patient care and treatment approaches, and measurable results were included in the inclusion criteria. Studies that were conducted for non-medically related conditions and lacked information about practical treatment outcomes were excluded.
- Manual citation validation: To supplement database searches, backward reference searching (also known as manual citation checking) was conducted. This involved reviewing the reference lists of key articles to identify additional relevant studies that were not retrieved through the initial search queries. This method helped uncover frequently cited foundational works and ensured a more comprehensive and representative literature base.
- Search modifications and duplications: This search approach was constantly sophisticated during the analysis. The search phrases were altered based on initial outcomes, ensuring a detailed and concentrated set of articles appropriate to the research aims.

Thus, this organised finding approach simplified the retrieval of relevant studies, offering a robust basis for the integrative analysis of DTs in medical care.

2.5. Eligibility Criteria (Inclusion and Exclusion)

Forming eligibility conditions is significant for choosing to add or remove studies based on verified, legitimate boundaries. So, these norms must be implemented in a search procedure to minimise preferences [21]. The criteria selected for this study are summarised in Table 1.

Table 1. The inclusion and exclusion criteria.

Inclusion Criteria	Exclusion Criteria
Peer-reviewed journal articles	Non-peer-reviewed sources such as opinion pieces, editorials, and conference abstracts without full papers
Published between 2019 and 2024	Articles published before 2019
Focus on the adoption or application of Digital Twins in healthcare settings	Articles focused on Digital Twins in non-healthcare domains, such as Digital Twins in manufacturing, aerospace, etc.
Discusses clinical relevance, patient care, implementation, or ethical/technical aspects of DT in healthcare	Articles lacking methodological transparency or practical relevance
Written in English	Articles published in other languages
Available as full text	Abstract-only records or inaccessible publications

2.6. Screening and Selection

To ensure methodological rigour, the screening process followed established integrative review practices [22]. After removing duplicates, articles were screened through title and abstract reviews, followed by full-text evaluations to assess alignment with the research objectives. Only studies directly addressing the clinical application, implementation challenges, or ethical dimensions of Digital Twin technologies in healthcare were retained

for analysis. Figure 2, a PRISMA flow diagram, illustrates the methods utilised to identify and organise the suitable articles.

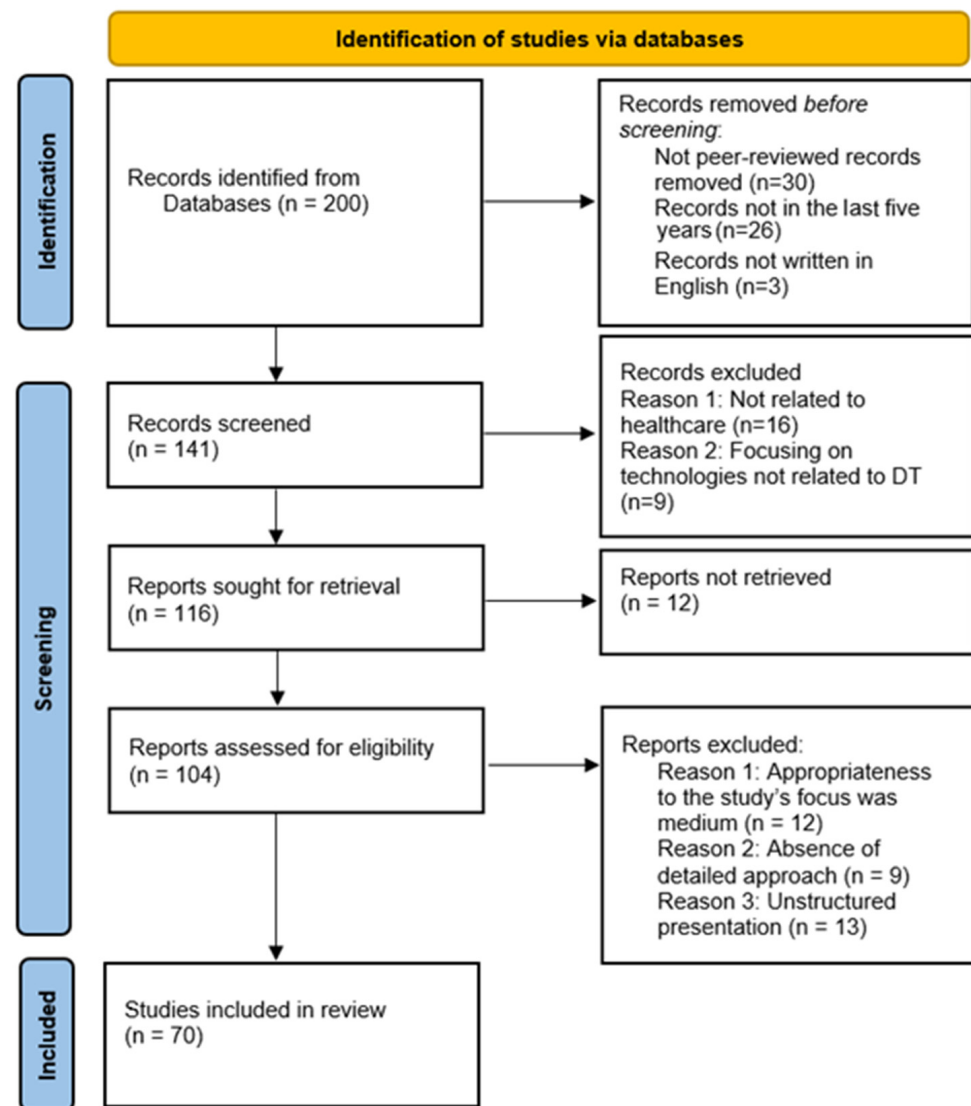


Figure 2. PRISMA flowchart.

2.7. Data Analysis Techniques

This study primarily adopted both content and thematic analyses to analyse the data from the selected articles [23]. Content analysis is a deductive, quantitative technique used to measure messages in an objective and reliable manner. In contrast, thematic analysis involves an emergent and interactive process of interpretation of a set of messages, with some thematic structure as the typical outcome. Nevertheless, the application of these two approaches is often viewed as complementary and provides the best outcome of integrative literature review methods [23].

3. Literature Review

3.1. Conceptualisation and Terms

The aim of this review was to determine the comprehension of generic key concepts about Digital Twin technology and its adoption in customised patient treatments and personalisation. Key terminologies used in this study are defined in Appendix A to support conceptual clarity and highlight the key terms applied. These definitions significantly con-

tribute to recognising and explaining the key terminology and advance the understanding of the research's key objectives and findings.

3.2. Study Overview

The influence of Digital Twin (DT) technologies in optimising clinical outcomes, particularly in personalised care, is gaining growing attention in the literature. While many existing reviews focus on DT applications in industrial contexts, studies specifically addressing healthcare remain comparatively limited. This gap highlights the importance of analysing the role and impact of DTs in medical environments. The research in [6] constitutes one of the prime studies in the healthcare sector, offering a detailed evaluation of DT4H. It crucially underlines the key ability of Digital Twin models to transform healthcare decisions and patient outcomes through developed treatment plans and customised medicines. Additionally, this study discusses the DT adoption challenges, such as ethical issues and data integration, stimulating vital debates regarding cooperation among diverse subjects [6]. This advancing technique advocates new advancements and aids participants in collaborating to address challenges.

Another study conducted by [24] analyses Digital Twin models' development in the metaverse, concentrating on breast cancer disease and care. Using ML tools like Random Forests, Gradient Boosting, Linear Regression, and Decision Trees, the study [23] seeks to produce concurrent, consistent DT replicas that greatly optimise customised treatments. It also shows a key development in breast cancer care-related reviews by indicating how these technologies could reform the disease diagnostic practices and medical plans. ML's incorporation into DTs provides a solid structure for enhancing correctness in identifying and healing breast cancer disease, ensuring that individuals obtain accurate, timely, and tailored measures. The potential to replicate illness sequence facilitates practitioners and medical service providers to provide more appropriate healing strategies and enhance continuous monitoring, resulting in optimised patient outcomes [24].

A separate study [14] substantially increases the comprehension of DTs' transformation of breast cancer disease treatment through improving predictive and customised drugs. Through examining the adoption of DT models' benefits and limitations in health processes, it details a complete structure which assists practitioners, patients, and health service providers [14]. The study underscores the great capacity of DT technology in individualising cancer cure arrangements. Further, by implementing stimulated patient models, medical experts can personalise care for each patient's condition and responses, enhancing successful outcomes. The addition of practical evidence significantly proves that these models can support thorough healthcare conclusions, leading to successful and timely interventions for individuals with breast cancer. All in all, this study demonstrates an important step towards fully implementing DT models in clinical trials, demonstrating a greater revolution in the sector [14].

3.3. Theories and Theoretical Models in Previous Research

As we analyse DT adoption in healthcare practices, various hypothetical models and structures have arisen to support their understanding and execution. In this section, this article expands on significant theories like system theory, the simulation concept, cyber-network system theory, the forecast analytical concept, the concept of collaboration between computers and humans, and decision-making system theory regarding the capability of DTs to improve prediction of patient responses and customised care and address significant DT integration challenges in healthcare strategies and practices.

System theory: This is the root of various frameworks for DT implementation in clinical practices, supporting a holistic perspective that pools data stimulations, knowledge centres,

and analytics. This theory also points out the significance of the unified collaboration among physical and stimulated systems. Through applying system theory, academics and medical practitioners can gain a stronger comprehension of how the diverse mechanisms of DT models, like actual data sets, Internet of Things sensors, and enhanced analytics, are connected to establish dynamic and approachable healthcare eco-friendly structures [6]. This detailed approach supports validating that all elements function together effectively, resulting in optimised patient results [6,8,11,24].

Simulation concept: This theory plays a key part in healthcare operations using DT technologies by facilitating the replication of actual situations in a simulated context, which allows experts to predict effects, find suitable advancements in remedy procedures, and trial several mediations without compromising patient data and safety [24]. By applying replications, clinical specialists can initiate appropriate decisions regarding patients' treatment, leading to optimised care success. The prominence of models across healthcare underlines how DT models can inspire and assist medical professionals to analyse various medical options in regulated circumstances [6,8,11,24].

Cyber-network system theory: The cyber-network system concept is substantially suitable for DT integration, as it explains the associations between real-world objectives and their virtual copies [11]. These DTs are significant examples of CPSs, where actual data, such as patient models and clinical devices, are persistently revealed in virtual replicas. This collaboration enables medical experts to participate in data-driven and appropriate decision-making, improving individual patient care and medical supply [6]. Through a clear picture of CPS principles, stakeholders such as patients and experts can obtain better insights into the difficulties involved in creating and managing eco-friendly DT systems [6,8,11,24].

Forecast analytical concept: This analytical theory indicates the significance of AI and ML applications in evaluating data and projecting medical treatment results. By following these innovative technologies, healthcare service providers can predict patient reactions, customise involvement for individual tailored requirements, and optimise overall patient treatment competency [8]. The forecasting opportunities provided through this concept are key for advancing patient treatment procedures and enhancing healthcare decisions [6,8,11,24].

Computer-human collaboration concept: Human and computer system connected theories emphasise the importance of user affiliation in DT technologies by performing analyses to understand how clinical specialists and patients collaborate with these advanced systems [23]. The efficiency of this concept is key to progressing insightful interfaces that allow a simple approach to DT technology models, guaranteeing that patients and healthcare providers can significantly apply these models for informed decisions. Through concentrating on the principles of these theories, researchers can improve the accessibility and usage of DT models, eventually resulting in healthier employment and improved healthcare practices [6,8,11,24].

Decision-making system theory: This delivers a basis for a theoretical approach for integrating Digital Twins into the decision-making stage in healthcare. This concept also focuses on how projective details and actual responses can be utilised to support medical practices and optimise patient care outcomes [6]. By adopting these DT models into current decision-making systems, experts can improve their potential to provide customised treatment, ensuring that findings are personalised and data-driven according to each patient's requirements. Thus, this implementation mirrors substantial innovations in healthcare structures, as it permits medical service providers and experts to make precise and suitable treatment selections [6,8,11,24].

To understand how Digital Twin technologies are applied in healthcare, it is essential to examine the theoretical foundations that underpin their development and integration. Figure 3 visually summarises these key models, and Table 2 provides supporting evidence by linking each concept to specific studies reviewed in this paper. These foundational theories, such as system theory, simulation modelling, cyber–physical networking, and forecast analytics, serve not only as explanatory tools but also as practical frameworks guiding implementation strategies in clinical environments.

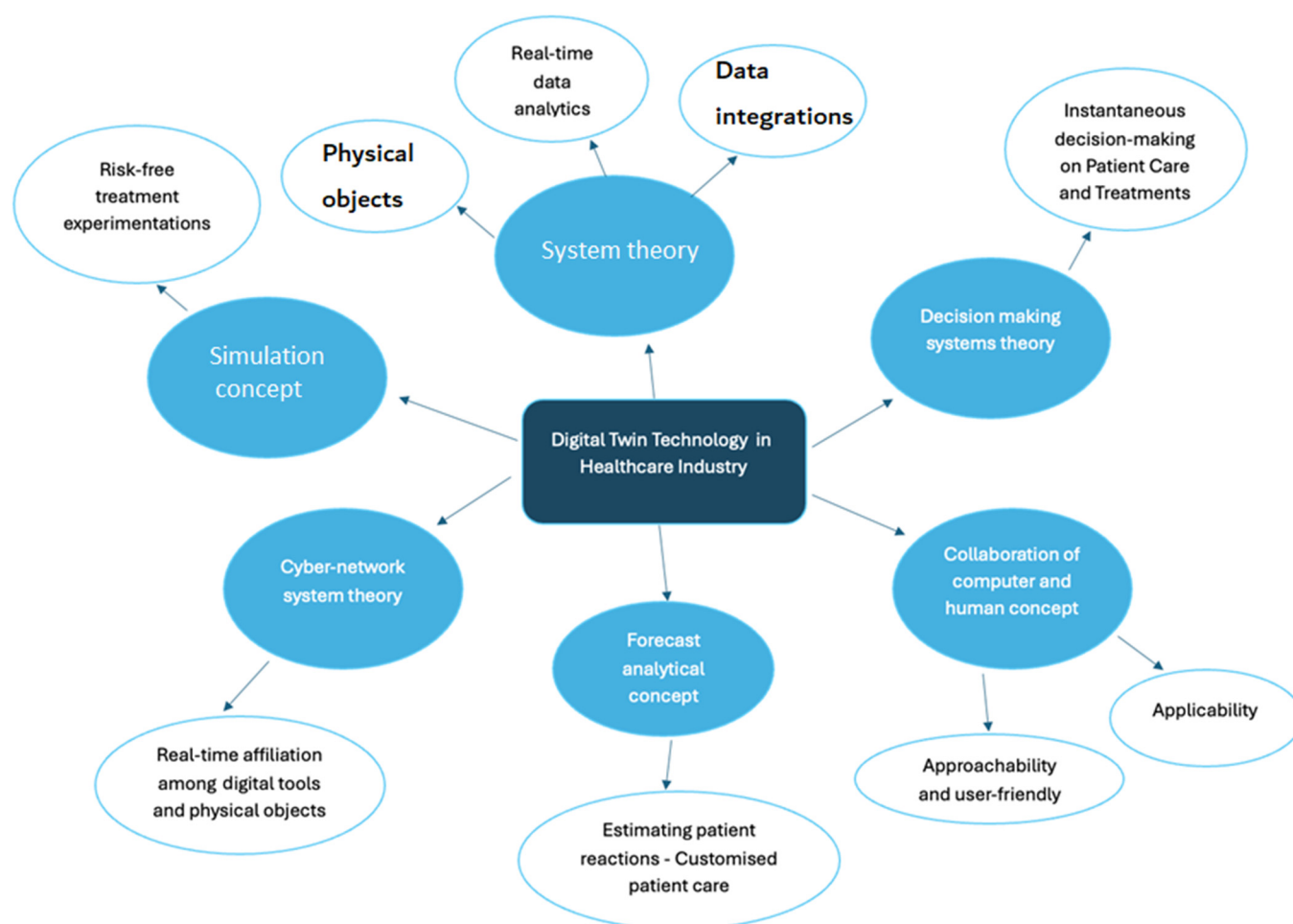


Figure 3. Conceptual foundations of Digital Twin technology in healthcare. Supporting sources for each model are detailed in Table 2.

Table 2. Theoretical foundations supporting Digital Twin implementation in healthcare.

Model/Concept	Typical DT-in-Healthcare Use	Supported Reference	How is it Used in the Cited Work
System Theory	Integrating real-time data, sensors, and physical entities into one cohesive “patient-twin” system	Katsoulakis et al., 2024 [6]; Laubenbacher et al., 2022 [10]	Both papers describe DT platforms as <i>systems of systems</i> that continuously blend clinical and cyber data streams
Simulation Concept	Risk-free experimentation and virtual trials	Rudnicka et al., 2024 [7]; Avanzato et al., 2024 [13]	Cardiac DT and lung DT frameworks run thousands of simulated treatment scenarios before real-world application

Table 2. *Cont.*

Model/Concept	Typical DT-in-Healthcare Use	Supported Reference	How is it Used in the Cited Work
Cyber-Network System Theory (CPS)	Tight, real-time coupling of IoT devices with their digital replicas	Dang et al., 2023 [8]; Mohapatra and Bose, 2020 [11]	Both describe DTs as cyber-physical systems where bedside devices feed live data to the twin for ICU decision support
Forecast Analytical Concept	AI/ML models that predict disease progression or therapy response	Chu et al., 2023 [9]; Vallée 2023 [12]	Diabetes DTs and system-level DTs rely on ML forecasts to adjust insulin or resource allocation proactively
Human–Computer Collaboration Concept	Clinician + DT co-decision workflows, XR visualisation for operators	Konopik et al., 2023 [14]; Wickramasinghe et al., 2023 [16]	Both papers study how clinicians interact with DT dashboards and XR overlays to fine-tune cancer and workflow decisions
Decision-Making System Theory	Real-time, data-driven clinical decision support layers atop the DT	Dang et al., 2023 [8]; Turab and Jamil, 2023 [15]	Stroke DT Delphi rules and metaverse-enabled DTs highlight algorithmic triage and automated alerts for rapid action

4. Findings

4.1. Conceptual Insights

Several studies have analysed various theoretical frameworks to assess the role of Digital Twins (DTs) in optimising the healthcare industry. Systems theory plays a major role in showcasing how DT models combine several elements like real-time analytics, data simulations, and actual objects to increase patient care outcomes [8]. Furthermore, predictive analytics theory is widely implemented to analyse and highlight the capability of DT technologies in predicting patients' responses to treatment, thereby facilitating more customised clinical interventions [11]. In addition, the literature has indicated that cyber-network theories have also been utilised to demonstrate DTs' dynamic association with physical objects and their virtual counterparts, increasing the potential to observe patients' medical conditions simultaneously [6]. Furthermore, studies have illustrated the substantial model concept that underlines how DT systems facilitate unhazardous experiments regarding healthcare involvement, resulting in more suitable medical healing practices. Moreover, decision-making systems utilisation is also noticeable, exhibiting the use of these models for instantaneous decision-making in healthcare settings [25]. Lastly, studies have found that human and computer connected theories have been used in studies to ensure that these DT systems are reachable and user-friendly for medical consultants, offering continuous collaboration with the technologies [6]. Thus, these incorporated methods provide significant insights into DTs' capabilities in tailored care and tackling vital limitations in their integration.

4.2. Ethical and Organisational Challenges to DT Adoption

The evaluated articles collectively highlight the pioneering potential of these enhanced DT systems in healthcare, aiming at tailored patient treatment and care, enhanced disease diagnostic accuracy, and improved results. Throughout several research articles, Digital Twin structures are demonstrated to be crucial in combining the latest technologies such as ML, AI, data analytics, and IoT, facilitating real-time observation and forecasting potentials.

Further, many studies have explained how these models, combined with Extended Reality (XR) and AI, could possibly optimise accuracy in areas like oncology and cardiology. Accordingly, these articles discuss the potential benefits of DT models in virtualising patients' health statuses, predicting clinical results, and enhancing customised care procedures. As an example, DTs applied in heart simulations improve disease detection and customised therapy, while they also assist predictive clinical treatment in breast cancer treatment, despite facing ethical and regulatory considerations.

The reviewed literature identifies a wide range of risks associated with Digital Twin implementation in clinical settings. These include high-stakes issues such as data breaches, patient privacy violations, algorithmic bias, and the potential over-reliance on automated decision-making. However, such risks are often discussed in isolation. To provide a more structured synthesis, Table 3 summarises fifteen recurring risk categories, their likelihood, potential impact, mitigation strategies, and responsible roles. This risk matrix enables a more nuanced understanding of DTS implementation barriers and how they intersect with ethical, technical, and organisational dimensions. The colour coding (green = low, orange = medium, red = high, dark red = critical) visually highlights the likelihood and impact of each risk, helping prioritise mitigation efforts.

Table 3. Risk identification for Digital Twins in healthcare.

Supporting Reference	Risk Description	Likelihood	Impact	Mitigation Strategy	Responsible Party
[26]	Data privacy breach	High	Critical	Enforce strict data encryption and access control	IT Security Officer
[11]	Incompatibility with legacy systems	Medium	High	Use middleware or APIs for integration	Systems Integration Manager
[6]	Patient data inaccuracies	High	High	Regular data audits and validation protocols	Data Analyst
[27]	Lack of clinician training on DT use	Medium	Medium	Conduct regular training sessions	HR & Clinical Trainer
[28]	Ethical concerns regarding AI-based decision-making	High	High	Establish an ethics review committee	Compliance & Ethics Officer
[29]	High cost of implementation	Medium	High	Seek phased rollout and apply for innovation grants	Finance & Project Manager
[30]	Regulatory non-compliance (e.g., privacy laws)	Low	Critical	Regular legal audits, compliance documentation	Legal Advisor
[31]	Resistance from staff or clinicians	Medium	Medium	Awareness campaigns and stakeholder involvement	Change Management Lead

Table 3. Cont.

Supporting Reference	Risk Description	Likelihood	Impact	Mitigation Strategy	Responsible Party
[32]	Cybersecurity threats	High	Critical	Employ multi-layered cyber defence systems	Cybersecurity Team
[33]	Over-reliance on DTs, reducing human judgement	Medium	High	Maintain hybrid decision models with human oversight	Clinical Governance Lead
[34]	Interoperability issues across departments	Medium	High	Standardise data protocols and integration frameworks	IT Architect
[35]	Legal liabilities from incorrect DT simulations	Low	High	Test extensively and ensure liability insurance	Legal & Risk Team
[36]	Misinterpretation of predictive analytics	Medium	Medium	Provide guidelines for data interpretation	Data Science Lead
[37]	Inequitable patient access to DT-powered care	Medium	High	Develop policies for inclusive access	Policy Advisor
[38]	Environmental risks from tech infrastructure	Low	Medium	Opt for green IT solutions and e-waste management	Sustainability Officer

Regarding answering RQ1: How does Digital Twin technology improve individualised patient treatments and care quality?, several studies have demonstrated how DT technology revolutionises customised medical care by advancing diagnostic precision, forecasting patient outcomes, and utilising optimised systems [6,39–42]. Meticulousness in detecting and tailoring patient treatment underlines Digital Twins’ potential to produce individualised clinical practices by simulating the specific conditions of each patient. In addition, the predictive analytic concept for patient care shows how these DTs project therapy reactions, permitting specialists to make informed decisions. By leveraging XR and AI tools for improved treatment, it aims to combine these two technologies into Digital Twins to provide immersive models and a detailed understanding, further fostering customised treatment and aftercare planning.

4.3. Personalised Medicine and Treatment

The implementation of accurate detection and personalised therapy in the clinical field has gained substantial momentum, with the innovation of DTs. These systems improve diagnostic accuracy and facilitate the individualised medical strategies through virtualising patient models’ reactions to diverse interventions in specific situations. The authors of [6] discuss the effectiveness of DTs in simulating illness progress, hence optimising medical outputs. The study in [43] illustrates the significance of accuracy in characterising individuals through thorough healthcare and molecular information, which is closely related to the personalised care focus. Further, regarding musculoskeletal structure, the authors of [41] explain that DTs can evaluate actual biomechanical properties for detection and

therapy that support and guide customised clinical practices. This enables a deep comprehension of each patient and their needs and aids personalised involvements that improve treatment outcomes. As demonstrated in Figure 4, the DT systems for the complete musculoskeletal health system are capable of tailored disease detection and care. As proposed in this research, Figure 4, adapted from [41], illustrates a four-stage Digital Twin healthcare framework. It begins with the physical space, where patient data are collected via imaging, morphology, and wearable devices. The connection layer enables real-time data flow to the digital space, which performs modelling, analysis, and visualisation.

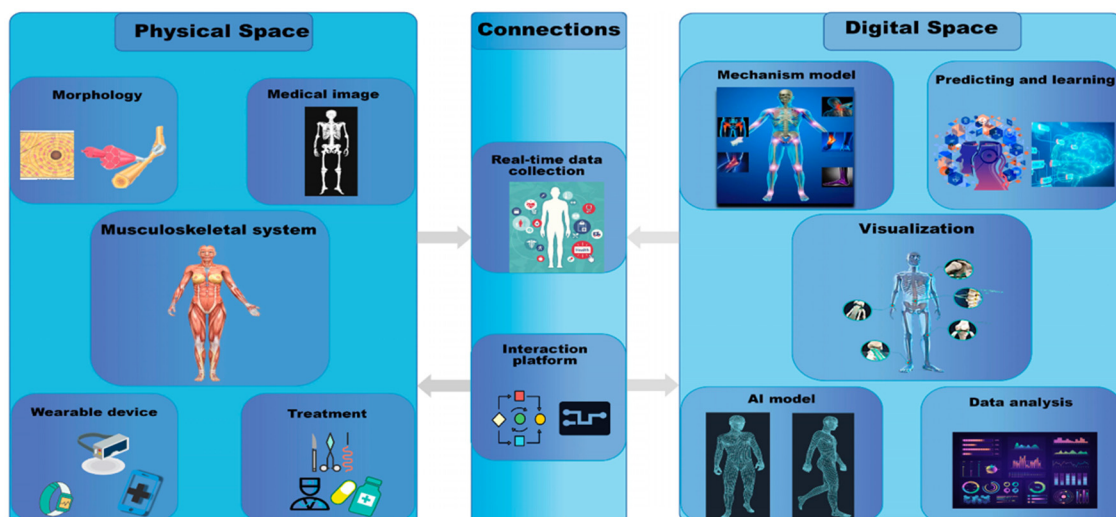


Figure 4. Major system components of Digital Twin implementation in healthcare.

Figure 4 visualises the interconnected structure of Digital Twin systems in healthcare by mapping the interactions between the physical and digital spaces. It shows how real-time data from the human body (e.g., morphology, musculoskeletal system, medical imaging, and wearable devices) are collected, transmitted, and processed through an interaction platform into the digital space for analysis, prediction, and clinical visualisation. This model provides a systemic view of how DTs operate across patient monitoring, diagnosis, and personalised treatment, reinforcing the integrative nature discussed throughout this review. In summary, the research study examines the revolutionary capabilities of these DTs in developing accurate disease detection and customised care, resulting in improved patient care outcomes and enhanced medical processes.

4.4. Predictive Analytics for Patient Care

This subsection addresses RQ2: What is the role of DTs technology in Accurately Predicting Patient Responses to Medical Intervention? The execution of predictive analysis for patient care output in DT applications in healthcare settings underlines the significant transformative impacts of DT technologies on patient treatment and medical results. The authors of [39] highlight DTs' ability to advance evidence-based medical drugs by producing replica control clusters in medical experiments, which permits more appropriate estimations of responses from patients for treatments. By applying this sub-theme, Digital Twins can evaluate unified patients' conditions and possibilities, diminishing physical control requirements and offering a customised method to health administrations [39]. Additionally, ref. [39] centres on the use of sensor-based Digital Twins in smart environments, which influence AI, ML, and IoT technologies to advance individual patient monitoring and real-time clinical assessments. By integrating wearable tools/devices with DTs, these simulations offer predictive details that allow appropriate interventions, aiding proactive

medical support in top-rated hospitals and homes [40]. Additionally, the combination of DTs enables individualised medical recommendations and targeted care, focusing on overall health improvement for patients and effective medical management.

In [44], the study focuses on Personal Digital Twin (PDT) technology to optimise treatment by applying pioneering predictive assessments to identify diseases, preventive approaches, and treatments for each patient. PDT technology is created to provide a mirror of the patient's specific physical characteristics and existing and previous health updates, facilitating enhanced, customised treatment suggestions and planning. Furthermore, by adopting pioneering technologies such as blockchain tools and AI, Personal Digital Twins provide accessible information that enables health experts to forecast patient outcomes and personalise interventions, as discussed in [44]. Instances such as COVID-19 pandemic care, personalised care for cancer patients, and osteoporosis prevention highlight the potential of PDT models to reduce medical risks and improve long-term patient outcomes through analytical estimates. This cited article focuses on facilitating the adoption of innovative, advanced, and patient-specific healthcare practices and systems, transforming the healthcare sector by integrating enhanced technologies and personalised treatment care [44]. Hence, the collective findings of these articles underscore how projective assessments, combined with DTs, could transform the clinical industry, steering customised and successful treatment practices.

4.5. Extended Reality and Artificial Intelligence for Advanced Treatments

The integration of Extended Reality (XR) and artificial intelligence (AI) with Digital Twin (DT) technologies is transforming the healthcare landscape. For example, Rudnicka et al. [7] highlighted how Health Digital Twins (HDTs) significantly enhance healthcare delivery by improving diagnostic precision and treatment accuracy. These advancements reflect the evolution of AI capabilities—particularly in visual differentiation—which is critical for enabling personalised therapeutic interventions. Similarly, Turab and Jamil [15] explored how DTs contribute to enriched simulated environments, allowing clinicians to replicate complex medical scenarios and optimise training and patient-specific treatment strategies. The concept of “virtual twins,” which digitally replicates an individual's biological profile, is further advancing tailored care pathways. Dang et al. [8] support this direction by demonstrating how intelligent medical systems leverage IoT and AI for real-time data analysis while maintaining privacy through decentralised learning approaches. To illustrate this, Figure 5 visualises the role of AI-enhanced health infrastructure, as described by [8], showcasing its integration across various clinical contexts.

As described by [13], the lung DT framework uses Internet of Things (IoT) sensors to recognise chest X-rays with 96.8% accuracy. This also permits real-time observation and empirical analyses, aiding in customised individual treatment procedures and detailed assessments. Additionally, these articles collectively explain the revolutionary probability of adopting XR and AI tools across the clinical sector, optimising informed healthcare decisions, patient commitments, and training. These articles further demonstrate the significance of tackling data security issues, ethical challenges, and the necessity for broad, prime data in enhancing prominent artificial intelligence systems. Lastly, the interaction of DTs, AI, and XR connects the ability of innovative patient care and treatment outputs and streamlined medical settings.

Table 4 shows the vital results for each article by offering a general idea, research methodologies, and significant insights.



Figure 5. Illustrative use cases and applications of Digital Twins in healthcare contexts.

Table 4. Summary of empirical findings on Digital Twin applications in healthcare studies (2018–2024).

Study	Focus Area	Methodology	Key Findings
[6]	Digital Twins' wide range of use in healthcare	Comprehensive literature analysis	Investigates the use of DTs in clinical systems, outlining gaps in forecasting analytics and adoption issues
[23]	Combination of metaverse and DTs in cancer therapy	Comprehensive case-study methodology integrated with an analytical approach	Discussing ML-powered DT models in cancer treatment, showcasing their part in metaverse for delivering advanced and collaborative patient care
[14]	Digital Twins' application in breast cancer therapy	Semi-structured interviews with 14 breast cancer patients	Illustrates DTs' challenges and concerns in breast cancer, indicating technological, operational, and ethical considerations
[45]	Digital Twins in cancer care	Deep Q-learning model	Highlights the potential of DTs for enhanced therapy choice, indicating the impacts of AI in customised patient treatments
[9]	Digital Twin use in diabetes control	Comprehensive mixed methodology	Explains DTs' ability for tailored control over diabetes, including customising care based on patient reaction prediction
[27]	Doctor's understanding about Digital Twins in patient treatments	Reflexive thematic–qualitative approach	Analyses about practitioners' understanding of DT models, highlighting issues about data safety, privacy, and potential harm to doctors' autonomy
[41]	Musculoskeletal detection and treatment using DTs	Case study	Evaluates how DTs function for customised diagnosis and care in musculoskeletal issues, showing the high-level opportunities in orthopaedics

Table 4. Cont.

Study	Focus Area	Methodology	Key Findings
[44]	Personal Digital Twin (PDT) utilisation in healthcare	Literature review	Assesses the ability of PDT models in optimising personalised treatment, analysing limitations in data privacy and administrative processes across the tailored clinical practices
[8]	Smart medical frameworks using artificial intelligence	Quantitative and qualitative methodologies using the DELPHI Consensus technique	Discusses the health system using AI and its capability to assist tailored patient care, highlighting DTs key role in smart and innovative healthcare settings

In this regard, there are many issues deemed to be investigated under RQ3: What are the significant challenges of integrating DTs technology into Healthcare? These are critical ethical issues in the integration of Digital Twin models in the clinical sector. The analysis of security concerns and data concealment concentrates on the weaknesses of managing confidential patient details in digital systems, covering the importance of robust practices to safeguard data reliability. Investigations of technical and legal issues regarding DT adoptions are conducted in accordance with medical regulations and the high-tech practices needed for successful execution. The legal and ethical complexities of AI-related decisions stress the ethical problems linked to the involvement of AI in healthcare decision-making, encouraging the requirement for accountable AI processes to safeguard patient data, well-being, and trust.

4.6. Data Privacy and Safety Issues

Risks to data security and the privacy of DTs used in the healthcare industry emphasise vital elements for securing sensitive and confidential information of patients and maintaining confidence in digital tools in healthcare practices. Research conducted in [6,39,40] underscores the importance of data and security issues in the application of DTs in medical fields, mainly in personalised healing processes. Additionally, a key moral issue involves the protection of patient autonomy and informed consent. Additionally, ref. [43] highlights the need for stringent regulations for the extensive, real-time data collected by HDT systems in elderly care, where sensitive data must be securely stored and maintained. According to [46], continuing to regulate control over the retrieval and application of their DT system data is vital for individuals with diseases, covering the significance of patient independence in pioneering digital clinical care. In countries such as New Zealand, the Data Privacy Act 2020 serves as a significant legal and regulatory framework for safeguarding the individual data of patients, such as medical details, across the digital healthcare structures [30]. This act strengthens individual privacy and confidentiality by ensuring that service providers securely store, utilise, and share patient data with accuracy and transparency. Additionally, this act holds data administrators and users accountable, mandating that medical service providers using Digital Twins create robust safeguards for confidential information. Moreover, this suitably supports the concerns raised in [46,47], indicating the need for rigorous access management and ethical commitments from health organisations to safeguard patient data and privacy.

Further, another key problem is the irregular and unequal approach to securing innovative healthcare systems. As studied by [47], the increasing expenses of healthcare technology impede accessibility, raising moral concerns about providing equitable treatment for vulnerable individuals. Although data precision is a problem, as [48] discusses, confidential issues can also weaken informational dependability, influencing treatment

outcomes. Moreover, ref. [47] advises that the requirement to gather details from several resources for DTs establishes secrecy risks. Even though this cluster is significant for virtual precision, it adds illegal access threads. Eventually, substantial technical limitations hinder the protection of these advanced systems. In addition, refs. [6] and [47] analyse the elevated requirements on computational resources for simultaneous data in DTs, highlighting the need for robust safety measures to stop violations.

4.7. Legislation and Technological Limitations

The technological and legislative issues related to DTs' adoption in the medical field display vital challenges that need to be tackled to unlock their potential. As demonstrated by [42], the streamlined information gathering deprivation is a key limitation to innovative healthcare adoption with DT models, highlighting that the data obtained from several wearable measures restricts detailed analysis and application of medical information. This concern is addressed by [47], according to which the continuous high-level collection of distinct data is important in preventing partialities and maintaining the healthcare appropriateness of DT replicas. In [49], it is revealed that device consistency and obtainability are significant issues, as they further emphasise the necessity for user-friendly and reasonably priced sensors suitable for providing precise clinical details. Also, without innovative technologies, the considerable data obtained might go unutilised. Drummond, and Coulet (2022) [49] also pointed out this issue by highlighting that linked medical tools for children require adoption with specific applicability aspects to guarantee their efficacy and efficiency while providing solutions for challenges related to age.

Moreover, interoperability persists as a vital technical issue; specifically, exclusive systems pose problems for effective data allocation through stages and complicate the integration of various mobile clinical apps [50]. According to [46], the key to solid systems for technical administration of the large range of data sets created using DTs is to highlight that existing technical systems could inadequately assist simultaneous data transfers. The authors of [46] analysed the autonomy of patients in their research, explaining that patients should maintain control over their information to foster confidence in pioneering medical results. Furthermore, ref. [48] emphasises the need for legitimate regulations that validate given agreements, particularly for vulnerable populations such as children and teenagers, who may be harmed by data-gathering approaches. Overall, the research articles showcase that although DT technologies represent significant advancements for innovating healthcare structures and practices, getting to grips with technical, legal, and regulatory limitations is vital. Moreover, constant innovations in data control, ethical regulations, and device structures will play a significant part in supporting efficient DT implementation in healthcare settings, leading to improved patient treatment outcomes.

4.8. Ethical Considerations of Artificial Intelligence-Related Decisions

Concentrating on the ethical issues of AI-related findings in the implementation of DTs in clinical settings highlights the significant need for robust ethical frameworks to mitigate the risks associated with confidential patient information. Also, according to [51], the difficulty of human nature and the adaptability of patient medical statuses argue for the consistent creation of AI simulations. The authors also express that, despite DTs combined with AI serving as a key potential for optimising customised medicinal drugs, moral issues regarding patient data safety, privacy, and consent should be vitally analysed to avoid discrimination and ensure unbiased results [51]. In addition, ref. [43] investigates the concerns created by the Electronic Health Records (EHRs) guidelines and narrowed quality, which could impact the learning of AI processes. Although [43] acknowledges that medical experimental data are generally of high quality, the authors emphasise that they

often lack adequate explanations, raising significant concerns about the generalizability of artificial intelligence estimates. Hence, this highlights the ethical need for effective data control procedures that safeguard patient data while enhancing the reliability of these AI infrastructures. Furthermore, ref. [49] recommends a systematic ethical procedure that is designed to methodically recognise and address ethical problems across various data control stages in DT advancements. This approach serves as a vital tool for software developers, aiding in proactive assessments of potential ethical limitations associated with working challenges and barriers, such as informed consent and data protection. Drummond & Coulet (2022) [49] also emphasised the need for additional, practical-based studies to thoroughly address specific ethical issues related to DTs, underscoring the requirement for a comprehensive understanding of the ethical foundations of these technologies. These findings collectively highlight the importance of detailed plans and approaches that integrate stakeholder views and facilitate progress in navigating the ethical considerations of AI-based conclusions in the medical field. By creating a context for ethical considerations, stakeholders can validate DTs' integrations with patient-specific morals, ultimately optimising treatment and care quality while addressing predicted ethical issues. Moreover, regular analyses of ethical concerns would be crucial for building confidence and facilitating the secure integration of DTs with AI tools in healthcare settings.

4.9. Methodological Approaches in a Targeted Subset of Articles on Digital Twin Applications

In analysing the research methods applied across a targeted subset of 45 peer-reviewed articles, selected for thematic analysis and their direct focus on Digital Twin applications in healthcare between 2019 and 2024, we identified a range of methodologies used, from qualitative to quantitative to conceptual. The qualitative approaches include in-depth interviews using semi-structured questionnaires and focus groups, although the former was more commonly used than the latter [6,14,52,53]. The key strengths of the qualitative method include its flexibility and ability to explore participants' responses in depth, although it frequently restricts compatibility, as the sample sizes of the articles were relatively small. Sampling frames for the qualitative studies included purposive, judgement, and convenience sampling. Most of these studies analysed data using content and thematic analysis. In contrast, several others adopted quantitative [8,11,23] with sampling frames ranging from convenience to random sampling. One study used G* power version 3.1.9.7 to estimate the sample size. Quantitative data were analysed using statistical tools such as Structural Equation Modelling (SEM) through AMOS and LISTREL. Other frequently used methodologies included integrative literature reviews, systematic literature reviews, and scoping reviews [1,9,19,21], most of which were conceptual in nature. A summary of use cases of Digital Twins in healthcare is presented in Table 5.

Table 5. Summary of investigated use cases of Digital Twins in healthcare.

Medical Field	Use Case	Technology Integrated	Clinical Function	Impact	Limitations/Challenges	Reference
Cardiology	Heart model simulation	IoT + AI + XR	Diagnosis and risk modelling	Better diagnosis, risk prediction	Data integration and real-time synchronisation	[8]
Oncology	Breast cancer treatment personalisation	ML, VR	Predictive modelling	Tailored chemo protocols	Model bias and scalability	[24]

Table 5. Cont.

Medical Field	Use Case	Technology Integrated	Clinical Function	Impact	Limitations/Challenges	Reference
Diabetes	Continuous glucose monitoring + predictive modelling	Wearables + AI	Real-time monitoring	Adaptive insulin delivery	Privacy concerns with wearable data	[9]
Orthopaedics	Musculoskeletal simulations	XR, sensor integration	Biomechanical modelling	Biomechanical optimisation	High sensor precision requirement	[41]
Smart Environments	Real-time clinical assessments	AI, ML, IoT	Ambient monitoring	Continuous patient monitoring	Security vulnerabilities in smart networks	[40]
General Medicine	Prediction of treatment outcomes	AI, simulation	Decision support	Evidence-based treatment planning	Interpretability of AI decisions	[39]
Healthcare Systems	Resource optimisation	IoT + AI	Operational management	Improved efficiency and responsiveness	Interoperability issues with legacy systems	[1]
Personalised Care	Predictive analytics for treatment planning	AI, blockchain	Individualised therapy	Tailored treatment suggestions	Ethical concerns with data ownership	[44]
Respiratory Care	Lung disease diagnostics	IoT sensors + ML	Diagnostic imaging	Real-time chest X-ray analysis	Need for robust image training datasets	[13]
Elderly Care	Health monitoring for seniors	HDT + AI	Geriatric monitoring	Support for independent living	Limited device access in low-income settings	[47]
Paediatrics	Child-specific device regulation	Custom IoT devices	Paediatric screening	Improved safety and diagnostics	Usability concerns with younger patients	[49]
Policy and Regulation	Ethical frameworks for DTs	AI, consent Protocols	Health governance	Safer data governance	Jurisdictional variation in laws	[28]
Doctor Representation	Digital Twins of Doctors (DTDs)	Simulation + data modelling	Training and simulation	Medical expertise replication	Concerns about autonomy and over-reliance	[27]
Breast Oncology	Stakeholder engagement in DT adoption	VR + digital modelling	Stakeholder-centred design	Improved patient-centred care	Varying stakeholder concerns	[14]
Diagnostics	Virtual patient replication	ML, simulation	Virtual trials	Advanced diagnosis accuracy	Model validity and generalisation	[45]

Table 5. Cont.

Medical Field	Use Case	Technology Integrated	Clinical Function	Impact	Limitations/Challenges	Reference
Chronic Disease	Individualised treatment response prediction	Wearables + ML	Long-term care Management	Optimised chronic care	Sensor fatigue and system calibration	[44]
Neuroscience	Simulation of neural activities	AI, predictive analytics	Cognitive disorder Modelling	Improved cognitive care strategies	Difficulty simulating complex neural behaviour	[36]
Migraine Care	Pattern analysis of triggers	Digital logs + AI	Preventative care	Personalised trigger avoidance plans	Need for long-term user input	[54]
General Practice	Clinician adaptation to DTs	Survey + thematic analysis	Attitude research	Awareness of DTs' limitations	Sample size limitations	[27]
Public Health	Privacy regulations in digital health	Legal frameworks + AI	Data ethics and regulation	Stronger data control	Disparities in data law enforcement	[46]

4.10. Research Gaps in the Literature

Even though DT models are credited for their transforming ability in clinical contexts, the current studies in the literature commonly report technical updates and the theoretical potential of Digital Twins. However, empirical real-world instances to strengthen these models' healthcare success in patient treatments are lacking [6,10]. Also, due to insufficient insights into the practical effects, this theoretical assumption can minimise the practical data of DTs' adoption into operational healthcare practices and results [11,12]. Additionally, many current studies tend to focus on specific clinical applications, such as oncology and cardiology, while offering comparatively less attention to other domains where Digital Twin technology could be equally impactful. This narrower focus may limit broader insights into the adaptability and usability of DT models across diverse patient populations with varying needs [6,13,44]. To address this, further longitudinal research is recommended, especially into underrepresented areas such as mental health, to better illustrate the comprehensive potential of DTs in personalised care delivery.

5. Theoretical and Practical Contributions

This study offers theoretical insights and practical implications for advancing research and implementation of Digital Twin technologies in healthcare contexts.

5.1. Theoretical Contribution

This research aims to provide extensive insights into DT utilisations in healthcare areas from a theoretical angle. Through investigating DTs' competence in improving customised treatments and appropriateness, the study underscores the current hypothetical structures of medical instructions, customised therapies, and medicinal drugs. Additionally, it offers a substantial contribution to the enhancement of the literature frame by examining digital system integration in healthcare contexts. These theoretical frameworks aid in the development and innovation of new digital models for integrating these technologies into healthcare practices, thereby improving key understanding for both researchers and

healthcare stakeholders, such as practitioners and management [9]. Although the current studies repeatedly concentrate on the hypothetical benefits and technical developments of DT models, there is a vital gap in the detailed evaluation of their impact on treatment results [10–12].

This study advances theoretical understanding of Digital Twin (DT) models within the medical field by addressing a key gap in the existing literature, namely, the limited exploration of how DTs influence clinical outcomes [6,10,28,52]. While many articles highlight technological developments, few provide an in-depth analysis of their implications for personalised treatment and diagnostic accuracy. By synthesising findings from 70 peer-reviewed articles, our review identifies critical research gaps and evaluates how DTs contribute to precision medicine. To support this analysis, we draw upon theoretical perspectives such as system theory, simulation-based modelling, and predictive analytics frameworks [55]. These perspectives help clarify the functional role of DTs in healthcare as integrative tools that link patient data, simulations, and decision-making processes. For instance, system theory conceptualises healthcare delivery as a dynamic interplay of components, with DTs acting as mediators between real-time patient data and clinical interventions [55–57]. Through this theoretical framing, the study not only bridges empirical findings with conceptual models but also offers a foundation for future research on the strategic implementation of DTs in personalised care. In doing so, it contributes to a more coherent and actionable understanding of how DTs can enhance therapeutic outcomes and inform the design of intelligent healthcare systems [7].

To address the complexity of implementing Digital Twin (DT) technologies in healthcare, this study proposes a four-step conceptual framework (see Figure 6) that integrates the technical, clinical, and ethical dimensions required for successful adoption. Each step is visually represented to align with stakeholder roles and implementation phases and is grounded in findings from the literature.



Figure 6. Conceptual framework for Digital Twin implementation in the healthcare industry.

The foundational stage (or stakeholder engagement) focuses on preparing the organisational and human elements for DT adoption. It involves gaining commitment from healthcare professionals, IT staff, patients, and policymakers. Key activities include awareness campaigns, training initiatives, ethical dialogue, and addressing resistance to

change. This step reflects the importance of cultural readiness and value alignment in technology-enabled healthcare environments.

Once stakeholder support is established, the DT modelling step centres on the technical deployment of Digital Twin models, which enable real-time patient monitoring, predictive analytics, and personalised simulation. It incorporates AI-driven modelling, multi-modal data input, and dynamic feedback loops. Use cases include virtual clinical trials, ICU simulations, and patient-specific treatment planning.

Clinical workflow integration must be embedded into clinical processes and electronic health record systems. This phase emphasises interoperability, clinician usability, data flow integration, and the alignment of DT functions with existing clinical pathways. It ensures that DTs support, rather than disrupt, standard care delivery practices.

The final step ensures that DT systems operate within robust governance frameworks that safeguard patient rights, data privacy, and model fairness. This phase includes ethical oversight, regulatory compliance, continuous model evaluation, and transparent outcome reporting. It also involves incorporating feedback to refine models and support continuous improvement.

Together, these four steps provide a holistic, actionable roadmap for deploying Digital Twins in healthcare, addressing not just technical feasibility but also organisational, clinical, and ethical imperatives.

5.2. Practical Contribution

Practically, this study demonstrates a significant understanding of Digital Twins' integration in healthcare systems. It further describes the important effects on healthcare practices, technology producers, and policy creators. By assessing the competencies of these technologies in patients' clinical outcomes, medical specialists and practitioners can gain better insight into how these DT models can impact patient treatment advancements [9]. It also practically evaluates the ability of DTs in projecting and examining patients' reactions and conditions with digital devices, such as wearables, to incorporate well-timed and suitable interventions by minimising obstacles and optimising an individual's health conditions [5]. On the other hand, this research analyses the practical issues that occur during Digital Twins' adoption, such as scalability, ethical problems, and data compatibility, supplying stakeholders with the information required to effectively tackle these limitations [6]. Additionally, by exploring how Digital Twin models can support individualised patient care approaches and inform medical decisions for policymakers, this study provides actionable, real-world insights to effectively develop treatment processes within healthcare structures. These insights are key to establishing healthcare strategies that provide efficient Digital Twin simulation integration, eventually resulting in advancements in patient treatment and care outcomes. Overall, the understanding from this literature analysis focuses on assisting DT application in the health field, advancing healing outcomes and optimising clinical frameworks.

The analysis of Digital Twins in medical practices displays substantial support towards methodological, theoretical, and real-world empirical settings [12,58]. By investigating existing studies and assessing the DTs' impact on patients' treatment results, this research study aims to address current research gaps by providing an in-depth understanding that can provide vital support for future studies in the healthcare industry. Understanding the actual impacts of DT models on patient therapeutic outcomes is crucial for assisting stakeholders in the efficient implementation and integration of these innovative technologies across healthcare processes [1]. Hence, our analyses highlight key adoption issues and challenges, such as data compatibility, ethical concerns, and scalability in relation to patient confidentiality and consent, as discussed by [15]. Numerous investigations have

significantly overlooked the empirical concerns faced by medical institutions, creating a substantial gap between theoretical advantages and their practical applications [3,16]. Furthermore, by recognising the challenges and recommending suitable solutions, we offer key insights to healthcare policymakers and doctors to navigate the challenges of adopting DTs. Thus, our study explains the key requirements for established interoperability and provides guidelines to facilitate the easier implementation of these DT models into existing medical processes. Additionally, by analysing DTs' improvement in decision-making and aiding the enhancement of customised patient treatment strategies, our study provides substantial practical suggestions that can lead to optimised patient therapy outcomes [8]. Hence, these critical details eventually focus on minimising research gaps between healthcare practices and theories, thereby bolstering the advantages of DTs to improve healthcare structures and treatments [59–61].

5.3. Limitations and Future Studies

Our study has several limitations that provide opportunities for future research. Firstly, the methodological approach relies on currently available articles, which poses fundamental limitations due to its significant dependence on secondary data reviews. An extensive literature review on DTs focuses on theoretical approaches and trial models [61], instead of actual applications, restricting practical demonstrations that might aid in understanding the real-world effects of using DTs on patient results [62]. Another significant limitation is the reduced concentration of many available articles on certain applications of Digital Twin models, as in [63,64]. This focused study scope vitally diminishes deep insight into DTs' execution within diverse health areas and patients with specific requirements [26,65]. By heavily depending on this literature content, our research may accidentally ignore how Digital Twins function effectively across a wide range of healthcare systems, possibly distorting the understanding of DTs technology's adaptability and flexibility in medical contexts [7,26].

Contextually, DTs' adoption in current clinical processes is challenged due to ethical problems, interoperability, and scalability issues [66]. Several healthcare institutions often face challenges with digitalised systems that were not designed to support DTs, making the adoption of DTs difficult and expensive [67]. Furthermore, our study inadequately analyses the structural and financial limitations that could significantly limit the implementation of DTs, particularly in health settings with limited resources [68,69]. In addition, the legal guidelines, such as the Data Privacy Act 2020 [30], significantly emphasise the need for stringent restrictions; however, the research may not have fully explored how this regulatory act affects the scalability and practicability of DTs on a global scale. Due to these challenges and limitations, our study findings may have been impacted, possibly portraying DT models as seamlessly consolidative and efficient, rather than indicating how they function in real-world practical circumstances [38,70].

To address the limitations in our research, future studies on Digital Twin technologies in clinical settings may focus on various critical factors. Primarily, practical studies are significant because they stretch beyond theoretical approaches to analyse the healthcare efficacy and actual influence of DT models on patient results. Long-term assessments that continuously monitor patient results over extended periods could be critical in analysing the sustained competency of DTs, particularly in managing chronic conditions such as heart disease. These future analyses could comprise randomised controlled trials or associated research to generate robust facts on the estimated precision and flexibility of these DT models in diverse medical conditions, thus increasing the credibility of the study results. In addition, increasing the scope of the study of DTs to include several healthcare experts and patient populations would be valuable [71]. Also, our study analyses DT execution in

diminished areas, such as mental issues, thus delivering details about how DT technologies can be fruitfully tailored for diverse patient clusters. This would also aim to address the unique requirements of patients, offering in-depth insights into how Digital Twins perform across various medical scenarios and identifying any necessary adjustments for accurate patient outcomes.

To acquire a deep understanding of DTs and their impacts, integrating a mixed research approach that includes both qualitative and quantitative data analysis would provide a detailed insight from a methodological viewpoint. Additionally, qualitative data analysis, including broad focus groups, randomised experiments, and interviews with patients, policy creators, and healthcare specialists, could provide vital insights into the opportunities, limitations, cross-cultural, and ethical considerations associated with DT models. This method would provide quantitative outcomes by highlighting the views and contextual aspects of healthcare stakeholders that impact the integration of DTs in the health sector. Furthermore, ethically, upcoming studies should aim to enhance regularised guidelines for the adoption of DT technologies, including patient consent, data privacy, and security. Reflecting the confidentiality and sensitivity of medical information, analysing encryption techniques, data strategies, and tightened data-sharing protocols could assist in tackling security and privacy issues and foster public trust in DTs. Lastly, technical innovations in Digital Twins, AI, and ML present advanced study opportunities. Future research on this topic could analyse how these pioneering technologies optimise the predictive potential of DTs, involving DT adaptation for customised care in real time. Investigating DT integration with developing technologies like virtual reality tools for appropriate learning could create new opportunities for enhancing healthcare practices. By focusing on these study topics, future assessments could provide in-depth and empirical insights into Digital Twin models in healthcare practices, facilitating protection, ethical application, and effectiveness.

6. Conclusions

This research critically evaluates how Digital Twin technologies can enhance the accuracy and personalisation of patient treatment and care. Through producing virtual models, Digital Twins significantly facilitate predictive evaluations and customised therapies to anticipate patient reactions to treatment, optimising medical outcomes and facilitating informed involvement, although key challenges, such as technological, data privacy, protection, and ethical issues, must be critically navigated to ensure successful implementation. The study findings outline the ability of Digital Twin technology to advance the healthcare industry by improving patient outcomes through proactive clinical approaches and decisions. Furthermore, future research must focus on addressing limitations to adoptions by implementing robust healthcare policies, practical applications, and interdisciplinary assessments, as well as establishing the incorporation of Digital Twins in healthcare practices to achieve the full benefits of personalised care and medicines.

Author Contributions: Conceptualization, S.S. and N.H.S.A.; methodology, S.S.; software, S.S.; validation, S.S., N.H.S.A. and Z.L.W.; formal analysis, S.S.; investigation, S.S.; resources, Z.L.W.; data curation, S.S.; writing—original draft preparation, S.S.; writing—review and editing, N.H.S.A. and Z.L.W.; visualization, S.S.; supervision, N.H.S.A.; project administration, Z.L.W.; funding acquisition, N.H.S.A. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Acknowledgments: The authors acknowledge Amr Adel for assistance with Figure 1.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Supplementary definitions.

Term	Definition	References
Digital Twin	A Digital Twin technology is a virtual model of a real human being that assists healthcare experts to identify and obtain significant insights, optimise medical treatments and practices, and provide customised individual care and treatment by adopting multiple data sources.	[25,39]
Healthcare	A system designed for diagnosing, treating, anticipating, and controlling patient's medical conditions, concentrated on enhancing well-being and supporting high-quality healthcare practices.	[8,40]
Personalised Treatment	Healthcare method which customises the clinical involvements based on each patient's particular conditions, needs, and characteristics, leveraging innovative technologies like artificial intelligence and Digital Twins to optimise medical care effectiveness.	[41,44]
Technology Advancements	The adoption and enhancements of advanced technologies to increase results and effectiveness in clinical and health sciences, confronting problems such as system interoperability and cybersecurity.	[36,42]
Patient Treatment Outcome	The clinical consequences and impacts for patients, mainly considering disease progress and its efficiency of involvements.	[45,56]
Virtual Models	Digital replicas that operate as alike counterparts to real physical objects, mirroring their exact attributes and behaviours. These virtual stimulations are coupled to real-time active data, allowing for virtual realities and evaluation to optimise comprehension and informed decisions in diverse implementations in healthcare.	[39,54]
Impacts	Digital Twins' considerable impacts on various areas, specifically in the healthcare sector, in terms of transmuting practices, increasing understanding, and fostering innovative adoptions in response to the benefits and challenges created through digitalisation practices.	[37,57]
Applications	Digital Twins' practical utilisations in research studies and healthcare contexts for virtualising and copying biological procedures and patients' health situations.	[59,60]

References

1. Safa, E.; Asan, O. Digital Twins for Managing Health Care Systems: Rapid Literature Review. *J. Med. Internet Res.* **2022**, *24*, e37641. [CrossRef]
2. Kulkarni, C.; Quraishi, A.; Mohan, R.; Shabaz, M.; Khan, M.A.; Varma, R.A.; Keshta, I.; Soni, M.; Byeon, H. Hybrid disease prediction approach leveraging digital twin and metaverse technologies for health consumer. *BMC Med. Inform. Decis. Mak.* **2024**, *24*, 92. [CrossRef]
3. Cellina, M.; Cè, M.; Ali, M.; Irmici, G.; Ibba, S.; Caloro, E.; Fazzini, D.; Oliva, G.; Papa, S. Digital Twins: The New Frontier for Personalized Medicine? *Appl. Sci.* **2023**, *13*, 7940. [CrossRef]
4. Palaniappan, R.; Surendran, S. A Digital Twin Approach for deepened Classification of Patients with Hepatitis, Fibrosis and Cirrhosis. *J. Phys. Conf. Ser.* **2022**, *2335*, 012034. [CrossRef]
5. Johnson, Z.; Saikia, M.J. Digital Twins for Healthcare Using Wearables. *Bioengineering* **2024**, *11*, 606. [CrossRef]
6. Katsoulakis, E.; Wang, Q.; Wu, H.; Shahriyari, L.; Fletcher, R.; Liu, J.; Achenie, L.; Liu, H.; Jackson, P.; Xiao, Y. Digital twins for health: A scoping review. *NPJ Digit. Med.* **2024**, *7*, 77. [CrossRef] [PubMed]
7. Rudnicka, Z.; Proniewska, K.; Perkins, M.; Pregowska, A. Cardiac Healthcare Digital Twins Supported by Artificial Intelligence-Based Algorithms and Extended Reality—A Systematic Review. *Electronics* **2024**, *13*, 866. [CrossRef]
8. Dang, J.; Lal, A.; Montgomery, A.; Flurin, L.; Litell, J.; Gajic, O.; Rabinstein, A. Developing DELPHI expert consensus rules for a digital twin model of acute stroke care in the neuro critical care unit. *BMC Neurol.* **2023**, *23*, 1–12. [CrossRef] [PubMed]

9. Chu, Y.; Li, S.; Tang, J.; Wu, H. The potential of the Medical Digital Twin in diabetes management: A review. *Front. Med.* **2023**, *10*, 1178912. [CrossRef]
10. Laubenbacher, R.; Niarakis, A.; Helikar, T.; An, G.; Shapiro, B.; Malik-Sheriff, R.S.; Sego, T.J.; Knapp, A.; Macklin, P.; Glazier, J.A. Building digital twins of the human immune system: Toward a roadmap. *NPJ Digit. Med.* **2022**, *5*, 64. [CrossRef]
11. Mohapatra, S.; Bose, S. An appraisal of literature for design and implementation of developing a framework for digital twin and validation through case studies. *Health Technol.* **2020**, *10*, 1229–1237. [CrossRef]
12. Vallée, A. Digital twin for healthcare systems. *Front. Digit. Health* **2023**, *5*, 1253050. [CrossRef] [PubMed]
13. Avanzato, R.; Beritelli, F.; Lombardo, A.; Ricci, C. Lung-DT: An AI-Powered Digital Twin Framework for Thoracic Health Monitoring and Diagnosis. *Sensors* **2024**, *24*, 958. [CrossRef] [PubMed]
14. Konopik, J.; Wolf, L.; Schöffski, O. Digital twins for breast cancer treatment—An empirical study on stakeholders' perspectives on potentials and challenges. *Health Technol.* **2023**, *13*, 1003–1010. [CrossRef]
15. Turab, M.; Jamil, S. A comprehensive survey of digital twins in healthcare in the era of metaverse. *BioMedInformatics* **2023**, *3*, 563–584. [CrossRef]
16. Wickramasinghe, N.; Ulapane, N.; Andargoli, A.; Shuakat, N.; Nguyen, T.; Zelcer, J.; Vaughan, S. Digital twin of patient in clinical workflow. *Proc. R. Soc. Vic.* **2023**, *135*, 72–80. [CrossRef]
17. Machado, T.M.; Berssaneti, F.T. Literature review of digital twin in healthcare. *Heliyon* **2023**, *9*, e19390. [CrossRef]
18. Cronin, M.A.; George, E. The why and how of the integrative review. *Organ. Res. Methods* **2023**, *26*, 168–192. [CrossRef]
19. Battistone, M.J.; Kemeyou, L.; Varpio, L. The Theoretical Integrative Review—A Reader's Guide. *J. Grad. Med. Educ.* **2023**, *15*, 449–452. [CrossRef]
20. Harari, M.B.; Parola, H.R.; Hartwell, C.J.; Riegelman, A. Literature searches in systematic reviews and meta-analyses: A review, evaluation, and recommendations. *J. Vocat. Behav.* **2020**, *118*, 103377. [CrossRef]
21. McCrae, N.; Blackstock, M.; Purssell, E. Eligibility criteria in systematic reviews: A methodological review. *Int. J. Nurs. Stud.* **2015**, *52*, 1269–1276. [CrossRef]
22. Chigbu, U.E.; Atiku, S.O.; Du Plessis, C.C. The science of literature reviews: Searching, identifying, selecting, and synthesising. *Publications* **2023**, *11*, 2. [CrossRef]
23. Neuendorf, K.A. Content analysis and thematic analysis. In *Advanced Research Method*; Routledge: Oxfordshire, UK, 2018.
24. Moztarzadeh, O.; Mohammad, J.; Saleh, S.; Jamshidi, A.; Baghalipour, N.; Mona Malekzadeh, M.; Hauer, L. Metaverse and Healthcare: Machine Learning-Enabled Digital Twins of Cancer. *Bioengineering* **2023**, *10*, 455. [CrossRef]
25. Meijer, C.; Uh, H.W.; El Bouhaddani, S. Digital Twins in Healthcare: Methodological Challenges and Opportunities. *J. Pers. Med.* **2023**, *13*, 1522. [CrossRef] [PubMed]
26. Iqbal, J.D.; Krauthammer, M.; Biller-Andorno, N. The Use and Ethics of Digital Twins in Medicine. *J. Law Med. Ethics* **2022**, *50*, 583–596. [CrossRef]
27. Zalake, M. Doctors' perceptions of using their digital twins in patient care. *Sci. Rep.* **2023**, *13*, 21693. [CrossRef] [PubMed]
28. Pei-hua, H.; Ki-hun, K.; Schermer, M. Ethical Issues of Digital Twins for Personalized Health Care Service: Preliminary Mapping Study. *J. Med. Internet Res.* **2022**, *24*, e33081. [CrossRef]
29. Duan, H.; Gao, S.; Yang, X.; Li, Y. The development of a digital twin concept system. *Digit. Twin* **2025**, *2*, 10. [CrossRef]
30. Privacy Commissioner. Privacy Act 2020: Privacy Principles. Privacy Commissioner New Zealand. 2020. Available online: <https://www.privacy.org.nz/privacy-act-2020/privacy-principles/> (accessed on 18 August 2025).
31. Abdullayev, K.; Gorvett, O.; Sochiera, A.; Laidlaw, L.; Chico, T.; Manktelow, M.; Buckley, O.; Condell, J.; Richard Van, A.; Diaz, V.; et al. Stakeholder perspectives on contributors to delayed and inaccurate diagnosis of cardiovascular disease and their implications for digital health technologies: A UK-based qualitative study. *BMJ Open* **2024**, *14*, e080445. [CrossRef]
32. Hu, W.; Zhang, T.; Deng, X.; Liu, Z.; Tan, J. Digital twin: A state-of-the-art review of its enabling technologies, applications and challenges. *J. Intell. Manuf. Spec. Equip.* **2021**, *2*, 1–34. [CrossRef]
33. Sharma, A.; Kosasih, E.; Zhang, J.; Brintrup, A.; Calinescu, A. Digital Twins: State of the art theory and practice, challenges, and open research questions. *J. Ind. Inf. Integr.* **2022**, *30*, 100383. [CrossRef]
34. Winter, P.D.; Chico, T.J.A. Using the Non-Adoption, Abandonment, Scale-Up, Spread, and Sustainability (NASSS) Framework to Identify Barriers and Facilitators for the Implementation of Digital Twins in Cardiovascular Medicine. *Sensors* **2023**, *23*, 6333. [CrossRef] [PubMed]
35. Ferlito, B.; De Proost, M.; Segers, S. Navigating the Landscape of Digital Twins in Medicine: A Relational Bioethical Inquiry. *Asian Bioeth. Rev.* **2024**, *16*, 471–481. [CrossRef] [PubMed]
36. Vidovszky, A.A.; Fisher, C.K.; Loukianov, A.D.; Smith, A.M.; Tramel, E.W.; Walsh, J.R.; Ross, J.L. Increasing acceptance of AI-generated digital twins through clinical trial applications. *Clin. Transl. Sci.* **2024**, *17*, e13897. [CrossRef]
37. Lehmann, J.; Lorenz, G.; Browne, R.; Ogawa, T.; Kokubun, K.; Taki, Y.; Jokinen, K.; Janboeck, S.; Lohr, C.; Wieching, R.; et al. Digital Twins for Supporting Ageing Well: Approaches in Current Research and Innovation in Europe and Japan. *Sustainability* **2024**, *16*, 3064. [CrossRef]

38. Tzachor, A.; Sabri, S.; Richards, C.E.; Schlüter, M.; Ruckelshaus, M.; Creutzig, F. Potential and limitations of digital twins to achieve the Sustainable Development Goals. *Nat. Sustain.* **2022**, *5*, 822–829. [\[CrossRef\]](#)
39. Armeni, P.; Polat, I.; De Rossi, L.M.; Diaferia, L.; Meregalli, S.; Gatti, A. Digital Twins in Healthcare: Is It the Beginning of a New Era of Evidence-Based Medicine? A Critical Review. *J. Pers. Med.* **2022**, *12*, 1255. [\[CrossRef\]](#)
40. Adibi, S.; Rajabifard, A.; Shojaei, D.; Wickramasinghe, N. Enhancing Healthcare through Sensor-Enabled Digital Twins in Smart Environments: A Comprehensive Analysis. *Sensors* **2024**, *24*, 2793. [\[CrossRef\]](#)
41. Sun, T.; Wang, J.; Moran, S.; Liu, X.; Huang, H.; Zhang, J.; Zhang, W.; Li, Z. The Digital Twin: A Potential Solution for the Personalized Diagnosis and Treatment of Musculoskeletal System Diseases. *Bioengineering* **2023**, *10*, 627. [\[CrossRef\]](#)
42. Vasiliu-Feltes, I.; Mylrea, M.; Christina Yan, Z.; Tyler Cohen, W.; Thornley, B. Impact of Blockchain-Digital Twin Technology on Precision Health, Pharmaceutical Industry, and Life Sciences Conv2X 2023 Report. *Blockchain Healthc. Today* **2023**, *6*. Available online: <https://blockchainhealthcaredtoday.com/index.php/journal/article/view/281> (accessed on 18 August 2025). [\[CrossRef\]](#)
43. Coorey, G.; Figtree, G.A.; Fletcher, D.F.; Snelson, V.J.; Vernon, S.T.; Winlaw, D.; Grieve, S.M.; McEwan, A.; Yang, J.Y.H.; Qian, P.; et al. The health digital twin to tackle cardiovascular disease—A review of an emerging interdisciplinary field. *NPJ Digit. Med.* **2022**, *5*, 126. [\[CrossRef\]](#)
44. Sahal, R.; Alsamhi, S.H.; Brown, K.N. Personal Digital Twin: A Close Look into the Present and a Step towards the Future of Personalised Healthcare Industry. *Sensors* **2022**, *22*, 5918. [\[CrossRef\]](#) [\[PubMed\]](#)
45. Tardini, E.; Zhang, X.; Canahuat, G.; Wentzel, A.; Mohamed, A.S.R.; Lisanne Van, D.; Fuller, C.D.; Marai, G.E. Optimal Treatment Selection in Sequential Systemic and Locoregional Therapy of Oropharyngeal Squamous Carcinomas: Deep Q-Learning With a Patient-Physician Digital Twin Dyad. *J. Med. Internet Res.* **2022**, *24*, e29455. [\[CrossRef\]](#) [\[PubMed\]](#)
46. Wang, M.; Hu, H.; Wu, S. Opportunities and challenges of digital twin technology in healthcare. *Chin. Med. J.* **2023**, *136*, 2895–2896. [\[CrossRef\]](#) [\[PubMed\]](#)
47. Md Shafiqur Rahman, J.; Emillia Vann, Y.; Ilodibe, A.; Eldabi, T. Ethical and Quality of Care-Related Challenges of Digital Health Twins in Older Care Settings: Protocol for a Scoping Review. *JMIR Res. Protoc.* **2024**, *13*, e51153. [\[CrossRef\]](#) [\[PubMed\]](#)
48. Volkov, I.; Radchenko, G.; Tchernykh, A. Digital Twins, Internet of Things and Mobile Medicine: A Review of Current Platforms to Support Smart Healthcare. *Program. Comput. Softw.* **2021**, *47*, 578–590. [\[CrossRef\]](#)
49. Drummond, D.; Coulet, A. Technical, Ethical, Legal, and Societal Challenges With Digital Twin Systems for the Management of Chronic Diseases in Children and Young People. *J. Med. Internet Res.* **2022**, *24*, e39698. [\[CrossRef\]](#)
50. Lee, J.-H.; Lee, H.-L.; Park, I.-Y.; On, S.-W.; Byun, S.-H.; Yang, B.-E. Effectiveness of creating digital twins with different digital dentition models and cone-beam computed tomography. *Sci. Rep.* **2023**, *13*, 10603. [\[CrossRef\]](#)
51. Adel, A.; HSAIani, N. Human-Centric Collaboration and Industry 5.0 Framework in Smart Cities and Communities: Fostering Sustainable Development Goals 3, 4, 9, and 11 in Society 5.0. *Smart Cities* **2024**, *7*, 1723–1775. [\[CrossRef\]](#)
52. Kolokotroni, E.; Abler, D.; Ghosh, A.; Tzamali, E.; Grogan, J.; Georgiadi, E.; Büchler, P.; Radhakrishnan, R.; Byrne, H.; Sakalis, V.; et al. A Multidisciplinary Hyper-Modeling Scheme in Personalized In Silico Oncology: Coupling Cell Kinetics with Metabolism, Signaling Networks, and Biomechanics as Plug-In Component Models of a Cancer Digital Twin. *J. Pers. Med.* **2024**, *14*, 475. [\[CrossRef\]](#)
53. Cho, R.-Y.; Soo-Hwan, B.; Sang-Min, Y.; Hee-Ju, A.; Yoo-Sung, N.; Park, I.-Y.; Sung-Woon, O.; Jong-Cheol, K.; Byoung-Eun, Y. Comparative Analysis of Three Facial Scanners for Creating Digital Twins by Focusing on the Difference in Scanning Method. *Bioengineering* **2023**, *10*, 545. [\[CrossRef\]](#)
54. Gazerani, P. Intelligent Digital Twins for Personalized Migraine Care. *J. Pers. Med.* **2023**, *13*, 1255. [\[CrossRef\]](#)
55. Kaul, R.; Ossai, C.; Forkan, A.R.M.; Jayaraman, P.P.; Zelcer, J.; Vaughan, S.; Wickramasinghe, N. The role of AI for developing digital twins in healthcare: The case of cancer care. *Wiley Interdiscip. Rev. Data Min. Knowl. Discov.* **2023**, *13*, e1480. [\[CrossRef\]](#)
56. Cen, S.; Gebregziabher, M.; Moazami, S.; Azevedo, C.J.; Pelletier, D. Toward precision medicine using a “digital twin” approach: Modeling the onset of disease-specific brain atrophy in individuals with multiple sclerosis. *Sci. Rep.* **2023**, *13*, 16279. [\[CrossRef\]](#) [\[PubMed\]](#)
57. Hassani, H.; Huang, X.; MacFeely, S. Impactful Digital Twin in the Healthcare Revolution. *Big Data Cogn. Comput.* **2022**, *6*, 83. [\[CrossRef\]](#)
58. Ebiloma, D.O.; Aigbavboa, C.O.; Anumba, C. Towards Digital Twin Maintenance Management of Health Facilities in Nigeria: The Need for Maintenance Documentation. *Buildings* **2023**, *13*, 1339. [\[CrossRef\]](#)
59. Emmert-Streib, F.; Yli-Harja, O. What Is a Digital Twin? Experimental Design for a Data-Centric Machine Learning Perspective in Health. *Int. J. Mol. Sci.* **2022**, *23*, 13149. [\[CrossRef\]](#)
60. Chakshu Neeraj, K.; Sazonov, I.; Nithiarasu, P. Towards enabling a cardiovascular digital twin for human systemic circulation using inverse analysis. *Biomech. Model. Mechanobiol.* **2021**, *20*, 449–465. [\[CrossRef\]](#)
61. Yeman, R. The Application of Agile to Large-Scale, Safety-Critical, Cyber-Physical Systems. Ph.D. Thesis, Colorado State University, Fort Collins, CO, USA, 2025.
62. Basaure, V. Models in medicine: The digital twin for health. *Ser. Selección De Textos* **2025**, *10*, 3–16. [\[CrossRef\]](#)

63. Botín-Sanabria, D.M.; Mihaita, A.S.; Peimbert-García, R.E.; Ramírez-Moreno, M.A.; Ramírez-Mendoza, R.A.; Lozoya-Santos, J.D.J. Digital twin technology challenges and applications: A comprehensive review. *Remote Sens.* **2022**, *14*, 1335. [[CrossRef](#)]
64. Fagherazzi, G. Deep Digital Phenotyping and Digital Twins for Precision Health: Time to Dig Deeper. *J. Med. Internet Res.* **2020**, *22*, e16770. [[CrossRef](#)] [[PubMed](#)]
65. Calcaterra, V.; Pagani, V.; Zuccotti, G. Digital Twin: A Future Health Challenge in Prevention, Early Diagnosis and Personalisation of Medical Care in Paediatrics. *Int. J. Environ. Res. Public Health* **2023**, *20*, 2181. [[CrossRef](#)] [[PubMed](#)]
66. Corrin, L.; Thompson, K.; Hwang, G.-J.; Lodge, J.M. The importance of choosing the right keywords for educational technology publications. *Australas. J. Educ. Technol.* **2022**, *38*, 1–8. [[CrossRef](#)]
67. Adel, A.; Alani, N.H.S.; Jan, T. Factories of the future in industry 5.0—Softwarization, servitization, and industrialization. *Internet Things* **2024**, *24*, 101431. [[CrossRef](#)]
68. Sigawi, T.; Yaron, I. Using Constrained-Disorder Principle-Based Systems to Improve the Performance of Digital Twins in Biological Systems. *Biomimetics* **2023**, *8*, 359. [[CrossRef](#)]
69. John, L.K. Harnessing Cloud Infrastructure for DevOps Excellence. *Int. J. Comput. Exp. Sci. Eng.* **2025**, *11*, 2. [[CrossRef](#)]
70. Papachristou, K.; Katsakiori, P.F.; Papadimitroulas, P.; Strigari, L.; Kagadis, G.C. Digital Twins' Advancements and Applications in Healthcare, Towards Precision Medicine. *J. Pers. Med.* **2024**, *14*, 1101. [[CrossRef](#)]
71. Mousavi, V.; Rashidi, M.; Mohammadi, M.; Samali, B. Evolution of Digital Twin Frameworks in Bridge Management: Review and Future Directions. *Remote Sens.* **2024**, *16*, 1887. [[CrossRef](#)]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.