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Review

Agentic AI-Enabled Digital Twins for Intelligent Non-Destructive Testing of 3D-Printed Rehabilitation Equipment—A Narrative Review

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Featured Application

A potential application of this work is the integration of AI-driven digital twins as complementary tools for non-destructive testing.

Abstract

Digital twins (DTs) based on agent-based artificial intelligence (Agentic AI) provide a transformative framework for streamlining nondestructive testing (NDT) of 3D-printed rehabilitation equipment. This study applies a conceptual research methodology based on the integration and analysis of recent advances in Agentic AI, digital twin architectures, additive manufacturing, NDT technologies, and intelligent rehabilitation systems to establish a framework for autonomous quality monitoring and lifecycle management of 3D-printed medical devices. By creating intelligent virtual replicas of physical devices, these systems enable continuous monitoring of structural integrity, functional performance, and degradation mechanisms throughout the product lifecycle. Unlike conventional AI-based DTs, Agentic AI-driven DTs can autonomously perceive, reason, plan, and execute corrective actions based on real-time sensor data, NDT results, manufacturing information, and historical knowledge. The main conclusion of this work is that Agentic AI-enhanced DTs have the potential to transform NDT from a passive inspection approach into an intelligent, predictive, and autonomous decision-support system for rehabilitation equipment. Advanced machine learning and autonomous decision-making algorithms enable the identification of early signs of material degradation, manufacturing defects, fatigue accumulation, and performance anomalies, supporting predictive maintenance and proactive quality assurance. Integrating Agentic AI DTs with additive manufacturing processes enables real-time optimization of printing parameters, adaptive process control, and continuous refinement of inspection strategies without production interruption or destructive sampling, thereby supporting Industry 4.0 and smart manufacturing principles. The main innovation of this research lies in proposing an autonomous closed-loop framework that combines Agentic AI, DTs, additive manufacturing, and NDT into a unified system capable of continuous learning, reasoning, and operational optimization. Compared with existing studies that

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mainly focus on AI-assisted defect detection or static digital twin models, this approach introduces autonomous agents capable of coordinating sensing, simulation, diagnosis, prediction, and corrective actions across the entire lifecycle of 3D-printed rehabilitation devices. The proposed concept extends current digital twin applications by incorporating virtual stress testing, autonomous simulation, patient-specific customization, and adaptive device management, reducing dependence on physical prototypes, minimizing material waste, and accelerating design validation. By combining autonomous reasoning with predictive analytics, Agentic AI-based DTs represent a next-generation solution for intelligent, adaptive, and sustainable nondestructive testing, advancing both additive manufacturing technologies and personalized rehabilitation engineering.

Keywords: healthcare; rehabilitation; physical therapy; non-destructive testing; assistive devices; artificial intelligence; agentic AI; machine learning; digital twins; 3D printing

1. Introduction

This article clearly distinguishes agent-based AI from traditional AI by emphasizing its capacity for autonomous perception, reasoning, planning, decision-making, and adaptive control, which are the defining characteristics expected in contemporary agent-based systems research. The emergence of AI-driven DTs for NDT of 3D-printed rehabilitation equipment was driven by the convergence of additive manufacturing, advanced sensor technologies, cyberphysical systems (CPS), and autonomous AI. Early implementations of DTs were developed primarily for the aerospace and industrial machinery industries, where virtual replicas enabled predictive maintenance and condition monitoring based on continuously collected operational data [1]. With the growing popularity of additive manufacturing in medicine and rehabilitation, scientists and clinicians recognized the need for intelligent quality assurance methods capable of verifying the integrity of highly personalized medical devices without compromising their functionality or patient-specific design [2]. This demand accelerated the development of NDT-assisted DTs. Integrating embedded sensors with additively manufactured structures provided a continuous stream of real-time data, essential for constructing synchronized virtual representations of physical devices. Initially, machine learning (ML) techniques enhanced these DTs, enabling defect detection and predicting material degradation [3]. Recent advances in agent-based AI have transformed DTs from passive analytical models into autonomous cybernetic–physical agents capable of perceiving, reasoning, planning, and acting in dynamic production and operational environments. Instead of merely identifying defects, AI-based, agent-based decision-making systems can autonomously determine the most appropriate inspection strategy, optimize testing parameters, recommend corrective actions, and continuously adapt their behavior to changing system conditions. The increasing structural and functional complexity of personalized rehabilitation devices (including patient-specific orthoses, prosthetic components, and exoskeletons) has further motivated the implementation of autonomous DTs capable of verifying performance and structural integrity before physical failures occur [4]. At the same time, advances in cloud computing, edge computing, the Internet of Things (IoT), and the Internet of Medical Things (IoMT) have enabled seamless synchronization between physical devices and their digital counterparts, supporting continuous monitoring and autonomous decision-making throughout the product lifecycle [5]. As a result, DTs have evolved from static design and simulation tools to intelligent, self-learning, and self-adaptive platforms that continuously improve through interaction with both manufacturing processes and operational environments. This evolution establishes Agentic AI-based DTs as a new generation of intelligent NDT systems capable of autonomous inspection planning, adaptive diagnostics, predictive maintenance, and closed-loop quality assurance in the additive manufacturing of rehabilitation equipment.

The selection of the appropriate NDT method still depends on material properties, anticipated failure mechanisms, production conditions, and operational requirements [6]. Conventional NDT techniques (including ultrasonic testing, acoustic emission testing, infrared thermography, radiographic testing, eddy current testing, and X-ray computed tomography) remain the primary inspection methods [7]. However, Agentic AI-based DTs significantly expand their capabilities by autonomously integrating multimodal sensor data, dynamically selecting optimal inspection procedures, interpreting complex diagnostic information, and continuously refining inspection strategies. As a result, Agentic AI introduces a new paradigm of intelligent, adaptive, and autonomous nondestructive testing, particularly for highly personalized 3D-printed rehabilitation equipment. Figure 1 clearly illustrates the transition from static digital models, through AI-driven DTs, to agent-driven digital transformation DTs.

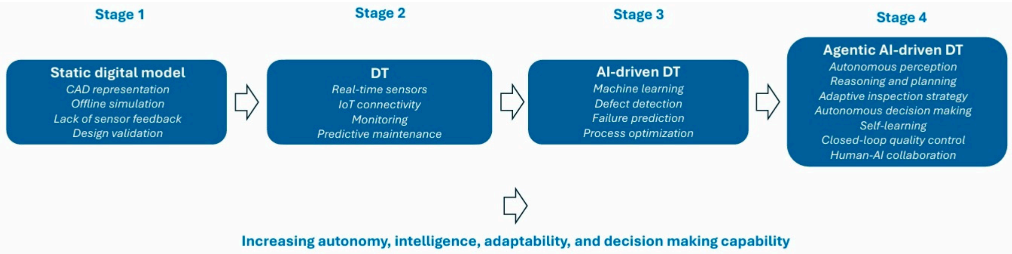

Figure 1. Evolution toward Agentic AI-Driven Digital Twins.

3D-printed rehabilitation equipment, including custom-tailored orthoses, prosthetic components, and exoskeletons, has become a cornerstone of personalized rehabilitation and physical therapy. Their customizable geometry, tailored material properties, and customized manufacturing processes make these devices particularly well-suited for Agentic AI-based digital twins, which create highly accurate virtual counterparts synchronized with their physical counterparts throughout the product lifecycle [8]. Unlike conventional digital twins, Agentic AI-based digital twins continuously perceive, interpret, and respond to changing operating conditions, enabling autonomous monitoring and intelligent decision support. Integrating embedded sensors into additively manufactured rehabilitation devices provides a continuous stream of structural and operational data that maintains real-time synchronization between the physical device and its digital representation [9]. Agent-based AI DTs have the potential to continuously integrate updated data from physical assets, adapt their digital representations and reasoning processes, and support context-aware decision-making through feedback-based interactions. Recent research highlights the convergence of agent-based AI and DTs in adaptive decision-making, continuous learning, real-time state synchronization, and feedback-based autonomy [10]. However, in the case of 3D-printed rehabilitation equipment, these capabilities remain largely conceptual and require experimental validation before they can be considered reliable for autonomous nondestructive testing and safety-critical decision-making. Because these devices are routinely exposed to highly individualized loading conditions resulting from patient-specific anatomy, movement patterns, and rehabilitation protocols, Agentic AI-based digital DTs continuously analyze user behavior to assess structural integrity and predict performance degradation [11]. Through autonomous reasoning and adaptive learning, these intelligent systems can identify emerging failure mechanisms, assess their severity, and recommend appropriate follow-up or maintenance actions. Patient-specific orthoses particularly benefit from AI-based monitoring, as autonomous DTs can detect local stress concentrations, progressive material degradation, or poor fit caused by repetitive loading long before visible damage occurs [12]. Similarly, wearable exoskeletons operate under complex and highly dynamic biomechanical loading conditions that require continuous assessment of the structural health. AI-based DT systems integrate physics-based simulations with machine learning and autonomous decision-making to predict fatigue, optimize structural durability, and improve operational safety throughout the rehabilitation process [13]. Beyond predictive diagnostics, AI-based DT systems actively support adaptive quality assurance by autonomously selecting inspection strategies, optimizing NDT procedures, and continuously refining predictive models using newly acquired sensor data [14]. Their ability to autonomously perceive, reason, plan, and make closed-loop decisions enables proactive maintenance, individual device adjustments, and continuous optimization without interruption. Furthermore, knowledge accumulated throughout the device lifecycle provides valuable feedback that allows for the improvement of future rehabilitation equipment designs by identifying relationships between printing parameters, material behavior, patient use patterns, and long-term structural performance [15]. Therefore, 3D-printed rehabilitation devices are not only advanced, personalized medical products but also intelligent CPSs that continuously generate valuable operational data. In this context, 3D-printed DTs based on Agentic AI represent a next-generation platform for intelligent, adaptive, and autonomous NDT, enabling predictive quality assurance, personalized rehabilitation support, and continuous optimization of additive manufacturing processes.

A conventional AI/ML model applied to 3D-printed rehabilitation devices typically performs specific analytical tasks, such as defect classification, performance prediction, or pattern recognition, using available datasets but does not necessarily represent a complete DT. A true DT requires a persistent virtual representation of the physical rehabilitation device that remains continuously synchronized with its real-world counterpart throughout its lifecycle. There is no universally accepted "true" or single DT model. The model described in our manuscript is a proposed, application-specific framework for NDT of 3D-printed rehabilitation equipment. The proposed framework should be understood as a conceptual architecture tailored to the requirements of a given application, not as a universal DT model. Different DT implementations may appropriately utilize different combinations of physical models, data-driven models, sensing mechanisms, AI/ML algorithms, communication interfaces, and feedback mechanisms, depending on their intended use. This interpretation is consistent with the broader DT literature, which recognizes significant variation in DT architectures and implementations across different application domains. The proposed agent-based AI-enabled architecture is presented as one possible approach to integrating NDT data, digital representation, AI-based reasoning, and feedback mechanisms for rehabilitation equipment. It is not intended to establish a universal standard for DT development or to suggest that other DT models used in different applications are less valid. In the context of 3D-printed rehabilitation devices, this synchronization involves real-time data acquisition from sensors, non-destructive testing systems, manufacturing records, and patient use monitoring. Unlike standalone AI/ML models, a DT enables bidirectional data flow, allowing the virtual model to be updated with information from the physical device, while AI-based insights from the digital twin can inform device adjustment, maintenance, or redesign. A DT model also integrates physics-based models, material behavior, structural integrity assessment, and operating conditions to simulate future performance rather than simply analyzing historical data. Agentic AI-powered DTs differ from generic AI/ML approaches by combining continuous connectivity, autonomous inference, predictive simulation, and closed-loop control, enabling safer, personalized, and adaptive management of rehabilitation devices. We define agentic AI not only by the presence of perception, reasoning, planning, or decision-making, but also by its ability to autonomously pursue specific goals through iterative cycles of perception–reasoning–planning–action–feedback, while simultaneously adapting its actions to changing conditions and incorporating feedback from the environment. This definition establishes more practical criteria for identifying an agentic AI system.

Agentic AI-based DTs provide a transformative approach to modeling the structural behavior of 3D-printed rehabilitation equipment by creating autonomous virtual representations capable of simulating mechanical parameters without physically loading the device, reducing material consumption, prototyping costs, and manufacturing waste. Through continuous interaction with physical assets and intelligent analysis of multimodal sensor data, these DTs can identify potential failure mechanisms, assess design reliability, and autonomously recommend design improvements before manufacturing, significantly shortening product development cycles [16]. Beyond the design phase, Agentic AI-based DTs enable continuous, non-destructive monitoring of rehabilitation equipment throughout its lifecycle, making them particularly valuable in remote healthcare and telerehabilitation environments [17]. By integrating patient-specific biomechanical data with real-time sensor measurements, these intelligent systems autonomously model individual user interactions with rehabilitation devices under varying physiological and environmental conditions. This capability supports the development and continuous adaptation of personalized orthoses, prostheses, and wearable exoskeletons, while improving both therapeutic efficacy and patient safety [18]. Despite these advantages, several technical challenges remain. Developing high-fidelity agentic AI-based decision-making systems requires extensive multimodal datasets, accurate material models, and robust representations of manufacturing and biomechanical processes, all of which require significant computational resources and specialized knowledge [19]. Furthermore, the reliability of autonomous decision-making depends on the quality of the underlying data. Predictions can become inaccurate when training datasets are incomplete, biased, poorly validated, or derived from fragmented historical records, limiting the effectiveness of autonomous reasoning and adaptive control [20]. Implementing embedded sensor technologies necessary for continuous synchronization between physical devices and their digital counterparts also increases system complexity, implementation costs, and cybersecurity requirements [21]. Although autonomous DTs based on Agentic AI significantly reduce the need for destructive testing, overreliance on simulation can miss rare or unexpected defects that can only be identified using complementary physical inspection methods. Therefore, autonomous DTs should be viewed as intelligent decision support systems that augment, rather than replace, conventional experimental validation and established NDT techniques. Maintaining autonomous DTs based on Agentic AI throughout the rehabilitation equipment lifecycle additionally requires continuous model updates, cloud-based computing infrastructure, secure data management, and interdisciplinary expertise in additive manufacturing, biomechanics, artificial intelligence, and medical engineering [22]. To facilitate broader clinical and industrial implementation, healthcare systems and research organizations should establish standardized reference datasets, validated DT frameworks, and pre-trained agent-based AI models that can be tailored to specific rehabilitation applications. Such common infrastructures would improve interoperability, reduce implementation costs, accelerate regulatory acceptance, and enable scalable implementation of autonomous digital twin technologies in personalized rehabilitation and additive manufacturing ecosystems [23].

Despite significant progress in digital twin technologies, a number of scientific, technological, and clinical challenges still limit the implementation of AI-based DTs for NDT of 3D-printed rehabilitation equipment. From a scientific perspective, it is still unclear how to accurately model the anisotropic, heterogeneous, and layer-dependent mechanical behavior of additively manufactured biomaterials used in rehabilitation technologies [24].

Existing AI and DT models are trained on limited or homogeneous datasets, which limits their ability to generalize across various additive manufacturing processes, printer configurations, material systems, and patient-specific geometries. Consequently, current DTs often lack the robustness and adaptability required for autonomous operation in highly variable clinical and production environments. Another technological challenge is the acquisition, integration, and interpretation of multimodal sensor data in real time. Many rehabilitation devices are not yet equipped with a sufficiently dense or heterogeneous sensor infrastructure to ensure continuous synchronization between the physical asset and its digital counterpart [25]. Furthermore, interoperability between computer-aided design (CAD) environments, finite element analysis (FEA) software, manufacturing execution systems, IoT platforms, and DTs architectures remains limited, hindering the implementation of intelligent cyber–physical manufacturing systems in clinical practice [26]. Existing NDT algorithms also exhibit limited sensitivity to subtle manufacturing defects—including microporosity, poor interlaminar adhesion, and residual stress distributions—which are often underrepresented in available training datasets [27]. From a clinical perspective, additional evidence is necessary to verify whether predictions generated by digital twins reliably translate into improved long-term rehabilitation outcomes and patient safety [28]. Furthermore, many healthcare professionals have limited experience interpreting advanced AI-assisted diagnostics, creating a gap between advanced computational models and routine clinical decision-making [29]. The regulatory framework governing autonomous AI systems in medical devices is also evolving, creating uncertainty regarding certification, transparency, accountability, and safety requirements for intelligent digital twin technologies [30,31]. Scalability remains a significant obstacle, as most existing DT implementations are limited to laboratory prototypes or pilot studies and have not yet developed into robust, clinically deployable systems capable of operating at scale.

We identify the limited convergence of agent-based AI, transformative testing, additive manufacturing, and NDT as a specific research gap. Rather than presenting agent-based AI as inherently superior to conventional AI, the article critically examines the conditions under which agent-based AI capabilities could add value, as well as the technical and safety constraints that must be considered before implementation in rehabilitation equipment inspection.

The integration of DTs, AI, and additive manufacturing opens new possibilities for improving the design, production, and validation of 3D-printed rehabilitation devices. However, current research remains fragmented, with limited work addressing the combined use of intelligent digital twins and autonomous AI systems for NDT and device lifecycle management. Traditional NDT techniques, including ultrasonic testing, computed tomography, thermography, and optical inspection, provide valuable information about structural defects but are often limited to periodic assessments and may not support continuous performance monitoring or predictive decision-making. In contrast, DTs and AI-based approaches enable real-time synchronization between physical devices and their virtual representations, enabling continuous assessment of structural integrity, functional performance, and degradation processes. Despite these advantages, existing DT applications in rehabilitation still focus primarily on monitoring and simulation, with insufficient attention paid to autonomous reasoning, adaptive control, and proactive intervention supported by agent-based AI. There is therefore a significant research gap in developing an integrated framework that combines additive manufacturing data, NDT results, patient-specific usage information, and intelligent Agentic AI into a closed-loop system. Filling this gap is essential to creating safer, more reliable, and personalized rehabilitation equipment with improved quality control and lower development costs.

Conventional AI agents are typically designed for relatively limited, task-specific, or rule-defined functions, whereas agent-based AI emphasizes greater autonomy, goal-directed behavior, dynamic task decomposition, tool/environment interaction, adaptation, and iterative decision-making. Autonomy exists on a continuum rather than representing a strict, binary distinction, thus avoiding overly broad characterizations of agent-based AI.

NDT of 3D-printed rehabilitation equipment is particularly challenging because defect detection is not an isolated classification problem. It requires the integration of heterogeneous sensor data, knowledge of additive manufacturing processes and material behavior, geometric and structural information, uncertainty assessment, defect interpretation, and potentially adaptive inspection planning. Existing AI-based NDT approaches often fragment the process, while DT-based approaches can provide monitoring and simulation capabilities without fully autonomous closed-loop reasoning and decision-making. This fragmentation motivates the investigation of whether Agentic AI can provide a more integrated and adaptive framework.

The novelty of this work lies in extending conventional AI-assisted DTs to Agentic AI-based DTs, which function not only as predictive analytical models but also as autonomous cybernetic–physical agents capable of perceiving, reasoning, planning, learning, and adaptive decision-making [32]. This shift from passive prediction to autonomous action represents a fundamental advance in intelligent quality assurance in additive manufacturing [33,34]. The main scientific contribution of this study is the introduction of an Agentic AI-based DT architecture specifically designed for non-destructive testing of personalized rehabilitation equipment manufactured using additive technologies. The proposed approach integrates continuous sensing, ML, autonomous reasoning, predictive simulation, and closed-loop decision-making.

The paper explicitly addresses issues such as hallucinations and fallible reasoning, limited interpretability and traceability of autonomous decisions, uncertainty propagation, insufficient robustness to distributional changes, difficulties in maintaining physical consistency between digital and physical twins, and challenges related to verification, validation, security, and human oversight. Particular attention is paid to the fact that increased autonomy can exacerbate errors when AI-generated decisions are propagated through sequential planning and action cycles.

The aim of this study is to evaluate the feasibility, effectiveness, and clinical utility of Agentic AI-based DTs as an intelligent NDT system for assessing the structural integrity, functional performance, and lifecycle reliability of 3D-printed rehabilitation equipment. To achieve this goal, the following research questions (RQs) were formulated:

- RQ1: To what extent can Agentic AI-based DTs autonomously detect and predict structural defects, degradation mechanisms, and failure modes of 3D-printed rehabilitation equipment compared to conventional NDT methods?
- RQ2: What combinations of material, geometric, biomechanical, and multimodal sensor data are necessary to develop reliable and adaptive development models of Agentic AI-based DTs for various categories of personalized rehabilitation devices?
- RQ3: How effectively can Agentic AI-based DTs development models support personalized rehabilitation by autonomously modeling patient-specific loading conditions, usage patterns, and rehabilitation progress while continuously adapting predictive models?
- RQ4: What scientific, technological, clinical, and regulatory challenges need to be addressed to enable routine implementation of Agentic AI-based DTs development models for intelligent quality assurance and nondestructive evaluation of 3D-printed rehabilitation equipment?

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2. Materials and Methods

2.1. Dataset

The aim of this bibliometric analysis was to investigate the current state of knowledge and research practice concerning the development, planning, and implementation of Agentic AI-based DTs strategies at different levels of application, with particular emphasis on their potential to enhance, complement, or provide alternatives to conventional NDT approaches. Analyses focused solely on localized applications, such as individual patients or narrowly defined patient groups, may underestimate the broader potential of these technologies, particularly when considering their interdisciplinary capabilities across engineering, manufacturing, healthcare, and data science domains. Therefore, this study employed bibliometric methods to evaluate the recent global scientific literature on AI-based and emerging Agentic AI-driven digital twin technologies. The analysis included publications from the last decade, covering the period from January 2016 to July 2026.

RQs addressing the most influential publication sources, key research themes, leading countries, institutions, researchers, and Sustainable Development Goals (SDGs) were formulated to characterize the global research landscape of AI-based and emerging Agentic AI-based DTs and assess their potential role in NDT of 3D-printed rehabilitation equipment. This approach enables the identification of major areas of scientific activity, innovation hubs, and institutional networks shaping the development and clinical translation of these technologies. The analysis provides insights into geographic and organizational factors that influence technological advancement, knowledge transfer, and practical implementation within healthcare and additive manufacturing domains. The inclusion of SDG-related perspectives allows the assessment of how AI-based and Agentic AI-driven DT technologies contribute to broader sustainability objectives, particularly those associated with health, medical technologies, responsible innovation, and advanced manufacturing. Collectively, these RQs establish a comprehensive framework for understanding not only the current research priorities and technological trends within this emerging field, but also the key actors driving innovation and the motivations underlying its development. The findings provide strategic guidance for future research directions, interdisciplinary cooperation, and international collaboration aimed at advancing intelligent, sustainable, and clinically applicable DTs solutions.

2.2. Methods

The narrative review and bibliometric analysis were not intended to represent competing paradigms but rather complementary methodological components serving different purposes. The bibliometric analysis was used to quantitatively map the intellectual and thematic structure of the available literature, including publication patterns, research clusters, keyword co-occurrences, and emerging topic areas. The narrative review was then used to interpret and conceptually integrate these mapped themes, particularly in interdisciplinary fields such as agent-based AI, DTs, additive manufacturing, and NDT. Therefore, the bibliometric results provided an evidence-based basis for identifying key technological and research dimensions, while the narrative synthesis was used to explore the relationships between these dimensions and develop a proposed framework for AI-assisted agent-based DTs for intelligent NDT of 3D-printed rehabilitation equipment.

This study conducted a comprehensive search across four major bibliographic databases: Web of Science (WoS), Scopus, PubMed, and DBLP. These databases were selected due to their extensive coverage of scientific literature across both engineering and medical disciplines, as well as their comprehensive metadata, international scope, and relevance to emerging interdisciplinary research areas (Table 1). To ensure the relevance and quality of the retrieved literature, predefined filters were applied, including restriction to

English-language publications. Following the initial screening process, all identified articles were independently evaluated by three reviewers according to established inclusion criteria. The final dataset was determined using a two-out-of-three consensus approach. The selected publications were subsequently analyzed with respect to key bibliometric characteristics, including leading authors, affiliated research groups and institutions, contributing countries, research domains, and emerging thematic trends.

Table 1. Customized bibliometric analysis methodology designed and implemented in this study.

Stage Name	Tasks
Defining research goal(s)	Defining goals of the bibliometric analysis
Selecting databases and data collections	Selecting appropriate dataset(s) and developing research queries according to the study goals
Data preprocessing	Cleaning the collected dataset(s) to remove duplicates and irrelevant records
Bibliometric software selection	Choosing suitable bibliometric software/tools for analysis
Data analysis	Description, author, journal, area, topics, institution, country, etc.
Visualisation (if possible)	Visualising the analysis results to present insights
Interpretation and discussion	Interpreting findings in the context of the research goals and RQs

Duplicate records were identified by consolidating all retrieved publications from the selected databases into a unified bibliographic management environment (Biblioshiny). Automated duplicate detection was performed by comparing key bibliographic attributes, including publication titles, Digital Object Identifiers (DOIs), author information, publication years, and other relevant metadata fields. Following the automated matching procedure, a manual verification process was conducted to evaluate ambiguous cases, such as conference papers and their corresponding extended journal versions, ensuring accurate classification and avoiding inappropriate removal of unique contributions. These combined automated and manual procedures ensured the elimination of duplicate and near-duplicate records prior to the screening phase, thereby maintaining the accuracy, consistency, and reliability of the final bibliometric dataset.

This study followed 10 selected elements of the PRISMA 2020 bibliographic review guidelines, with emphasis placed on the following components: rationale (item 3), objectives (item 4), eligibility criteria (item 5), information sources (item 6), search strategy (item 7), selection process (item 8), data collection process (item 9), synthesis methods (item 13a), synthesis results (item 20b), and discussion (item 23a). Detailed descriptions of these elements are provided in the Supplementary Materials. The bibliometric analysis was conducted using analytical tools available within the Web of Science (WoS), Scopus, PubMed, and DBLP databases. The adopted methodology enables transparent and reproducible research by supporting systematic classification and evaluation of scientific outputs according to concepts, research domains, authors, documents, and publication sources. The obtained results are presented in tabular form, facilitating further interpretation, comparative analysis, and flexible visualization of research trends and patterns.

Variations in the quality of literature across databases (WoS, Scopus, PubMed, and DBLP) were addressed through the use of predefined inclusion criteria, database-specific selection procedures, and standardized quality assessment frameworks to assess methodological rigor, validity, and risk of bias.

3. Results

3.1. Data Sources

To enhance the precision and relevance of the literature retrieval process, advanced search filters were applied, restricting the results to English-language publications. The final search strategy was structured as follows:

- In WoS: using the "Subject" field (consisting of title, abstract, keywords, and other keywords);
- In Scopus: using the article title, abstract, and keywords;
- In PubMed and dblp: using manual keyword sets.

The selected databases were queried using predefined keyword combinations, with only the most effective and relevant search terms included to maximize the accuracy and efficiency of literature retrieval: ("artificial intelligence" OR "machine learning" OR agentic) AND "digital twin" AND "non-destructive" AND ("rehabilitation" OR "physical therapy" OR "physiotherapy") (Table 2).

Table 2. Databases retrieval strategy and search terms.

Parameter/Feature	Detailed Description
Inclusion criteria	Books, chapters in books, articles (original, reviews, communication, editorials), and conference proceedings, in English
Exclusion criteria	Older than 10 years, letters, conference abstracts without full text, other languages than English
Exact keywords used	("artificial intelligence" OR "machine learning" OR agentic) AND "digital twin" AND "non-destructive" AND ("rehabilitation" OR "physical therapy" OR "physiotherapy")
Used field codes (WoS)	"Subject" field (consisting of title, abstract, keyword plus and other keywords): ("artificial intelligence" OR "machine learning" OR agentic) AND "digital twin" AND "non-destructive" AND ("rehabilitation" OR "physical therapy" OR "physiotherapy")
Used field codes (Sopus)	Article title, abstract and keywords: ("artificial intelligence" OR "machine learning" OR agentic) AND "digital twin" AND "non-destructive" AND ("rehabilitation" OR "physical therapy" OR "physiotherapy")
Used field codes (PubMed)	Manually: ("artificial intelligence" OR "machine learning" OR agentic) AND "digital twin" AND "non-destructive" AND ("rehabilitation" OR "physical therapy" OR "physiotherapy")
Used field codes (dblp)	Manually: ("artificial intelligence" OR "machine learning" OR agentic) AND "digital twin" AND "non-destructive" AND ("rehabilitation" OR "physical therapy" OR "physiotherapy")
Boolean operators used	Yes, e.g., ("rehabilitation" OR "physiotherapy" OR "physical therapy")
Applied filters	Results refined by publication year, document type (e.g., articles, reviews), and subject area (e.g., industry, engineering).
Iteration and validation options	Queries are run iteratively, refined based on results, and validated by ensuring that relevant publications appear among the top results
Leverage truncation and wildcards used	Used symbols like * for word variations and ? for alternative spellings

The initially identified publication set was subsequently refined through a manual screening process, during which irrelevant records and duplicate entries were removed.

This procedure ensured the establishment of a final dataset containing only publications meeting the predefined inclusion criteria and suitable for further analysis (Figure 2). Critical appraisal of the included studies was performed by two independent experts using standard quality assessment tools to assess methodological rigor, risk of bias, data reliability, and strength of evidence. This article distinguishes between well-confirmed results from high-quality experimental or clinical studies and novel claims based on limited datasets, theoretical frameworks, or preliminary studies, highlighting differences in the strength of evidence across research areas.

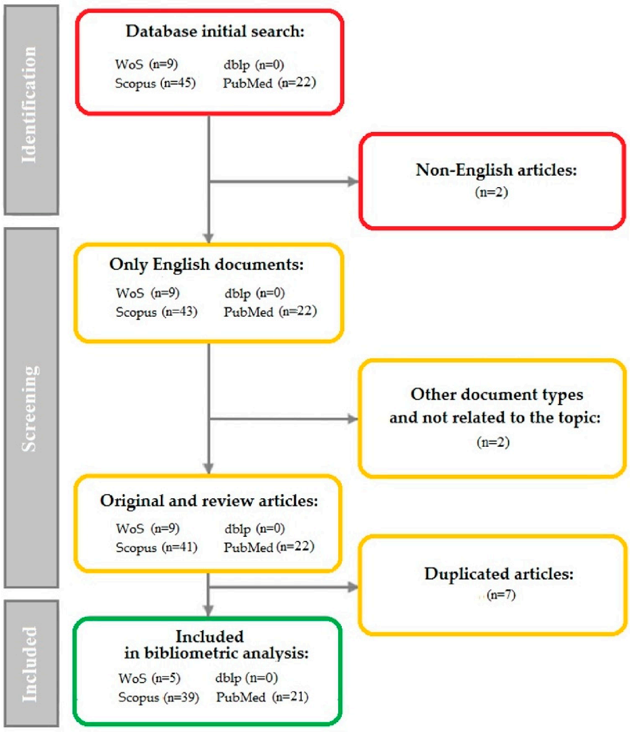

Figure 2. PRISMA flow diagram based on selected PRISMA 2020 guidelines.

The PRISMA 2020 flowchart presented above provides a systematic overview of the study identification, screening, eligibility assessment, and final inclusion processes, supporting methodological transparency, accuracy, and reproducibility of the review. The process begins with the identification stage, in which records are retrieved from selected databases and other relevant sources, documenting the total number of potentially eligible publications before duplicate removal. During the screening stage, titles and abstracts are evaluated according to predefined inclusion and exclusion criteria, allowing the removal of studies that are not relevant to the scope of the review or the analyzed rehabilitation devices. Subsequently, in the eligibility assessment stage, the full texts of potentially relevant articles are examined in detail to evaluate their methodological quality, relevance to data acquisition and security aspects, and contribution to the development of the investigated technologies. The final inclusion stage presents the number of studies retained after the exclusion process, representing the evidence base used for subsequent synthesis and analysis. Interpretation of the PRISMA flowchart enhances understanding of the review methodology by demonstrating not only the volume and progression of analyzed literature but also the justification for individual exclusion decisions. This transparent reporting approach strengthens the reliability, reproducibility, and validity of the conclusions derived from the review.

3.2. General Results of Analysis

A summary of the bibliographic analysis results is presented in Table 3 and Figures 3–10. Sixty-five articles published in the last 10 years (January 2016–July 2026) were analyzed, but articles published between 2016 and 2018 were not included due to their lack of references. Older articles were not included due to the rapid replacement of older knowledge with new knowledge.

Table 3. Summary of bibliographic analysis results (all databases: WoS, Scopus, PubMed, dblp).

Parameter/Feature	Value
Leading types of publication	Article (37.80%), conference paper (26.70%), review (26.70%)
Leading areas of science	Engineering (32.30%), Materials science (17.20%), Computer science (11.10%), Physics and astronomy (11.10%)
Leading countries	USA (24.44%), China (15.55%), India (11.11%)
Leading scientists	None observed
Leading affiliations	None observed
Leading funders (where information available)	None observed
Sustainable development goals	Industry, Innovation and Infrastructure, Sustainable Cities and Communities, Responsible consumption and Production

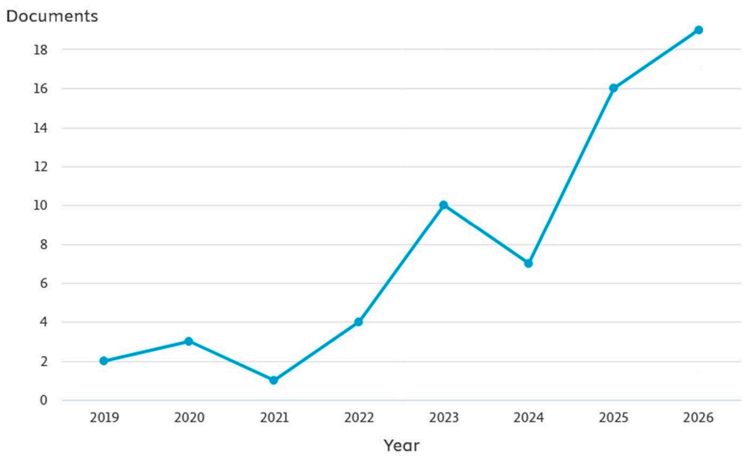

Figure 3. Documents by year.

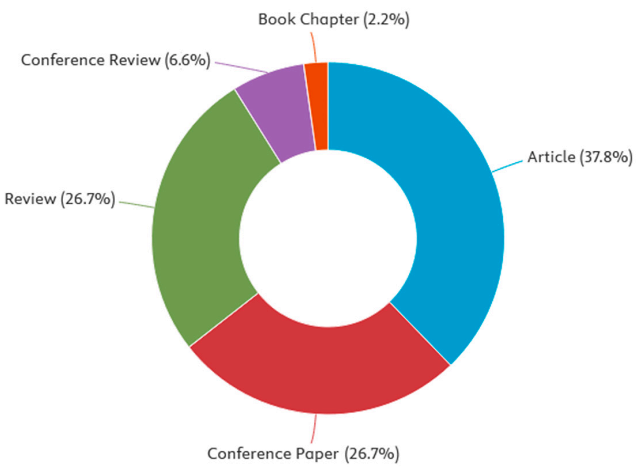

Figure 4. Documents by type.

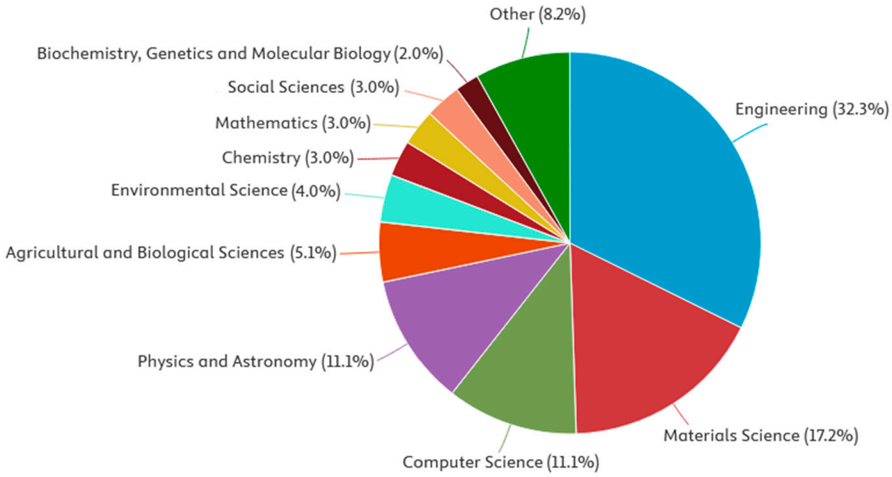

Figure 5. Documents by subject area.

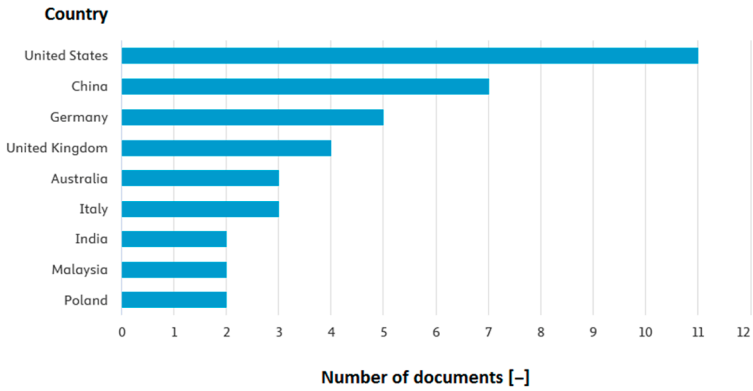

Figure 6. Documents by country/territory.

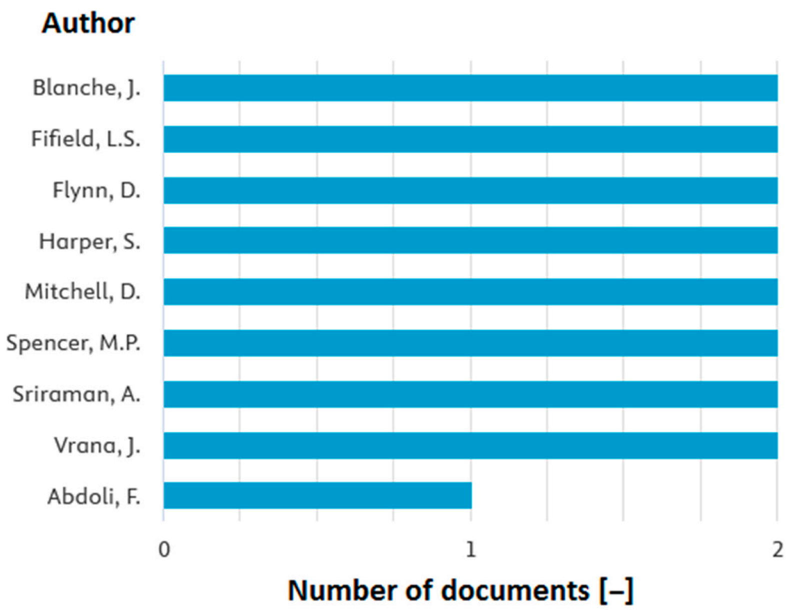

Figure 7. Documents by author.

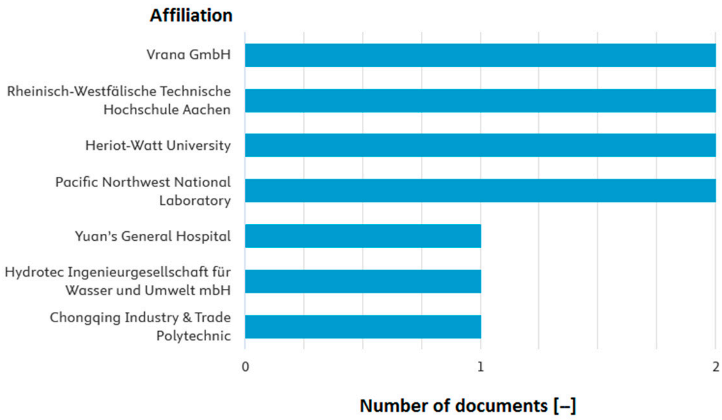

Figure 8. Documents by affiliation.

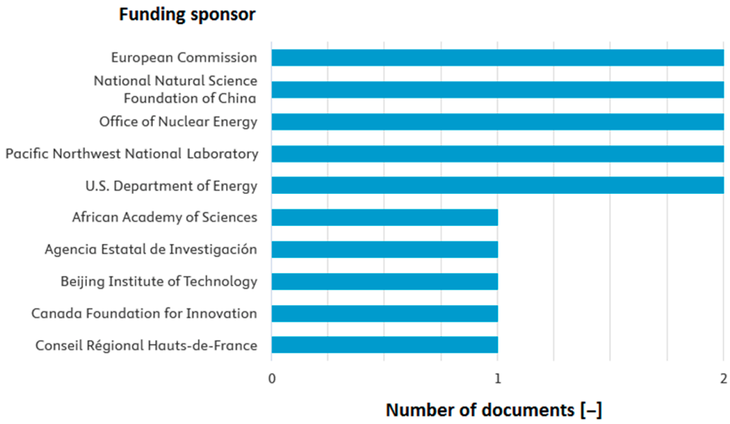

Figure 9. Documents by funding.

Figure 10. Documents by SDGs.

The implications of these bibliometric findings suggest that the high percentage of conference reviews may indicate a field still in the conceptual phase, reflecting the article's emphasis on proposed architectures rather than their practical/clinical validation. Most research was conducted in materials science and computer science fields, suggesting an early stage of technological maturity. The lack of clearly dominant authors, institutions, or research groups is not solely attributed to the immaturity of the field. Other explanations include the emerging and highly interdisciplinary nature of the research area, fragmentation across disciplinary databases and publication venues, the relatively narrow interconnectedness of search terms, and the potential effects of database selection and search strategy.

Bibliometric patterns vary depending on the databases, search terms, document types, and inclusion criteria used. Therefore, the observed lack of dominant authors or institutions should be interpreted as a characteristic of the literature covered by our search strategy, rather than as definitive evidence of their absence in the broader research landscape. The leading countries were the United States, China, and India, but no leading researchers or affiliations were recorded, suggesting significant research dispersion. The most frequently observed SDGs indicate a distinct industrial and developmental context.

The observed increase in publications after 2023 is due to recent advances in AI (including generative AI and Agentic AI), DTs, additive manufacturing, and new strategic initiatives supporting smart healthcare and the transformation of Industry 4.0. The predominance of materials science and engineering stems from the current gap between technological development and clinical implementation, particularly with respect to the validation, regulatory approval, and implementation of 3D-printed rehabilitation devices in healthcare. The geographic distribution, with countries such as the United States, China, and India leading the way, reflects their research priorities, available technological infrastructure, funding environments, potential regional biases, and opportunities for international collaboration. The absence of leading authors, research groups, and institutions has so far indicated the immaturity of the field, emerging knowledge networks, and emerging centers of excellence. This makes it difficult to see where and how research activity is distributed, and the patterns they reveal about the evolution, limitations, and future directions of the field are only just emerging and require further ongoing observation to be detected.

Not all publications included in the review had SDGs defined by the authors, and this was not a criterion for inclusion. Although the SDGs have been adopted by the UN as guidelines for 2030, they are not required in some countries/research centers. However, including articles with and without SDGs allows the review to consider diverse perspectives, including the role of sustainable development and any constraints imposed, voluntarily or unintentionally, by researchers/countries/institutions in achieving it.

The selection of 65 studies reflects the deliberately focused scope of the review and the stringent eligibility criteria used to ensure direct relevance to the intersection of the four main areas addressed in this work. The goal was not to create an exhaustive bibliometric inventory of every publication independently related to AI, DTs, AM, or NDT, but rather to identify and synthesize literature sufficiently relevant to their convergence in the context of rehabilitation equipment. Therefore, the resulting sample represents the intersection of the predefined inclusion criteria rather than the entire body of literature within these broad disciplines. We also acknowledge this as a limitation and explicitly state that the proposed framework should be considered a conceptual framework based on synthesis, which can be further validated and refined as the emerging body of literature grows. Greater transparency in the study selection process would improve reproducibility. This was achieved by expanding the description of the search, selection, eligibility, and inclusion procedures and clarifying the use of the PRISMA-based workflow. We also strengthened the reporting of exclusion criteria and reasons for exclusion at appropriate screening stages, based on the PRISMA flowchart and Supporting Information, to provide greater transparency in study selection. The bibliometric component provides quantitative evidence for literature mapping, while the narrative component provides qualitative interpretation and conceptual integration. As a result, we refined the methodological logic, framework development process, rationale for study selection, and review limitations.

3.3. Traditional AI-Based vs. Agentic AI-Based DTs

A comparison between traditional AI-based DTs and Agentic AI-based DTs in rehabilitation can be framed around their architecture, functional layers, autonomy, and decision-making capabilities (Table 4).

Table 4. Comparison between traditional AI-based DTs and Agentic AI-based DTs in rehabilitation (own elaboration).

Feature	Traditional AI-Based DTs in Rehabilitation	Agentic AI-Based DTs in Rehabilitation
Primary concept	A virtual representation of a patient, device, or rehabilitation process enhanced with AI analytics	An autonomous cyber-physical system that can perceive, reason, plan, learn, and act on behalf of the patient/device/process
Main purpose	Monitoring, prediction, simulation, and decision support	Autonomous monitoring, adaptive optimization, decision-making, and closed-loop intervention
System role	Passive or semi-active analytical assistant	Active intelligent agent collaborating with clinicians, patients, and devices
Autonomy level	Low to moderate; requires human interpretation and intervention	High; capable of autonomous reasoning, planning, and execution within defined boundaries
Data processing approach	AI models analyze collected data and generate predictions	AI agents continuously interpret data, evaluate context, decide actions, and adapt strategies
Human interaction	Clinician remains the primary decision-maker	Human remains supervisor while AI agent provides recommendations or executes approved actions

Figure 11 highlights the main architectural novelty of Agentic AI-based digital twins, where

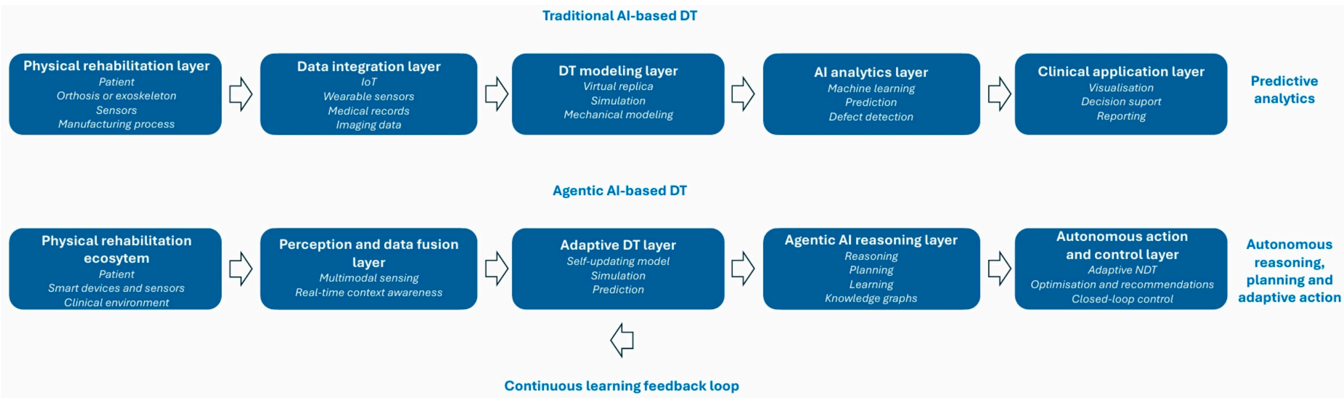

Figure 11. Main architectural novelty of Agentic AI-based DTs.

- Traditional AI-DT was described by the following sequence: Sense → Analyze → Predict → Human decides;
- Agentic AI-DT is described now by the following sequence: Sense → Understand → Reason → Plan → Act → Learn (Figure 10).

Traditional AI-based digital twins in rehabilitation typically function as virtual replicas of patients, rehabilitation devices, or therapeutic processes, integrating sensor data, simulations, and machine learning models to monitor performance and predict potential problems. They support clinicians by analyzing biomechanical parameters, detecting anomalies, estimating device degradation, and helping optimize personalized rehabilitation equipment such as orthoses and exoskeletons. These systems primarily function as decision-support tools, where AI generates predictions and recommendations that require interpretation and action from healthcare professionals. Agent-based DTs extend these capabilities by incorporating autonomous mechanisms for perception, reasoning, planning, and adaptive decision-making [35]. They can continuously assess patient behavior, device performance, and rehabilitation progress, autonomously adjusting models, optimizing nondestructive testing procedures, and recommending or initiating corrective actions within predefined safety limits [36]. As a result, they enable the creation of closed, personalized and adaptive rehabilitation systems that go beyond prediction towards autonomous management and continuous improvement of rehabilitation processes (Table 5) [37].

Table 5. Key architectural differences.

Layer	Traditional AI-DT	Agentic AI-DT
Physical layer	Device/patient generates data	Device/patient becomes an interactive intelligent ecosystem
Data layer	Collects and stores sensor information	Continuously collects, prioritizes, and interprets relevant information
Model layer	Static or periodically updated model	Self-adaptive and continuously evolving model
AI layer	Predictive analytics	Reasoning + planning + autonomous decision-making
Control layer	Human executes decisions	AI agent can execute validated actions
Knowledge layer	Historical datasets	Dynamic knowledge base combining clinical, engineering, and operational knowledge
Feedback loop	Human-in-the-loop	Human-on-the-loop with autonomous adaptation

The proposed agent-based AI DT platform integrates sensor/NDT data, biomechanical data, manufacturing information, and physics-based simulations to create a continuously updated representation of 3D-printed rehabilitation equipment and its interaction with the patient. Sensor and NDT data provide real-time information on structural health and emerging defects, while biomechanical data capture patient-specific loading, movement patterns, and rehabilitation progress. Manufacturing data provides the material, geometric, process, and microstructural context necessary for accurate DT modeling. DT simulations combine these heterogeneous inputs to replicate device behavior, assess degradation and failure mechanisms, and generate predictive information, which is then interpreted by the Agentic AI layer. Unlike conventional DT architectures that primarily monitor, simulate, or visualize system states, the proposed platform leverages Agentic AI to autonomously combine multimodal data, continuously update models, detect anomalies, predict future states and remaining service life, and recommend or initiate appropriate corrective or personalized interventions. As a result, the closed-loop interaction between sensor, biomechanical, and production data, DT simulations, and autonomous AI decision-making enables the creation of a dynamic, adaptive, and personalized framework that combines structural health monitoring with predictive maintenance and rehabilitation optimization.

The proposed framework establishes a closed-loop decision-making system between structural health monitoring, personalized rehabilitation, and manufacturing quality assurance by integrating sensor/NDT observations of device health with manufacturing data on materials, geometry, microstructure, and process parameters. Simultaneously, biomechanical data characterize patient-specific loads, movement patterns, interaction forces, and changes in functional performance during rehabilitation. These complementary data streams continuously feed DT simulations, which link the mechanical and structural behavior of the 3D-printed device with its patient-specific loading environment to distinguish changes related to manufacturing or degradation from changes caused by use and rehabilitation progress. Simultaneously, Agentic AI autonomously integrates evidence, updates DT, and predicts defects, performance changes, and failure risk. Unlike conventional DT architectures that largely recreate and monitor the system based on predefined data flows, the proposed framework creates an adaptive decision-making loop where Agentic AI actively combines manufacturing history, NDT/sensor evidence, biomechanical response, and simulation results to optimize device performance, personalize rehabilitation interventions, and support proactive maintenance and failure prevention.

The prototype implementation phase begins with the development of an Agentic AI-based DT architecture that integrates patient-specific rehabilitation requirements, 3D printing parameters, material properties, and NDT data streams. The next step involves creating virtual models of 3D-printed rehabilitation devices and calibrating them using experimental measurements from sensors, mechanical testing, and NDT techniques such as ultrasonic inspection, thermography, computed tomography, and optical scanning. Simulation studies are then conducted to assess the DTs' ability to predict structural behavior, detect defects, estimate fatigue progression, and optimize device performance under various load and use scenarios [38]. Agentic AI algorithms are validated by comparing autonomous predictions and recommendations with conventional NDT results, expert assessments, and experimentally measured device responses. Real-world validation involves testing prototypes in clinical and laboratory settings to assess reliability, accuracy, safety, and adaptability during repeated rehabilitation cycles [39]. Benchmarking against established NDT datasets and reference devices enables quantitative assessment using metrics such as defect detection accuracy, prediction error, computational efficiency, and estimated remaining useful life [39]. The final stage focuses on continuously improving the Agentic AI-powered DTs through feedback from real-world operations, ensuring robust performance, regulatory compliance, and practical usability in personalized rehabilitation and smart healthcare environments [40].

Because this paper is narrative in nature rather than an experimental study, we do not claim to empirically validate the proposed framework. Instead, we identify relevant future validation dimensions, including fault detection performance, decision latency, robustness to sensor uncertainty, and the safety and consistency of agent-based AI decisions.

3.4. Case Studies

The case studies presented in this section are conceptual and illustrative scenarios developed to demonstrate the potential application of AI-assisted DTs for intelligent non-destructive testing. They do not constitute empirical validation or experimental evidence of the proposed framework.

An example of an Agentic AI-based DT in rehabilitation works by continuously collecting and integrating multimodal information from a physical rehabilitation device, the patient, and the therapeutic environment. The input layer combines real-time sensor data from devices such as orthoses or exoskeletons with the patient's gait patterns, biomechanical loads, material degradation rates, previous failure records, and rehabilitation progress data [41]. The DT continuously updates its virtual representation of the rehabilitation device and compares current operating conditions with historical and simulated performance data [42]. The Agentic AI component analyzes this input using autonomous reasoning mechanisms to identify emerging risks, cause–effect relationships, and potential performance limitations [43]. For example, the AI agent might determine that increasing stress concentrations are associated with altered patient gait patterns and repeated asymmetric loading conditions. Based on predictive simulations and accumulated knowledge, the agent can estimate the increased probability of structural failure within a specific time period, for example, within the next 14 days. It can also evaluate possible mitigation strategies, such as alternative reinforcement geometries, modified materials, or optimized manufacturing parameters. Following this reasoning process, the Agentic AI-based DT system can autonomously propose or execute predefined actions, including increasing inspection frequency, recommending design modifications, updating additive manufacturing parameters, or adapting rehabilitation protocols [44]. All decisions remain within established clinical and engineering safety constraints, enabling effective collaboration between the AI system and healthcare professionals [45]. The system then incorporates the results of implemented actions into its knowledge base, continuously improving future predictions and recommendations [46]. This creates a closed-loop learning process, following a cycle of

Observe → Reason → Plan → Act → Learn, enabling adaptive, personalized, and continuously optimized rehabilitation supported by the intelligent DT.

A representative example of Agentic AI-based DT for NDT is the continuous monitoring of the structural integrity of a personalized, 3D-printed ankle–foot orthosis, manufactured using a fused deposition method using carbon fiber-reinforced poly(LLA). The orthosis was designed for a stroke patient and is subjected to highly individualized loading conditions that evolve during rehabilitation. Unlike conventional NDT methods, which rely on scheduled inspections using techniques such as ultrasound, X-ray computed tomography, infrared thermography, or visual inspection, Agentic AI-based DT technology continuously assesses the device's structural integrity during daily clinical use. DT integrates multimodal data collected from embedded strain gauges, fiber Bragg grating sensors, inertial measurement units (IMUs), pressure sensors, and environmental sensors measuring temperature and humidity [47]. This data is combined with patient gait characteristics, biomechanical loading patterns, rehabilitation progress, additive manufacturing parameters, material properties, finite element simulation results, and historical failure databases. The virtual model continuously synchronizes with the physical orthosis, providing a real-time representation of its structural health while predicting the evolution of internal defects that cannot be directly observed through conventional inspection intervals [48]. The Agentic AI component autonomously analyzes the incoming information using physics-based ML models, probabilistic inference, and causal inference techniques. During routine monitoring, the AI agent identifies an abnormal increase in local stress near the heel support/lateral brace junction. By correlating the sensor measurements with finite element simulations and previous failure events, the system determines that the increased stress is primarily caused by progressive changes in the patient's gait symmetry as muscle strength improves during rehabilitation. At the same time, DT predicts gradual delamination between adjacent print layers initiated by cyclic fatigue loading and identifies this defect as a precursor to structural failure. Using continuously updated predictive simulations, Agentic AI estimates that the probability of crack initiation will exceed an acceptable safety threshold within approximately two weeks if current loading conditions persist [49]. Instead of simply issuing a warning, the autonomous agent evaluates several intervention strategies by simulating multiple design and manufacturing alternatives. These include increasing local wall thickness, modifying the lattice topology, changing the raster orientation, increasing interlayer bonding through optimized printing temperature, and replacing the existing PLA composite with a higher fatigue-resistant polymer such as PETG-CF or PA12-CF. The AI ranks these alternatives based on predicted structural performance, manufacturing costs, patient comfort, and expected rehabilitation outcomes. After selecting the optimal strategy, according to predefined clinical and engineering constraints [50], Agentic AI recommends increasing the frequency of targeted NDT around the identified high-risk area while suggesting a redesigned reinforcement geometry for the next orthosis produced. When integrated into an intelligent manufacturing environment, the system can automatically update additive manufacturing process parameters before producing a replacement device. Simultaneously, the DT informs medical professionals that temporary modifications to rehabilitation exercises can reduce asymmetric loading until an improved orthosis is available, thus minimizing the risk of premature structural failure without interrupting therapy [51]. Once these recommendations are implemented, the DT continuously monitors the performance of the redesigned orthosis and compares the predicted behavior with actual sensor observations. Any discrepancies between predicted and observed structural responses are incorporated into the AI knowledge base through continuous learning, allowing for improved future predictions and reduced uncertainty in decision-making. As patient cases increase, the system becomes increasingly capable of recognizing subtle degradation mechanisms, optimizing follow-up schedules, and recommending personalized design improvements. This case study illustrates how Agentic AI transforms DTs from passive monitoring systems into autonomous decision support platforms capable of intelligent, non-destructive assessment, predictive structural health monitoring, adaptive rehabilitation support, and continuous optimization of personalized, 3D-printed rehabilitation equipment. The resulting closed-loop structure follows an autonomous lifecycle:

Observe → Analyze → Reason → Predict → Plan → Act → Learn

Where continuous sensing, autonomous reasoning, predictive simulation, and adaptive learning enable intelligent quality assurance throughout the lifecycle of personalized rehabilitation devices.

The cases presented in the article are primarily conceptual use cases rather than experimentally verified prototypes. We emphasize this throughout the manuscript to clearly distinguish the following:

- Capabilities demonstrated in existing research;
- Transferable technologies that could potentially support the proposed architecture;
- Future research proposals specific to agent-based AI-enabled DTs for rehabilitation equipment.

The proposed cases are presented as conceptual scenarios intended to illustrate the possibilities of integrating existing technologies, rather than as claims about completed physical prototypes or simulation-verified systems.

3.5. Personalization vs. Global Standards Using Agentic AI

Agentic AI-based DTs enable personalized NDT of 3D-printed rehabilitation equipment by continuously adapting inspection and prediction models to each patient's unique biomechanics, device usage patterns, and rehabilitation progress. Unlike traditional NDT methods based on fixed global inspection standards, Agentic AI dynamically adjusts defect detection thresholds and maintenance schedules based on individual operating conditions. The DT integrates patient-specific biomechanical data, material behavior, manufacturing parameters, and sensor information in real time to create an accurate virtual image of the rehabilitation device throughout its lifecycle. At the same time, global engineering and regulatory standards remain crucial, defining minimum requirements for safety, quality assurance, and compliance with EU Medical Device Regulations (MDR), which autonomous systems cannot exceed or ignore. Agentic AI combines these two perspectives, ensuring that personalized recommendations always operate within predefined engineering, clinical, and regulatory constraints. This hybrid approach allows each 3D-printed rehabilitation device to receive a personalized assessment of its structural health while maintaining consistency with international safety and reliability standards. Continuous learning from multiple patients enables DT to refine global predictive models while maintaining personalized decision-making for each user. As a result, DTs powered by Agentic AI create a balanced approach where standardized quality assurance provides a solid foundation, while personalized intelligence maximizes the performance, durability, and clinical effectiveness of 3D-printed rehabilitation equipment.

3.6. Paradigm-Related Applications

Within the Industry 4.0 paradigm, AI-based DTs act as intelligent virtual counterparts to 3D-printed rehabilitation devices, enabling continuous, data-driven non-destructive testing. They integrate real-time sensor data and predictive algorithms to monitor equipment performance throughout the production and use cycle [52]. DTs improve quality control by detecting deviations in print quality or material behavior without the need for physical stress testing [53]. AI-based models support rapid design iterations by simulating stress, wear, and potential failure points before producing a physical prototype [54]. Their ability to learn from collected data aligns with Industry 4.0's focus on adaptive, self-improving systems. Through cloud connectivity, DTs enable remote diagnostics and predictive maintenance of rehabilitation devices in clinical environments [55]. They facilitate interoperability between additive manufacturing systems, sensors, and digital platforms, a fundamental principle of smart factories. DTs help personalize rehabilitation equipment by incorporating patient-specific biomechanical data into simulation models [56]. They contribute to sustainable production by reducing waste, lowering testing costs, and minimizing the need for repeated physical examinations. In this way, AI-based DTs support the transition to fully automated, intelligent, and patient-centric manufacturing processes, crucial for Industry 4.0.

In the Industry 5.0 paradigm, AI-powered DTs support non-destructive testing of 3D-printed rehabilitation equipment, emphasizing human-centric, safe, and personalized device validation. They enable clinicians and engineers to collaborate more effectively by providing interpretable simulations of device performance and structural integrity [57]. DTs contribute to more inclusive rehabilitation solutions by modeling patient-specific biomechanical needs with greater precision. Their predictive capabilities help ensure that assistive devices meet high standards of safety and comfort, reflecting Industry 5.0's emphasis on human well-being [58]. AI-powered models reduce the need for invasive or physically destructive testing, enabling more ethical and patient-friendly evaluation processes. By integrating human feedback, DTs can adapt simulations to real-world usage patterns that traditional automated systems might miss [59]. They also support sustainability goals by minimizing resource consumption and optimizing material utilization in additive manufacturing. DTs enhance resilience by enabling rapid redesign and quality assurance when supply chains, materials, or patient needs change [60]. Their ability to combine human expertise with advanced analytics embodies the ideal of Industry 5.0—the synergy between humans and intelligent systems [61]. AI-based DTs help create rehabilitation equipment that is not only technically sound but also aligned with human values, needs, and long-term well-being.

In the emerging Industry 6.0 paradigm, AI-based digital twins play a key role in the non-destructive testing of 3D-printed rehabilitation equipment, integrating cyber–physical systems with autonomous, hyperconnected ecosystems. They function as constantly evolving virtual models that draw on real-time data streams from sensors, cloud platforms, and edge computing [62]. Digital twins support ultra-precise prediction of structural behavior by combining AI, quantum-assisted simulation, and advanced computational models. Their autonomous diagnostic capabilities enable the immediate detection of micro-defects and anomalies that traditional inspection methods might otherwise miss [63]. In Industry 6.0, digital twins contribute to self-healing manufacturing processes, where devices can be automatically reprinted, adjusted, or optimized based on diagnostic data [64]. They help create hyper-personalized rehabilitation equipment by combining patient biomechanics, environmental data, and predictive usage patterns in test simulations. DTs also facilitate decentralized manufacturing by ensuring consistent quality control across distributed 3D printing centers [65]. Their ability to combine digital and physical intelligence supports ethical, transparent, and human-centric quality assurance processes. They enhance sustainability through adaptive materials management and the reduction of unnecessary physical prototyping [66,67]. In this way, AI-based DTs provide the foundation for autonomous, robust, and intelligent nondestructive testing systems, envisioned in Industry 6.0.

The introduction of Agentic AI to DTs in NDT of 3D-printed rehabilitation devices represents a paradigm shift from reactive inspection to autonomous, predictive, and continuously adaptive quality assurance throughout the device lifecycle. Such DTs can autonomously coordinate multimodal NDT techniques, integrate sensor and production data in real time, identify design flaws, predict material degradation and remaining service life, and recommend corrective actions or design modifications without interrupting clinical use. This new paradigm supports closed-loop intelligent rehabilitation systems, where additive manufacturing, digital twins, nondestructive testing, and autonomous AI agents collaborate to enable the creation of personalized, resilient, and sustainable rehabilitation technologies with continuous learning and optimization.

3.7. Scalable AI-Based DTs Platforms in Rehabilitation

Scalable, AI-powered DT platforms enable continuous, data-driven monitoring of 3D-printed rehabilitation equipment without damaging it. These platforms integrate sensor data, material models, and AI algorithms to create virtual replicas that evolve with the physical object. This scalability allows for simultaneous monitoring of multiple rehabilitation devices, even in small, custom-made batches [67]. AI-enhanced DT platforms can detect subtle variations in structural behavior that traditional NDT might miss [68]. ML models embedded in the DT platform analyze stress patterns, vibration signatures, and geometric changes in near-real time [69]. The system predicts potential failures early, helping experimenters and engineers ensure patient safety. Cloud-based scalability enables remote diagnostics and collaboration between medical, engineering, and manufacturing teams [70]. The DT platform can simulate various loading scenarios to assess the durability of 3D-printed components before clinical use. Continuous feedback loops improve future prints by revealing manufacturing defects related to infill density, material aging, or print orientation [71]. Scalable AI-powered DT platforms have the potential to enhance the reliability, efficiency, and personalization of nondestructive testing for rehabilitation equipment.

3.8. Roadmap for Agentic AI-Based DTs in Rehabilitation

AI-based DTs should begin by creating patient-specific virtual models that integrate biomechanical, physiological, and rehabilitation data from wearable sensors and clinical assessments. These DTs should continuously adapt rehabilitation plans through autonomous reasoning, predictive analytics, and real-time feedback, while maintaining oversight from medical professionals. The next step should involve integrating DTs with 3D-printed rehabilitation devices, including orthoses, prostheses, splints, and therapeutic assistive devices, to simulate their mechanical performance under realistic loading conditions. Advanced NDT techniques, such as ultrasonic inspection, infrared thermography, X-ray computed tomography, acoustic emission monitoring, and 3D optical scanning, should be implemented to identify internal defects, material degradation, and structural inconsistencies without damaging the devices. Agent-based AI should autonomously analyze NDT data to detect anomalies, estimate remaining useful life, and recommend maintenance, redesign, or replacement of rehabilitation equipment before failure occurs. The DT ecosystem should integrate patient health data, equipment status, environmental factors, and rehabilitation progress into a unified cyber-physical system supporting personalized therapy. Federated learning (FL), secure cloud computing, and XAI should enable continuous model improvement while maintaining patient privacy and compliance with healthcare regulations. Validation should include clinical trials, mechanical verification of 3D-printed devices, benchmarking of AI decision-making, and standardized NDT protocols to ensure safety, reliability, and repeatability. The implementation phase should focus on interoperability with electronic medical records (including electronic health records-EHR), rehabilitation robotics, wearable IoT devices, additive manufacturing platforms, and hospital IT systems, leveraging international standards (HL7, JSON, as well as compliance with MDR, AI Act, NIS2, and GDPR). The long-term vision is an autonomous, trustworthy, and sustainable rehabilitation ecosystem in which agent-based AI continuously optimizes patient recovery, predicts equipment failures using DTs and NDT intelligence, and supports evidence-based clinical decision-making. It is worth noting that Agentic AI can utilize separate agents or entire modules for neurological, cardiac, or geriatric rehabilitation, depending on the patient's specific needs and the rehabilitation tools and methods used (in outpatient, home, or hybrid rehabilitation settings) (Table 6).

Table 6. Phases of roadmap.

Roadmap Phase	Agentic AI Digital Twin Activities	Role of NDT	Expected Outcome
Data acquisition	Collect patient, sensor, biomechanical, and rehabilitation equipment data	Baseline inspection of 3D-printed devices using CT, ultrasound, thermography, and optical scanning	High-quality multimodal datasets
DT Development	Create patient and equipment digital twins with physics-informed AI models	Integrate structural integrity information into equipment models	Accurate virtual representation
Intelligent monitoring	Continuous AI-driven monitoring and adaptive rehabilitation planning	Detect cracks, voids, delamination, wear, and fatigue without damaging equipment	Early fault detection and personalized therapy
Predictive decision support	Autonomous prediction of patient recovery and equipment degradation	Remaining useful life estimation and maintenance recommendations	Improved safety and reduced downtime
Clinical validation and deployment	Validate AI recommendations and integrate with clinical workflows	Standardized NDT quality assurance throughout equipment lifecycle	Reliable, safe, and scalable rehabilitation ecosystem

Beyond privacy concerns, cybersecurity is crucial for the secure implementation of AI-enabled agent-based DTs in IoMT environments. Technical cybersecurity threats, including unauthorized access, data interception, sensor data manipulation, and attacks on connected medical devices and DT infrastructure, must be explicitly addressed. We emphasize practical risk mitigation strategies, such as end-to-end encryption of IoMT data in transit and at rest, secure communication protocols, strong authentication and role-based access control, device identity management, network segmentation, continuous monitoring, and secure firmware updates. We also emphasize that cybersecurity should be considered throughout the DT lifecycle, from device deployment and data acquisition, through AI data processing and storage, to clinical decision support.

3.9. Implicaions to Sustainability

AI-based DTs support sustainability by reducing the need for physical prototypes, thereby minimizing material waste during the development of 3D-printed rehabilitation equipment. Their predictive capabilities allow manufacturers to optimize printing parameters and material usage, reducing the environmental impact of additive manufacturing processes [72]. Nondestructive testing using DTs extends product life by early identification of potential weaknesses, enabling the production of more durable and reliable rehabilitation devices. By virtually simulating failure modes, DTs reduce the energy consumption associated with repeated physical testing cycles. Continuous monitoring helps plan maintenance more efficiently, preventing premature disposal and supporting circular economy practices. DTs facilitate local, on-demand production of personalized rehabilitation devices, reducing transportation-related emissions and logistics losses. AI-based optimization improves resource allocation in distributed manufacturing systems, increasing overall eco-efficiency. Their ability to detect micro-defects early reduces the number of products that need to be scrapped or reprinted. Knowledge from DTs encourages the use of more sustainable materials, enabling detailed evaluation of alternative polymers or composites before physical testing [73]. AI-based DTs contribute to a more sustainable manufacturing ecosystem in the healthcare sector by promoting efficient design, reducing waste, and providing longer-lasting rehabilitation equipment. The introduction of Agentic AI to DTs in rehabilitation enhances sustainability by continuously optimizing personalized therapy, reducing unnecessary clinical visits, minimizing resource consumption, and improving healthcare efficiency. Agentic AI supports sustainable lifecycle management of rehabilitation equipment by predicting maintenance needs, extending the lifespan of 3D-printed assistive devices through integration with non-destructive testing, and reducing material waste associated with premature replacement. Furthermore, intelligent digital twin ecosystems facilitate data-driven decision-making, remote rehabilitation, and healthcare practices based on a circular economy, contributing to environmental, economic, and social sustainability while maintaining high standards of patient care.

AI-based DTs can often predict structural weaknesses and failure modes of 3D-printed rehabilitation equipment with greater sensitivity than many conventional NDT methods. Because DTs continuously collect sensor data in real time, they can detect subtle mechanical changes that may not be visible during periodic ultrasonic or visual inspections. ML models can identify complex, nonlinear patterns related to material fatigue, microporosity, or anisotropy induced by printing, which traditional techniques may miss. AI-based simulations within DT enable repeated virtual stress testing, enabling failure prediction under various loading scenarios without physically stressing the device. However, the accuracy of these predictions depends largely on the quality of the input data and the fidelity of the underlying material and geometric models [74]. In some cases, traditional NDT methods, such as X-ray tomography or acoustic testing, can still outperform DT in identifying very small internal defects. DTs are particularly effective when personalized usage patterns influence structural degradation, which conventional methods cannot easily capture. Their predictive capabilities improve over time as more operational data is collected, making them increasingly reliable for long-term monitoring. However, the uncertainty in AI-based decision-making can make it difficult to interpret risk levels with the same confidence as established NDT standards [75]. AI-based NDT can complement, if not replace, conventional methods by offering a more dynamic and context-sensitive picture of structural integrity.

Creating reliable AI-based DTs for 3D-printed rehabilitation products requires detailed material data, such as polymer grade, composite composition, and fill density, and mechanical properties such as tensile strength and fatigue resistance. Geometric data must reflect the full 3D model of the device, including layer orientation, wall thickness, internal lattice structures, and any patient-specific customizations. Information on printing process parameters (nozzle temperature, print speed, and layer height) is essential, as these factors strongly influence structural integrity [76]. Sensory data from embedded strain gauges, accelerometers, or load cells helps monitor stress and strain in real time during device use. Thermal and environmental sensors provide information on temperature cycling and moisture exposure, which impact the long-term performance of the material. High-resolution imaging or surface scanning data can reveal geometric deviations or surface defects introduced during printing. Vibration and acoustic sensors can detect subtle internal changes associated with crack initiation or delamination. Data on usage patterns, such as gait force or joint motion cycles, help personalize DT for specific rehabilitation scenarios. Historical maintenance and repair records further enhance predictive models by linking sensor patterns to observed failures [77,78]. These material, geometric, and sensory datasets enable AI-based digital twins to provide accurate and contextual, non-destructive assessments of rehabilitation equipment.

DTs can be very effective in supporting the personalization of rehabilitation equipment by simulating patient-specific loading conditions and daily use patterns. They incorporate biomechanical data such as gait cycles, joint angles, muscle forces, and body weight distribution to create personalized load profiles. By continuously updating these models with new sensor data, DTs can adjust predictions as the patient's mobility improves or changes over time [78]. AI algorithms identify each patient's interaction patterns with the device, allowing the digital twin to predict wear points specific to that individual. This enables early detection of personalized failure risks that cannot be captured with generic testing. DTs can also simulate alternative design variants to determine which geometry best withstands the specific loads applied by a given patient. These personalized insights support medical professionals in selecting or adjusting device parameters such as stiffness, thickness, and material selection. This predictive capability simultaneously helps optimize comfort and durability, improving rehabilitation outcomes [79]. Over time, aggregated personalized data contributes to the creation of more reliable models for similar patient profiles. In this way, DTs significantly enhance the personalization capabilities of 3D-printed rehabilitation devices through precise, patient-centric modeling.

Implementing AI-based DTs for routine evaluation and quality assurance of 3D-printed rehabilitation equipment faces a number of technological and clinical barriers. From a technological perspective, high-fidelity DT systems require extensive sensor integration, which is challenging for small or flexible rehabilitation devices. Many clinics or even research centers lack the in-house computing infrastructure necessary to process real-time data and run complex simulations [80]. Translational medicine centers are emerging with expanded capabilities in this area. Inconsistencies in 3D printing materials and processes limit the transferability of trained AI models across manufacturers. Data interoperability poses another challenge, as clinical systems, printers, and sensors often use incompatible standards. In clinical practice, staff may have limited familiarity with AI-based tools, leading to hesitation or misinterpretation of DT results. Regulatory uncertainty hinders clinics from implementing DT systems without clear guidelines for liability, validation, and certification. The need to protect patient-specific biomechanical data creates additional privacy and compliance burdens. Reimbursement systems rarely include advanced digital monitoring, reducing incentives for its implementation. Confidence in AI predictions remains variable among medical professionals, who may prefer established physical monitoring methods over algorithmic assessments.

4. Discussion

The proposed distinctions between traditional AI and agentic AI (such as autonomy, goal-directed planning, tool use, adaptive decision-making, and multi-stage orchestration) reflect architectural and functional differences between the two approaches, not experimentally proven performance advantages in NDT of 3D-printed rehabilitation equipment. Where the relevant literature provides empirical examples of autonomous AI, DTs, predictive maintenance, anomaly detection, or intelligent inspection, these studies are cited as the evidence base for the relevant capabilities.

The limited number of publications does not allow for broader comparisons with previous studies, but in a later part of the article we discuss key issues from the perspective of the development and applicability of research in the discussed area, answering our RQs:

- RQ1: Agentic AI-based DTs have the potential to autonomously detect and predict structural defects, degradation mechanisms, and failure modes in 3D-printed rehabilitation equipment by continuously integrating real-time sensor data, simulation results, and historical performance records. Unlike conventional NDT, which is typically periodic and inspection-based, they provide continuous monitoring and proactive anomaly detection. Their autonomous inference capabilities allow them to identify the evolution of hidden defects, estimate remaining service life, and recommend corrective actions without continuous human intervention. The effectiveness of these systems depends on the availability of high-quality multimodal data, accurate physics-based models, and robust AI algorithms. In this way, Agentic AI-based DTs will surpass conventional NDT methods in predictive maintenance, adaptability, and real-time decision-making.
- RQ2: Reliable Agentic AI-based DT development models require the integration of diverse material, geometric, biomechanical, and multimodal sensor data to accurately model personalized rehabilitation devices. Material properties, internal microstructure, manufacturing parameters, and geometric accuracy must be combined with patient-specific biomechanical loading conditions and movement patterns. Additional data from embedded sensors, wearable devices, imaging systems, and environmental monitoring improve the model's ability to detect degradation and predict failure. Agentic AI continuously combines these heterogeneous data sources to update DT models as device status changes over time. This comprehensive data integration enables the creation of adaptive, reliable, and personalized predictive models suitable for various categories of rehabilitation equipment.
- RQ3: Agentic AI-based DT development models have the potential to enhance personalized rehabilitation by autonomously modeling patient-specific loading conditions, device use behaviors, and rehabilitation progress. These models continuously learn from patient interactions, wearable sensors, and patient feedback to update predictions throughout the rehabilitation process. By adapting to the patient's changing condition, they can optimize device performance, recommend individualized interventions, and predict potential device failures before they occur. Continuous model adaptation improves both rehabilitation outcomes and device reliability while reducing the need for frequent manual assessments. Consequently, Agentic AI-based DT

development models provide an intelligent and dynamic framework for personalized rehabilitation support.

- RQ4: Routine implementation of Agentic AI-based DTs requires overcoming a number of scientific, technological, clinical, and regulatory challenges. From a scientific perspective, accurate multiphysics modeling, reliable uncertainty quantification, and explainable artificial intelligence (XAI) methods are essential to ensuring reliable predictions. Technological challenges include seamless integration of multimodal sensors, interoperability across healthcare systems, cybersecurity, and a scalable computing infrastructure to support a real-time digital twin. Clinical implementation depends on extensive validation, acceptance by medical professionals, patient safety, and demonstrating clear improvements over existing NDT quality assurance methods. Furthermore, before widespread implementation becomes possible, a regulatory framework, standardized validation protocols, ethical AI governance, and compliance with medical device regulations must be established (Table 7).

Table 7. Mapping each RQ to major themes and key representative citations.

RQ	Major Themes	Citations
RQ1	Autonomous defect detection and prediction Predictive maintenance and autonomous decision-making Multimodal data and physics-informed intelligence	[56,57,60]
RQ2	Multimodal and heterogeneous data integration Dynamic DT updating and adaptation Personalized and reliable predictive modelling	[47–49]
RQ3	Patient-specific modelling and personalization Continuous learning and adaptive rehabilitation Intelligent intervention and device reliability	[43–45]
RQ4	Scientific and technological reliability Clinical validation and adoption Regulatory, ethical and standardization framework	[58,61,81]

Calling a specific architecture a "true DT" may inadvertently invalidate other, well-established digital twin models developed for different applications. There is no single, universal, or true AI/ML or DT architecture; these models are typically designed according to their intended use and context of use.

The article emphasizes that this contribution is not merely another general review of AI, DTs, or NDT. The review integrates these areas in the context of 3D-printed rehabilitation equipment and develops a conceptual path toward a closed-loop, agent-based AI DT system for intelligent NDT. Specifically, the review connects the defect detection and assessment process in NDT with DT representation, autonomous AI reasoning, decision support, and feedback, thus identifying an integrated research direction that is insufficiently addressed when these technologies are considered separately. The article also identifies technical requirements, anticipated interfaces, validation needs, and research gaps that must be addressed before such systems can be implemented in practice.

4.1. Limitations

AI-based DTs used for NDT of 3D-printed rehabilitation equipment still face several significant limitations. Their accuracy is highly dependent on the quality and completeness of sensor data, which can be inconsistent for custom rehabilitation devices. Material models for 3D-printed polymers or composites are often simplified, limiting the DTs' ability to capture complex behaviors related to aging or fatigue [82]. AI algorithms can misinterpret noise or minor variations in sensor readings as structural defects. Creating and maintaining high-quality DTs can be computationally expensive, limiting real-time performance in large-scale deployments. Limited standardization of 3D printing processes hinders the generalization of trained AI models across printers, materials, or geometries. Validation of DT predictions requires physical testing, slowing their implementation in clinical and engineering environments [82]. Privacy and data security concerns can limit the integration of patient-specific usage data necessary for accurate modeling. Overreliance on AI-generated assessments can cause engineers to miss physical inspection cues that the model cannot capture. DTs may struggle to predict unexpected failure modes resulting from rare defects or novel rehabilitation device designs. The introduction of Agentic AI into DTs in rehabilitation is limited by the availability, quality, and interoperability of multimodal clinical, biomechanical, and sensory data necessary for accurate model development. Agentic AI's autonomous decision-making capabilities also pose challenges related to model transparency, clinical validation, patient privacy, cybersecurity, regulatory compliance, and the need for ongoing human oversight to ensure safe and ethical use. Furthermore, implementing DTs using Agentic AI requires significant computational resources, specialized expertise, and integration with existing healthcare infrastructure, which can limit scalability and adoption, especially in resource-constrained clinical settings.

Technical barriers include not only challenges related to data availability, model accuracy, and computational requirements but also limited interdisciplinary integration between engineering, materials science, AI, and clinical rehabilitation. The dominance of engineering and materials science in the distribution of disciplines suggests that insufficient collaboration with healthcare professionals may hinder the translation of technological advances into clinically validated and patient-centered solutions. This highlights the importance of issues such as real-time data integration, device-specific modeling, sensor interoperability, structural health prediction, and clinical validation.

Limitations also apply to bibliometric analysis itself, including database selection bias, varying indexing practices, limitations of citation-based assessment, and the possibility that new but underrepresented research areas may not be fully covered.

Limitations such as model uncertainty, data quality dependence, imperfect defect detection, and the potential for AI to make erroneous or insufficiently explained decisions can have direct clinical implications if these systems are used to support safety-critical decisions. In the case of 3D-printed rehabilitation equipment, undetected manufacturing defects or incorrect AI-assisted assessments can compromise structural integrity, device performance, and ultimately patient safety. The use of agent-based AI and DTs does not replace qualified human inspection, validation, or clinical judgment, particularly when demonstrating regulatory compliance and device safety. Clinical implementation requires appropriate verification and validation, traceability of AI-assisted decisions, data management, risk management, and compliance with applicable medical device regulations and standards.

4.2. Technological Implications

AI-based digital twins are driving advances in sensor integration, requiring more precise, miniaturized, and robust sensors to capture real-time data from rehabilitation equipment. They are driving the development of high-fidelity material models that can accurately represent the complex behavior of 3D-printed structures, layer by layer. The need for seamless data exchange is accelerating innovation in interoperability standards between CAD systems, printers, simulation tools, and clinical software [83]. DTs require a powerful computing infrastructure, including cloud, edge, and potentially quantum-enhanced processors, to support continuous simulation and large datasets. Their implementation fosters the development of automated quality-control processes that can identify defects and initiate corrective actions without human intervention. AI-based predictive models are driving improvements in machine learning algorithms tailored to additive manufacturing and medical device testing [84]. DTs are encouraging the use of advanced visualization technologies, such as augmented and mixed reality, to support the clinical interpretation of structural parameters. They are accelerating the implementation of decentralized manufacturing networks, where consistent quality control is ensured through shared digital twin platforms. This technology is increasing the need for robust cybersecurity measures to protect sensitive patient data and devices used in simulations. AI-based DTs are transforming technology ecosystems by combining manufacturing intelligence, real-time analytics, and autonomous diagnostics into a unified nondestructive testing platform. The introduction of Agentic AI into DTs in rehabilitation enables the real-time integration of data from wearable sensors, medical imaging systems, rehabilitation robots, and IoT devices, creating adaptive and constantly evolving virtual representations of patients and rehabilitation equipment. From a technological perspective, Agentic AI enhances DTs with autonomous reasoning, predictive analytics, and self-optimizing decision-making, enabling personalized therapy planning, early detection of clinical risks, and predictive maintenance of 3D-printed rehabilitation devices. However, successful implementation requires interoperable digital infrastructure, high-performance edge and cloud computing, robust cybersecurity, understandable AI models, and standardized data exchange protocols to ensure reliable, scalable, and clinically safe operation.

4.3. Economic and Organizational Implications

AI-based DT technologies can reduce manufacturing costs by minimizing the number of physical prototypes needed during the design and testing of rehabilitation equipment. They reduce costs associated with destructive testing by enabling virtual structural assessments that do not consume materials or damage devices. Improved defect detection accuracy reduces the financial burden of reprints, product recalls, and warranty claims. Shorter validation cycles shorten time to market, giving manufacturers an economic advantage [85]. DTs support more efficient material use, reducing waste and lowering overall production costs. This technology enables predictive maintenance, reducing long-term operating costs for clinics using 3D-printed rehabilitation devices. Initial implementation costs (sensor integration, data infrastructure, and AI model development) can be high, presenting a barrier for small manufacturers. However, scalable DT platforms can create new business models, including remote diagnostic services and subscription-based quality assurance tools. Improved product reliability increases customer confidence, potentially increasing demand and improving revenue streams. AI-based DTs offer significant long-term economic benefits by optimizing production efficiency, reducing risk, and improving device performance in the rehabilitation sector [86]. Introducing Agentic AI to DTs in rehabilitation can reduce long-term healthcare costs by optimizing treatment pathways, enabling predictive maintenance of rehabilitation equipment, minimizing device failures, and supporting remote patient monitoring. From an organizational perspective, healthcare providers must adapt clinical processes, invest in digital infrastructure, develop interdisciplinary expertise, and establish governance frameworks for AI oversight, data management, and regulatory compliance. Successful implementation also depends on staff training, interoperability across healthcare systems, and collaboration between clinicians, engineers, AI specialists, rehabilitation equipment manufacturers, and policymakers to ensure scalable, efficient, and sustainable rehabilitation services.

4.4. Social Implications

AI-based digital twins can improve access to high-quality rehabilitation equipment by enabling faster, safer, and more reliable manufacturing processes. They support greater personalization, enabling individuals with diverse needs to receive devices tailored to their functional, anatomical, and lifestyle requirements. Increased reliability of rehabilitation equipment increases user confidence and can lead to better treatment adherence. By reducing waste and resource consumption, DTs contribute to more sustainable healthcare practices, valued by society. This technology can help reduce healthcare disparities by enabling local, on-demand manufacturing in underserved regions [87]. At the same time, unequal access to advanced digital infrastructure can widen the gap between well-resourced and under-resourced healthcare facilities. Increased data collection for digital twin modeling raises public concerns about privacy, data protection, and the responsible handling of patient information. Integrating AI-based assessments into clinical practice requires public trust in automated decision-support systems. Widespread implementation could create new workforce demands, which in turn will require upskilling among clinicians, engineers, and technicians. AI-based DTs have the potential to enhance societal well-being by supporting safer, more inclusive, and more effective rehabilitation technologies, provided ethical considerations and equitable access are addressed [88]. The introduction of agentic AI to DTs in rehabilitation has the potential to improve access to personalized rehabilitation services by enabling remote monitoring, adaptive therapy, and ongoing support for patients in underserved or rural areas [89]. From a societal perspective, these technologies can enhance patient engagement, independence, and quality of life by providing personalized interventions and timely feedback, while also strengthening collaboration between patients, caregivers, and healthcare providers [90]. However, their widespread implementation also requires addressing digital literacy, equitable access to advanced technologies, patient trust, and ethical issues related to data privacy, algorithmic bias, and the appropriate role of autonomous AI in clinical decision-making (Figure 12).

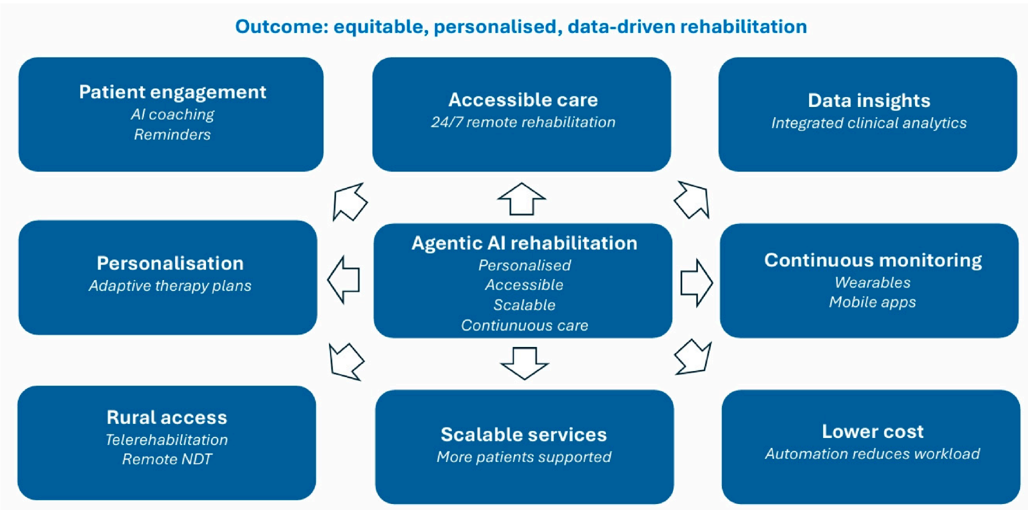

Figure 12. Democratising rehabilitation through Agentic AI.

4.5. Ethical and Legal Implications

AI-based DTs used in non-destructive testing of 3D-printed rehabilitation equipment raise a number of ethical and legal concerns. These systems often rely on patient-specific data, necessitating strict privacy protections and informed consent [91]. The opacity of AI decision-making can make it difficult to explain why the DT flags a defect or risk (as defined by eXplainable AI (XAI)), potentially complicating clinical liability [92]. If a DT performs an inaccurate assessment that leads to equipment failure or patient harm, questions arise about whether clinicians, engineers, manufacturers, or developers are liable [93]. Unequal access to advanced DT technologies can exacerbate the disparity between well-funded and underfunded rehabilitation centers [94,95]. Ethical issues also arise when AI models are trained on biased or incomplete datasets, which can lead to unreliable assessments for certain user groups or device types. Regulators struggle to keep up with rapid innovation, leaving gray areas in the certification requirements for AI-powered NDT tools [96]. Intellectual property concerns can arise when DT simulations incorporate proprietary printing parameters or material models [97]. Ensuring cybersecurity is crucial, as manipulation of DT data can compromise patient safety or device integrity [98]. Responsible implementation requires transparent governance, a clear legal framework, and ongoing ethical oversight to maintain trust in AI-powered rehabilitation technologies [99]. The introduction of Agentic AI into DTs in rehabilitation raises ethical and legal challenges related to patient privacy, informed consent, data ownership, and the secure management of confidential medical information generated by connected digital systems [100]. Agentic AI's autonomous decision-making capabilities require a clear governance framework that defines accountability, transparency, human oversight, and responsibility for clinical decisions, particularly when AI-generated recommendations impact patient care or rehabilitation outcomes [101]. Compliance with healthcare regulations, medical device standards, and AI governance frameworks is essential to ensure fairness, prevent algorithmic bias, maintain patient trust, and support the safe and legal implementation of Agentic AI-based DTs in rehabilitation [102].

4.6. Key Directions of Further Studies

Future research on AI-based DTs for nondestructive testing of 3D-printed rehabilitation equipment should focus on improving the fidelity of material and structural models [103–105]. Researchers must develop better representations of 3D-printed polymers and composites, accounting for anisotropy, microporosity, and long-term degradation [106–109]. Advances in multimodal sensors and data fusion will help digital twins extract more accurate, real-time information from complex rehabilitation devices [110–112]. AI models must become more transparent and understandable to support clinical decision-making and regulatory approvals [113–117]. Another key direction is the creation of standardized datasets and benchmarking methods to ensure reproducibility across printers, materials, and patient-specific geometries [118–120]. Scalable architectures that reduce computational burden while maintaining model accuracy will be essential for widespread implementation [121–124]. Integrating DTs systems with hybrid cloud platforms can enable secure, low-latency analysis in clinical settings [125–127]. Research should also explore predictive maintenance algorithms that take into account personalized usage patterns and varying load conditions [128–130]. Research focused on cybersecurity will be essential to protecting sensitive health and performance data in digital twin ecosystems [131–134]. Future research on the introduction of agentic AI into DTs in rehabilitation should focus on developing reliable, understandable, and clinically validated autonomous agents capable of providing safe, personalized, and adaptive rehabilitation while maintaining effective human supervision [135–137]. Further research is needed to integrate multimodal data from wearable sensors, medical imaging, rehabilitation robotics, electronic medical records, and nondestructive testing of 3D-printed rehabilitation equipment to improve predictive accuracy, interoperability, and real-time decision-making [138,139]. Research should also establish a unified evaluation framework, ethical and regulatory guidelines, cybersecurity strategies, and large-scale clinical validation to demonstrate the long-term effectiveness, safety, scalability, acceptation, and sustainability of agentic AI-based DTs in rehabilitation [140–142].

There is a need for future experimental validation using representative 3D-printed rehabilitation components, sensor data, DTS models, NDT measurements, and agent-based decision-making processes. The transition from Industry 4.0 to Industry 5.0 and the emerging concepts of Industry 6.0 is not simply an advancement in the number of DT functions. Rather, it reflects a shift in expectations for DT, decision-making, and the relative roles of automation, human participation, autonomy, resilience, and sustainability. This interpretation distinguishes the following paradigms:

- Industry 4.0: emphasizes connectivity, automation, cyber–physical integration, data acquisition, monitoring, and optimization, with DT functioning primarily as a computational representation for real-time monitoring and predictive/diagnostic processes.
- Industry 5.0: places a greater emphasis on human-centricity, human–machine collaboration, resilience, personalization, and sustainability. Therefore, DT is positioned not only as an optimization tool but also as an interface supporting human decision-making, personalized production, and collaborative inspection.
- Industry 6.0 is treated with caution as a new and evolving paradigm, not as a well-established industry standard. In our view, its significance is associated with higher levels of autonomy, distributed intelligence, adaptive systems, cognitive collaboration, and potentially self-developing digital ecosystems.

We explicitly acknowledge that the conceptual boundaries of Industry 6.0 are still in development, and therefore we avoid assigning it final technical functions.

5. Conclusions

AI-based digital twins, powered by Agentic AI technology, are becoming a powerful complement to NDT for 3D-printed rehabilitation equipment, providing continuous, autonomous insight into device health, structural integrity, and clinical performance. By integrating real-time sensor data, advanced simulation, machine learning, and autonomous reasoning, Agentic AI technology improves the accuracy, timeliness, and adaptiveness of fault detection, predictive maintenance, and personalized rehabilitation planning. Their ability to model individual patient characteristics, equipment behavior, and dynamic usage patterns improves the safety, reliability, and effectiveness of rehabilitation interventions. Furthermore, Agentic AI technology enables DTs to proactively support decision-making by continuously learning from new data, optimizing treatment strategies, and recommending maintenance or redesign of rehabilitation devices before failure occurs.

The proposed framework remains conceptual, and conclusions regarding its effectiveness, reliability, safety, and clinical/practical utility cannot yet be considered empirically proven. The lack of experimental datasets, validation in real-world NDT settings, long-term DT tests, and clinical/human evaluation limits the credibility with which the potential benefits of agent-based AI can currently be assessed. Therefore, we present the proposed architecture as a research roadmap rather than a proven operational system and emphasize the need for systematic experimental, comparative, and application-specific validation.

Despite current limitations related to data quality, model fidelity, interoperability, computational requirements, ethical issues, and regulatory uncertainty, Agentic AI-based DTs demonstrate significant potential for transformation in both clinical rehabilitation and biomedical engineering. Continued interdisciplinary research, extensive clinical validation, and responsible implementation will be essential to ensure their safety, transparency, and regulatory compliance, while maximizing clinical and societal benefits. Agentic AI-powered DTs represent a significant step toward smarter, safer, more autonomous, and adaptive rehabilitation technologies, supporting sustainable healthcare and next-generation intelligent rehabilitation systems.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial intelligence
CAD	Computer aided design
CPS	Cyber-physical system
DT	Digital twin
IoMT	Internet of medical things
IoT	Internet of things
ML	Machine learning
RQ	Research question
XAI	eXplainable AI

References

1. Mikołajewska, E.; Mikołajewski, D.; Mikołajczyk, T.; Paczkowski, T. Generative AI in AI-Based Digital Twins for Fault Diagnosis for Predictive Maintenance in Industry 4.0/5.0. *Appl. Sci.* **2025**, *15*, 3166. [CrossRef]
2. Łukaniszyn, M.; Majka, Ł.; Grochowicz, B.; Mikołajewski, D.; Kawala-Sterniuk, A. Digital Twins Generated by Artificial Intelligence in Personalized Healthcare. *Appl. Sci.* **2024**, *14*, 9404. [CrossRef]
3. Mikołajewska, E.; Masiak, J.; Mikołajewski, D. Applications of Artificial Intelligence-Based Patient Digital Twins in Decision Support in Rehabilitation and Physical Therapy. *Electronics* **2024**, *13*, 4994. [CrossRef]
4. Mineo, C. Advancements in integrated robotic sensing: A European perspective. *Open Res. Eur.* **2024**, *4*, 39. [CrossRef] [PubMed]
5. Smits Serena, R.; Hinterwimmer, F.; Burgkart, R.; von Eisenhart-Rothe, R.; Rueckert, D. The Use of Artificial Intelligence and Wearable Inertial Measurement Units in Medicine: Systematic Review. *JMIR mHealth uHealth* **2025**, *13*, e60521. [CrossRef] [PubMed]
6. Tai, J.L.; Sultan, M.T.H.; Łukaszewicz, A.; Józwik, J.; Oksiuta, Z.; Shahar, F.S. Recent Trends in Non-Destructive Testing Approaches for Composite Materials: A Review of Successful Implementations. *Materials* **2025**, *18*, 3146. [CrossRef] [PubMed]
7. Abdollahi-Mamoudan, F.; Ibarra-Castanedo, C.; Maldague, X.P.V. Non-Destructive Testing and Evaluation of Hybrid and Advanced Structures: A Comprehensive Review of Methods, Applications, and Emerging Trends. *Sensors* **2025**, *25*, 3635. [CrossRef] [PubMed]
8. Mikołajewska, E.; Mikołajewski, D. Integrated IT environment for people with disabilities: A new concept. *Cent. Eur. J. Med.* **2014**, *9*, 177–182. [CrossRef]
9. Patel, V.; Orchanian-Cheff, A.; Wu, R. Evaluating the Validity and Utility of Wearable Technology for Continuously Monitoring Patients in a Hospital Setting: Systematic Review. *JMIR mHealth uHealth* **2021**, *9*, e17411. [CrossRef] [PubMed]
10. Hasan, A.; Trong Nguyen, D. Integrating agentic AI and digital twins for intelligent decision-making systems. *Array* **2026**, *29*, 100721. [CrossRef]

11. Propkopowicz, P.; Mikołajewski, D.; Tyburek, K.; Mikołajewska, E. Computational gait analysis for post-stroke rehabilitation purposes using fuzzy numbers, fractal dimension and neural networks. *Bull. Pol. Acad. Sci. Tech. Sci.* **2020**, *68*, 191–198. [CrossRef]
12. Qin, C.; Luo, X.; Yang, Y.; Lun, Y.; Yang, S.; Chen, L. Therapeutic outcomes of customized 3D-printed ankle-foot orthoses in children with spastic cerebral palsy: A case series study. *Front. Pediatr.* **2025**, *13*, 1661098. [CrossRef] [PubMed]
13. Thomas, S.; Hu, X. A 3D-Printed Hand Exoskeleton for Affordable and Accessible Upper Limb Rehabilitation. In *2025 47th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*; IEEE: Piscataway, NJ, USA, 2025; pp. 1223–1228. [CrossRef]
14. Liew, S.L.; Cotton, R.J.; Burdet, E.; Bermúdez, I.; Badia, S.; Celnik, P.; Cole, J.H.; Liu, R.; Soekadar, S.R.; Winstein, C.; et al. Collaborative AI for precision neurorehabilitation: A roadmap. *J. Neuroeng. Rehabil.* **2025**, *22*, 269. [CrossRef] [PubMed]
15. Chen, J.; Clos, J.; Price, D.; Caleb-Solly, P. Analyzing Gait Adaptation with Hemiplegia Simulation Suits and Digital Twins. In *2025 47th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*; IEEE: Piscataway, NJ, USA, 2025; pp. 1–7. [CrossRef] [PubMed]
16. Noce, A.L.; De Vicariis, C.; Sanguineti, V. Interplay of compensation and true recovery in upper limb movements post-stroke: A computational model. In *2025 47th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*; IEEE: Piscataway, NJ, USA, 2025; pp. 1–6. [CrossRef] [PubMed]
17. García-Rudolph, A.; Wright, M.A.; Teixidó-Font, C.; Sanchez-Carrion, R.; Cedersund, G.; Opisso, E. Digital twins in stroke rehabilitation: A scoping review of objectives, data sources, mechanisms, outcomes, and desirable properties. *Top. Stroke Rehabil.* **2026**, *33*, 704–718. [CrossRef] [PubMed]
18. Khan, M.M.R.; Zarif, M.I.I.; Pillai, A.; Wang, I.; Rahman, M.H. Investigating a Telerehabilitation Platform Integrated with a Rehabilitation Robot Using Microsoft HoloLens 2 for Upper-Limb Therapy: Pilot Usability Study. *JMIR Rehabil. Assist. Technol.* **2025**, *12*, e75907. [CrossRef] [PubMed]
19. Chaparro-Cárdenas, S.L.; Ramirez-Bautista, J.A.; Terven, J.; Córdova-Esparza, D.M.; Romero-Gonzalez, J.A.; Ramírez-Pedraza, A.; Chavez-Urbiola, E.A. A Technological Review of Digital Twins and Artificial Intelligence for Personalized and Predictive Healthcare. *Healthcare* **2025**, *13*, 1763. [CrossRef] [PubMed]
20. Ifeoma Anene, J.; Sharma, A.; Sharma, A.; Fatima, I.; Kancherla, N.; Ponnada, S.C.; Ravuru, S.K.; Thymalil, C.; Rajeshwara, S.; Chauhan, A.; et al. Exploring the Potential of Artificial Intelligence (AI) and Augmented Reality (AR) in Neurological Disease Management: A Narrative Review. *Cureus* **2025**, *17*, e86614. [CrossRef] [PubMed]
21. Chiu, Y.H.; Lee, U.H.; Song, C.; Hu, M.; Kang, I. Learning Speed-Adaptive Walking Agent Using Imitation Learning with Physics-Informed Simulation. In *2025 International Conference On Rehabilitation Robotics (ICORR)*; IEEE: Piscataway, NJ, USA, 2025; pp. 835–841. [CrossRef] [PubMed]
22. Tan, C.K.; Wang, C.; Lyu, S.; Hodossy, B.K.; Schumacher, P.; Wilson, E.B.; Caggiano, V.; Kumar, V.; Farina, D.; Gionfrida, L.; et al. Myoassist 0.1: Myosuite for Dexterity and Agility in Bionic Humans. In *2025 International Conference On Rehabilitation Robotics (ICORR)*; IEEE: Piscataway, NJ, USA, 2025; pp. 437–442. [CrossRef]
23. Falkowski, P.; Zawalski, K.; Jeznach, K.; Oleksiuk, J.; Aktan, M.E.; Omurlu, V.E.; Niedbalski, P.; Akdogan, E.; Kolodziejski, P. Investigation of Delays and Connection Stability in Teleoperation via VR Capabilities for Remote Exoskeleton-Aided Physiotherapy. In *2025 International Conference On Rehabilitation Robotics (ICORR)*; IEEE: Piscataway, NJ, USA, 2025; pp. 308–313. [CrossRef] [PubMed]
24. Serrano-Diaz, S.; Huaman Levano, L. Makita Hapiy 2.0: Design and Development of a Low-Cost and Lightweight Myoelectric Transradial Prosthesis using 3D Printing. In *2025 47th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*; IEEE: Piscataway, NJ, USA, 2025; pp. 1–5. [CrossRef] [PubMed]
25. Chen, P.; Xia, Y.; Wu, Y.; Wu, X.; Wang, Y.; Dai, H. 3D-printed scaffolds with ROS-clearing capacity for critical-sized bone defect regeneration. *Biomater. Adv.* **2025**, *180*, 214575. [CrossRef]
26. Rojek, I.; Kotlarz, P.; Dorożyński, J.; Mikołajewski, D. Sixth-Generation (6G) Networks for Improved Machine-to-Machine (M2M) Communication in Industry 4.0. *Electronics* **2024**, *13*, 1832. [CrossRef]
27. Grabec, T.; Veres, I.A.; Ryzy, M. Surface acoustic wave attenuation in polycrystals: Numerical modeling using a statistical digital twin of an actual sample. *Ultrasonics* **2022**, *119*, 106585. [CrossRef] [PubMed]
28. Cecchetti, F.; Spuntarelli, M.; Mazza, D.; Di Girolamo, M.; Baggi, L. Guided sinus lift: Virtual planning of surgical templates for lateral access. *J. Biol. Regul. Homeost. Agents* **2021**, *35*, 139–145. [CrossRef] [PubMed]
29. Zsidai, B.; Hilkert, A.S.; Kaarre, J.; Narup, E.; Senorski, E.H.; Grassi, A.; Ley, C.; Longo, U.G.; Herbst, E.; Hirschmann, M.T.; et al. A practical guide to the implementation of AI in orthopaedic research—Part 1: Opportunities in clinical application and overcoming existing challenges. *J. Exp. Orthop.* **2023**, *10*, 117. [CrossRef] [PubMed]
30. Ratschat, A.; Lomba, T.M.C.; Gasperina, S.D.; Marchal-Crespo, L. Development and Validation of a Kinematically Accurate Upper-Limb Exoskeleton Digital Twin for Stroke Rehabilitation. In *2023 International Conference on Rehabilitation Robotics (ICORR)*; IEEE: Piscataway, NJ, USA, 2023; pp. 1–6. [CrossRef] [PubMed]

31. Wang, W.; He, Y.; Li, F.; Li, J.; Liu, J.; Wu, X. Digital twin rehabilitation system based on self-balancing lower limb exoskeleton. *Technol. Health Care* **2023**, *31*, 103–115. [CrossRef] [PubMed]
32. Zou, J.; Topol, E.J. The rise of agentic AI teammates in medicine. *Lancet* **2025**, *405*, 457. [CrossRef] [PubMed]
33. Dutta Roy, T.P. Bioethics Artificial Intelligence Advisory (BAIA): An Agentic Artificial Intelligence (AI) Framework for Bioethical Clinical Decision Support. *Cureus* **2025**, *17*, e80494. [CrossRef] [PubMed]
34. Shahin, M.H.; Goswami, S.; Lobentanzer, S.; Corrigan, B.W. Agents for Change: Artificial Intelligent Workflows for Quantitative Clinical Pharmacology and Translational Sciences. *Clin. Transl. Sci.* **2025**, *18*, e70188. [CrossRef] [PubMed]
35. Yigit, Y.; Ferrag, M.A.; Ghanem, M.C.; Sarker, I.H.; Maglaras, L.A.; Chrysoulas, C.; Moradpoor, N.; Tihanyi, N.; Janicke, H. Generative AI and LLMs for Critical Infrastructure Protection: Evaluation Benchmarks, Agentic AI, Challenges, and Opportunities. *Sensors* **2025**, *25*, 1666. [CrossRef] [PubMed]
36. Schmutz, J.B.; Outland, N.; Kerstan, S.; Georganta, E.; Ulfert, A.S. AI-teaming: Redefining collaboration in the digital era. *Curr. Opin. Psychol.* **2024**, *58*, 101837. [CrossRef] [PubMed]
37. Liawrungrueang, W. Artificial Intelligence (AI) Agents Versus Agentic AI: What's the Effect in Spine Surgery? *Neurospine* **2025**, *22*, 473–477. [CrossRef] [PubMed]
38. Venerito, V.; Lopalco, G.; Iannone, F.; Gupta, L. Agentic AI in rheumatology. *Lancet Rheumatol.* **2026**, *8*, e486–e491. [CrossRef] [PubMed]
39. Tripathi, S.; Cook, T.S.; Kim, W. Agentic AI in Radiology. *Radiology* **2026**, *318*, e252730. [CrossRef] [PubMed]
40. Salehi, S.; Singh, Y.; Horst, K.K.; Hathaway, Q.A.; Erickson, B.J. Agentic AI and Large Language Models in Radiology: Opportunities and Hallucination Challenges. *Bioengineering* **2025**, *12*, 1303. [CrossRef] [PubMed]
41. Huang, K.; Zhang, S.; Wang, H.; Qu, Y.; Lu, Y.; Roohani, Y.; Li, R.; Qiu, L.; Li, G.; Zhang, J.; et al. Biomni: A General-Purpose Biomedical AI Agent. *bioRxiv* **2025**, 2025.05.30.656746. [CrossRef] [PubMed]
42. Khosravi, B.; Rouzrokh, P.; Akinci D'Antonoli, T.; Moassefi, M.; Faghani, S.; Mansuri, A.; Bressem, K.; Tejani, A.; Gichoya, J. Agentic AI in Radiology: Evolution from Large Language Models to Future Clinical Integration. *Radiol. Artif. Intell.* **2026**, *8*, e250651. [CrossRef] [PubMed]
43. Evans, J.; Bratton, B.; Agüera, Y.; Arcas, B. Agentic AI and the next intelligence explosion. *Science* **2026**, *391*, eaeg1895. [CrossRef] [PubMed]
44. Hartung, T. AI, agentic models and lab automation for scientific discovery—The beginning of scAInce. *Front. Artif. Intell.* **2025**, *8*, 1649155. [CrossRef] [PubMed]
45. Gavai, A.K.; Meuwissen, M.P.M. Agentic AI as a coordination paradigm in digital health and agri-food systems. *Patterns* **2026**, *7*, 101496. [CrossRef] [PubMed]
46. Shi, P.; Ren, T.; Xie, Y.; Gichoya, J.W.; Wong, T.Y.; Ji, X.; Wang, N.; Yuan, W. Agentic AI in global health equity for high altitude populations. *npj Digit. Med.* **2026**. [CrossRef] [PubMed]
47. Barra, F.L.; Rodella, G.; Costa, A.; Scalogna, A.; Carenzo, L.; Monzani, A.; Della Corte, F. From prompt to platform: An agentic AI workflow for healthcare simulation scenario design. *Adv. Simul.* **2025**, *10*, 29. [CrossRef] [PubMed]
48. Gorenshtein, A.; Omar, M.; Glicksberg, B.S.; Nadkarni, G.N.; Klang, E. AI Agents in Clinical Medicine: A Systematic Review. *medRxiv* **2025**, 2025.08.22.25334232. [CrossRef] [PubMed]
49. Adabara, I.; Olaniyi Sadiq, B.; Nuhu Shuaibu, A.; Ibarahim Danjuma, Y.; Venkateswarlu, M. A Review of Agentic AI in Cybersecurity: Cognitive Autonomy, Ethical Governance, and Quantum-Resilient Defense. *F1000Research* **2025**, *14*, 843. [CrossRef] [PubMed]
50. Sharma, D.; Meshkat, S.; Perivolaris, A.; Kamaleddin, M.A.; Teferra, B.G.; Rueda, A.; Samavi, R.; Jetly, R.; Mago, V.; Wu, Y.; et al. Reimagining psychiatric care with agentic AI: Promise, challenges, and a roadmap forward. *npj Digit. Med.* **2026**, *9*, 252. [CrossRef] [PubMed]
51. He, J.; Lai, H.; Saigiridharan, L.; Ghiandoni, G.M.; Jenei, K.; Gokalp, U.; Nuković, A.; Engkvist, O.; Janet, J.P.; Genheden, S. Democratising real-world drug discovery through agentic AI. *Drug Discov. Today* **2026**, *31*, 104605. [CrossRef] [PubMed]
52. Moiceanu, G.; Paraschiv, G. Digital Twin and Smart Manufacturing in Industries: A Bibliometric Analysis with a Focus on Industry 4.0. *Sensors* **2022**, *22*, 1388. [CrossRef] [PubMed]
53. Kumar, R.; Rani, S.; Awadh, M.A. Exploring the Application Sphere of the Internet of Things in Industry 4.0: A Review, Bibliometric and Content Analysis. *Sensors* **2022**, *22*, 4276. [CrossRef] [PubMed]
54. Gallala, A.; Kumar, A.A.; Hichri, B.; Plapper, P. Digital Twin for Human-Robot Interactions by Means of Industry 4.0 Enabling Technologies. *Sensors* **2022**, *22*, 4950. [CrossRef] [PubMed]
55. Filipescu, A.; Simion, G.; Ionescu, D.; Filipescu, A. IoT-Cloud, VPN, and Digital Twin-Based Remote Monitoring and Control of a Multifunctional Robotic Cell in the Context of AI, Industry, and Education 4.0 and 5.0. *Sensors* **2024**, *24*, 7451. [CrossRef] [PubMed]
56. Simion, G.; Filipescu, A.; Ionescu, D.; Filipescu, A. Cloud/VPN-Based Remote Control of a Modular Production System Assisted by a Mobile Cyber-Physical Robotic System-Digital Twin Approach. *Sensors* **2025**, *25*, 591. [CrossRef] [PubMed]

57. Yang, T.; Razzaq, L.; Fayaz, H.; Qazi, A. Redefining fan manufacturing: Unveiling industry 5.0's human-centric evolution and digital twin revolution. *Heliyon* **2024**, *10*, e33551. [CrossRef] [PubMed]
58. Modoni, G.E.; Sacco, M. A Human Digital-Twin-Based Framework Driving Human Centricity towards Industry 5.0. *Sensors* **2023**, *23*, 6054. [CrossRef] [PubMed]
59. Ionescu, D.; Filipescu, A.; Simion, G.; Filipescu, A. Internet of Things-Cloud Control of a Robotic Cell Based on Inverse Kinematics, Hardware-in-the-Loop, Digital Twin, and Industry 4.0/5.0. *Sensors* **2025**, *25*, 1821. [CrossRef] [PubMed]
60. Bukowski, L.; Werbinska-Wojciechowska, S. Towards Maintenance 5.0: Resilience-Based Maintenance in AI-Driven Sustainable and Human-Centric Industrial Systems. *Sensors* **2025**, *25*, 5100. [CrossRef] [PubMed]
61. Crnjac Zizic, M.; Gjeldum, N.; Mladineo, M.; Bilic, B.; Aljinovic Mestrovic, A. Towards Sustainable Personalized Assembly Through Human-Centric Digital Twins. *Sensors* **2025**, *25*, 5662. [CrossRef] [PubMed]
62. Samuels, A. Examining the integration of artificial intelligence in supply chain management from Industry 4.0 to 6.0: A systematic literature review. *Front. Artif. Intell.* **2025**, *7*, 1477044. [CrossRef] [PubMed]
63. Gelashvili-Luik, T.; Vihma, P.; Pappel, I. Navigating the AI revolution: Challenges and opportunities for integrating emerging technologies into knowledge management systems. Systematic literature review. *Front. Artif. Intell.* **2025**, *8*, 1595930, Erratum in *Front. Artif. Intell.* **2025**, *8*, 1664837. https://doi.org/10.3389/frai.2025.1664837. [CrossRef] [PubMed]
64. Karnehed, S.; Larsson, I.; Petersson, L.; Erlandsson, L.K.; Tyskbo, D. Navigating artificial intelligence in home healthcare: Challenges and opportunities in nursing wound care. *BMC Nurs.* **2025**, *24*, 660. [CrossRef] [PubMed]
65. Shen, L.; Li, Z.; Liang, Y.; Feng, Y.; Zhang, Z. Artificial intelligence adoption and corporate ESG performance: Evidence from a refined large language model. *Front. Artif. Intell.* **2025**, *8*, 1691468. [CrossRef] [PubMed]
66. Li, L.; Wang, S.; Chen, Y. The impact of ESG performance on corporate innovation-Empirical evidence from Chinese pharmaceutical listed companies. *PLoS ONE* **2025**, *20*, e0332906. [CrossRef] [PubMed]
67. Sosa Méndez, D.; García Cena, C.E.; Bedolla-Martínez, D.; Martín González, A. Innovative Metaheuristic Optimization Approach with a Bi-Triad for Rehabilitation Exoskeletons. *Sensors* **2024**, *24*, 2231. [CrossRef] [PubMed]
68. Hussain, F.; Goecke, R.; Mohammadian, M. Exoskeleton robots for lower limb assistance: A review of materials, actuation, and manufacturing methods. *Proc. Inst. Mech. Eng. H* **2021**, *235*, 1375–1385. [CrossRef]
69. Meng, Q.; Fei, C.; Jiao, Z.; Xie, Q.; Dai, Y.; Fan, Y.; Shen, Z.; Yu, H. Design and kinematical performance analysis of the 7-DOF upper-limb exoskeleton toward improving human-robot interface in active and passive movement training. *Technol. Health Care* **2022**, *30*, 1167–1182. [CrossRef] [PubMed]
70. Gupta, S.; Agrawal, A.; Singla, E. Architectural design and development of an upper-limb rehabilitation device: A modular synthesis approach. *Disabil. Rehabil. Assist. Technol.* **2024**, *19*, 139–153. [CrossRef]
71. Proietti, T.; Crocher, V.; Roby-Brami, A.; Jarrasse, N. Upper-Limb Robotic Exoskeletons for Neurorehabilitation: A Review on Control Strategies. *IEEE Rev. Biomed. Eng.* **2016**, *9*, 4–14. [CrossRef] [PubMed]
72. Kelly-Hedrik, M.; Abd-El-Barr, M.M.; Aarabi, B.; Curt, A.; Howley, S.P.; Harrop, J.S.; Kirshblum, S.; Neal, C.J.; Noonan, V.; Park, C.; et al. Importance of Prospective Registries and Clinical Research Networks in the Evolution of Spinal Cord Injury Care. *J. Neurotrauma* **2023**, *40*, 1834–1848. [CrossRef] [PubMed]
73. Langan, R.; O'Connor, S.; O'Keeffe, S.; Whyte, E. "I feel a lot more connected with my body after a session": A focus group exploration of the impact of exoskeleton walking on highly experienced robotic exoskeleton walkers. *Disabil. Rehabil.* **2026**, *48*, 2906–2919. [CrossRef]
74. Mikołajewska, E.; Mikołajewski, D. Wheelchair development from the perspective of physical therapists and biomedical engineers. *Adv. Clin. Exp. Med.* **2010**, *19*, 771–776.
75. Grobelna, I.; Wiśniewski, R.; Grobelny, M.; Wiśniewska, M. Design and Verification of Real-Life Processes with Application of Petri Nets. *IEEE Trans. Syst. Man Cybern. Syst.* **2017**, *47*, 2856–2869. [CrossRef]
76. Lubkowski, P.; Krygier, J.; Sondej, T.; Dobrowolski, A.P.; Apiecionek, L.; Znaniecki, W.; Oskwarek, P. Decision Support System Proposal for Medical Evacuations in Military Operations. *Sensors* **2023**, *23*, 5144. [CrossRef]
77. Grobelna, I. Formal Verification of Control Modules in Cyber-Physical Systems. *Sensors* **2020**, *20*, 5154. [CrossRef] [PubMed]
78. Różanowski, K.; Sondej, T.; Piotrowski, Z.; Sawicki, K. Architecture of Car Measurement System for Driver Monitoring. In *Communication Technologies for Vehicles. Nets4Cars/Nets4Trains 2012*; Vinel, A., Mehmood, R., Berbineau, M., Garcia, C.R., Huang, C.M., Chilamkurti, N., Eds.; Lecture Notes in Computer Science; Springer: Berlin/Heidelberg, Germany, 2012; Volume 7266. [CrossRef]
79. Kawala-Janik, A.; Podpora, M.; Pelc, M.; Piatek, P.; Baranowski, J. Implementation of an inexpensive EEG headset for the pattern recognition purpose. In *2013 IEEE 7th International Conference on Intelligent Data Acquisition and Advanced Computing Systems (IDAACS)*; IEEE: Piscataway, NJ, USA, 2013; pp. 399–403. [CrossRef]
80. Gajos, A.; Wójcik, G.M. Independent component analysis of EEG data for EGI system. *Bio-Algorithms Med-Syst.* **2016**, *12*, 67–72. [CrossRef]

81. Heindl, B.; Ramirez, L.; Joseph, L.; Clarkson, S.; Thomas, R.; Bittner, V. Hybrid cardiac rehabilitation—The state of the science and the way forward. *Prog. Cardiovasc. Dis.* **2022**, *70*, 175–182. [CrossRef] [PubMed]
82. He, Y.; Jan, Y.H.; Yang, F.; Ma, Y.; Chen, X.Y.; Pei, C. The fatigue status feature of bicycle movement based on deep learning and signal processing technology. *Sci. Rep.* **2025**, *15*, 39328. [CrossRef] [PubMed]
83. Xie, S.; Zhan, M.; Li, Y.; Xi, F. The virtual-real interaction system design and interaction characteristics research of an ankle rehabilitation robot based on digital twin. *Technol. Health Care* **2025**, *33*, 2279–2304. [CrossRef] [PubMed]
84. Chang, W.; Sun, W.; Chen, P.; Xu, H. Construction and Validation of a Digital Twin-Driven Virtual-Reality Fusion Control Platform for Industrial Robots. *Sensors* **2025**, *25*, 4153. [CrossRef] [PubMed]
85. GBD 2021 Stroke Risk Factor Collaborators. Global, regional, and national burden of stroke and its risk factors, 1990–2021: A systematic analysis for the Global Burden of Disease Study 2021. *Lancet Neurol.* **2024**, *23*, 973–1003. [CrossRef] [PubMed]
86. Mensah, G.A.; Fuster, V.; Murray, C.J.L.; Roth, G.A. Global Burden of Cardiovascular Diseases and Risks, 1990–2022. *J. Am. Coll. Cardiol.* **2023**, *82*, 2350–2473. [CrossRef] [PubMed]
87. Cisek, K.K.; Nguyen, T.N.Q.; Garcia-Rudolph, A.; Saurí, J.; Becerra Martinez, H.; Hines, A.; Kelleher, J.D. Predictors of social risk for post-ischemic stroke reintegration. *Sci. Rep.* **2024**, *14*, 10110. [CrossRef] [PubMed]
88. Nakao, M.; Izumi, S.; Yokoshima, Y.; Matsuba, Y.; Maeno, Y. Prediction of life-space mobility in patients with stroke 2 months after discharge from rehabilitation: A retrospective cohort study. *Disabil. Rehabil.* **2020**, *42*, 2035–2042. [CrossRef] [PubMed]
89. He, Y.; Jan, Y.H.; Yang, F.; Ma, Y.; Pei, C. A novel method for assessing cycling movement status: An exploratory study integrating deep learning and signal processing technologies. *BMC Med. Inform. Decis. Mak.* **2025**, *25*, 71. [CrossRef] [PubMed]
90. Hlophe, M.C.; Maharaj, B.T. From Cyber–Physical Convergence to Digital Twins: A Review on Edge Computing Use Case Designs. *Appl. Sci.* **2023**, *13*, 13262. [CrossRef]
91. Alzahrani, A.; Alshehri, M.; AlGhamdi, R.; Sharma, S.K. Improved Wireless Medical Cyber-Physical System (IWMCPS) Based on Machine Learning. *Healthcare* **2023**, *11*, 384. [CrossRef] [PubMed]
92. Turab, M.; Jamil, S. A Comprehensive Survey of Digital Twins in Healthcare in the Era of Metaverse. *BioMedInformatics* **2023**, *3*, 563–584. [CrossRef]
93. Safhi, A.M.; Keserle, G.C.; Blanchard, S.C. AI-Driven Non-Destructive Testing Insights. *Encyclopedia* **2024**, *4*, 1760–1769. [CrossRef]
94. Lee, T.; Kim, M.O. Next-Gen Nondestructive Testing for Marine Concrete: AI-Enabled Inspection, Prognostics, and Digital Twins. *J. Mar. Sci. Eng.* **2025**, *13*, 2062. [CrossRef]
95. Wang, W.; Chen, J.; Han, G.; Shi, X.; Qian, G. Application of Object Detection Algorithms in Non-Destructive Testing of Pressure Equipment: A Review. *Sensors* **2024**, *24*, 5944. [CrossRef] [PubMed]
96. Gkintoni, E.; Halkiopoulos, C. Digital Twin Cognition: AI-Biomarker Integration in Biomimetic Neuropsychology. *Biomimetics* **2025**, *10*, 640. [CrossRef] [PubMed]
97. Nguyen, P.; Kim, M.; Nichols, E.; Yoon, H.-S. AI-Driven Digital Twins for Manufacturing: A Review Across Hierarchical Manufacturing System Levels. *Sensors* **2026**, *26*, 124. [CrossRef] [PubMed]
98. Pichai, A.K.; Thillai Govindarajan, S.K.; Sadhanandham, S.; Karthik, R. A Review of the Digital Era of Cardiac Rehabilitation: From Centres to Screens. *J. Mod. Rehabil.* **2026**, *20*, 2. [CrossRef]
99. Gámez Díaz, R.; Yu, Q.; Ding, Y.; Laamarti, F.; El Saddik, A. Digital Twin Coaching for Physical Activities: A Survey. *Sensors* **2020**, *20*, 5936. [CrossRef] [PubMed]
100. Amawi, A.T.; Grivas, G.V.; Alkasasbeh, W.J. Digital twin for Taekwondo athletes: Integrating sports nutrition and psychological readiness using artificial intelligence. *Front. Public Health* **2026**, *14*, 1822194. [CrossRef] [PubMed]
101. Barricelli, B.R.; Cerutti, F.; Morzenti, S. Human digital twins in sports and rehabilitation: A systematic review. *Behav. Inf. Technol.* **2026**, 1–22. [CrossRef]
102. Liu, Y.; Yan, K.; Ma, S.; Deng, H.; Kong, J. AI-Driven Digital Twin Architecture for Multimodal Prediction and Adaptive Intervention in Cognitive Aging. *JMIR AI* **2026**, *5*, e87768. [CrossRef] [PubMed]
103. Zhou, T.; Hu, C.; Liu, D.; Duan, Y.; Zhang, Z. Digital twins and artificial intelligence for predictive maintenance in microelectromechanical systems (MEMS): A techno-economic perspective. *Microsyst. Technol.* **2026**, *32*, 111. [CrossRef]
104. Qolbi, A.N.; Sekti, B.A. Introduction and the Importance of Green Cities. In *Green Infrastructure and Intelligent Systems for Smart Cities*; IGI Global Scientific Publishing: Hershey, PA, USA, 2026; pp. 1–32.
105. He, C.; Wu, R.; Zhang, Y.; Kuang, L.; Dong, L. Integration of AI-enhanced Digital Twin and Image Recognition in Bone Tumor Surgical Education: A Short Review. *J. Mech. Med. Biol.* **2026**, *26*, 2630005. [CrossRef]
106. Alharthi, S.; El-Saddik, A. Digital Twin-Enhanced Smart Environments: An IoT-AI Framework for Contextual Personalization. In *2026 International Conference on Artificial Intelligence, Computer, Data Sciences and Applications (ACDSA)*; IEEE: Piscataway, NJ, USA, 2026; pp. 1–6.
107. Han, B.; Deng, X.; Zhang, B.; Zhang, X. Optimization of youth soccer training under machine learning and AI digital twins technology. *J. Mech. Med. Biol.* **2026**, *26*, 2640040. [CrossRef]

108. Kokareva, S.; Kokarev, B.; Kokarev, A.; Shylo, S.; Katschan, A. Optimizing Strategies for the Development of a New Competitive Routine Image in Aerobic Gymnastics Through the Application of Artificial Intelligence Systems. In *2026 IEEE 6th International Conference on Smart Information Systems and Technologies (SIST)*; IEEE: Piscataway, NJ, USA, 2026; pp. 1–7.
109. Alkasasbeh, W.J.; Amawi, A.T.; Grivas, G.V.; Orhan, B.E.; Alawamleh, T. Artificial intelligence and wearables in sport: Performance, injury risk, and wellbeing. *Front. Artif. Intell.* **2026**, *9*, 1838507. [CrossRef] [PubMed]
110. Kuchta, E.; Wrzosek, K.; Ponikowski, K.; Makaryczew, M.; Kowalczyk, Z.; Gumółka, P.; Piecewicz-Szczęsna, H. Artificial Intelligence and Machine Learning in Athlete Monitoring, Injury Prediction and Performance Optimization: A Narrative Review. *Qual. Sport* **2026**, *63*, 73176. [CrossRef]
111. Chen, M.Y.; Hung, P.C.; Wu, H.T. Guest editorial special issue on multimodal generative ai in computational biomechanics and intelligence systems: Innovations, applications, and research frontiers. *J. Mech. Med. Biol.* **2026**, *26*, 2602002. [CrossRef]
112. Tiwari, A.; Krisnawati, D.I.; Chen, C.Y.; Kuo, T.R. AI-driven nanomedicine for cancer theranostics. *Mol. Cancer* **2026**, *25*, 78. [CrossRef] [PubMed]
113. Olawade, D.B.; Almarzook, S.; Ogunbona, M.A.; Makanjuola, B.D.; Olawuyi, O.F.; Wada, O.Z. Digital twin applications in healthcare for people living with disability. *Int. J. Med. Inform.* **2026**, *212*, 106359. [CrossRef] [PubMed]
114. Goel, K.; Singh, T.G.; Paudel, K.R.; MacLoughlin, R.; Islam, M.S.; Kulkarni, M.P.; Mujwar, S. Molecular modelling–driven formulation design for targeted pulmonary drug delivery. *Int. J. Pharm.* **2026**, *697*, 126873. [CrossRef] [PubMed]
115. Ghram, A.; Loureiro Diaz, J.; Raghavan, P.; Hautala, A.J.; Kaddoura, R.; Laukkanen, J.A.; Ben Saad, H. Toward Precision Cardiac Rehabilitation: Current Limitations and Future Opportunities of Omics and Artificial Intelligence. *Sports Med.* **2026**, 1–22. [CrossRef] [PubMed]
116. Alharthi, S. AI-powered in silico twins: Redefining precision medicine through simulation, personalization, and predictive healthcare. *Saudi Pharm. J.* **2026**, *34*, 1. [CrossRef] [PubMed]
117. Glinkowski, W.M.; Gieroba, T.; Śliwczyński, A. Digital Twins in Orthopedics and Trauma: Concepts, Emerging Evidence, and Barriers to Clinical Translation. *J. Clin. Med.* **2026**, *15*, 4127. [CrossRef] [PubMed]
118. Carda, S.; Molteni, F.; Grana, E. Artificial Intelligence in Spasticity Assessment. *Phys. Med. Rehabil. Clin.* **2026**, *37*, 341–356. [CrossRef] [PubMed]
119. Tariq, M.U. Robotic and IoT Integration in Post-Acute Rehabilitation: Enhancing Patient Recovery Through Data-Driven Assistive Systems. In *Robotics and IoT Synergy in Next-Generation Healthcare*; IGI Global Scientific Publishing: Hershey, PA, USA, 2026; pp. 163–188.
120. Menghwar, A.K.; Ali, M. How industry 4.0 affected prostheses manufacturing. *J. Innov. Bus. Ind.* **2026**, *4*, 55–68. [CrossRef]
121. Guan, S.; Mei, Y. Biomechanics and Obesity in Osteoarthritis: From Mechanism to Precision Medicine. *Int. J. Rheum. Dis.* **2026**, *29*, e70539. [CrossRef] [PubMed]
122. Patil, C.; Kamble, S. AI and Digital Twins for Personalized Physiotherapy Simulations. In *AI-Driven Innovations in Physiotherapy and Oncology 5: Next-Generation Care in Physio and Oncology*; ISTE Ltd.: London, UK, 2026; pp. 43–60.
123. Mohite, S.; Bainalwar, P. AI-Driven Decision Support Systems for Personalized Physiotherapy Plans. In *AI-Driven Innovations in Physiotherapy and Oncology 4: Intelligent Care for Rehabilitation and Cancer Treatment*; ISTE Ltd.: London, UK, 2026; pp. 101–119.
124. Verma, R.K.; Agarwal, G.; Pandey, N. AI and ML for Privacy-Preserving Digital Twins: Challenges and Opportunities. In *Ensuring Privacy in Digital Twin Ecosystems*; Scrivener Publishing LLC: Beverly, MA, USA, 2026; pp. 245–272.
125. Rabinowitz, A.; Trauger, M.; Williams, M. Reining in Unbridled AI Enthusiasm: Protecting the Integrity of Rehabilitation Science and Clinical Care. *Arch. Phys. Med. Rehabil.* **2026**, *in press*. [CrossRef] [PubMed]
126. Kadam, N.; Deshpande, V. AI-Enhanced Biomechanics: Personalizing Physiotherapy for Optimal Recovery. In *Physiotherapy Using Artificial Intelligence: Enhancing Biomechanics for Optimal Rehabilitation*; Scrivener Publishing LLC: Beverly, MA, USA, 2026; pp. 379–398.
127. Gayathri, J.; Esitha, M. IoT-Driven Real-Time Patient Monitoring Platform with Artificial Intelligence Assisted Cloud Environment. In *2026 13th International Conference on Computing for Sustainable Global Development (INDIACom)*; IEEE: Piscataway, NJ, USA, 2026; pp. 1–6.
128. Gudur, R.; Nimbarte, M. AI-Driven Digital Twins for Simulating Physiotherapy Outcomes in Cancer Care. In *AI-Driven Innovations in Physiotherapy and Oncology 3*; ISTE Ltd.: London, UK, 2026; pp. 123–139.
129. Pavel, M.I.; Mahmud, M.R. Immersion Without Instability: A Digital Twin Approach to Solve Imbalance Issues in Virtual Reality. In *Proceedings of the 2026 1st International Workshop on User Interface and Experience for Software Engineering*; Association for Computing Machinery: New York, NY, USA, 2026; pp. 61–64.
130. Shah, S.T.A.; Santos, J.P.O.; Constantinescu, G.; Fernandes, J.M.A.; Pereira, A.M.D.B. Physio-Digital Twin for Human-Centered IoT Mobility: A Proof-of-Concept Implementation on the E-Bike Platform. In *Proceedings of the 2026 9th International Conference on Information and Computer Technologies*; Association for Computing Machinery: New York, NY, USA, 2026; pp. 494–500.
131. Lee, J.; Hong, Y.M.; Kim, E.; Seo, H.; Chung, W.G.; Park, W.; Park, J.U. AI-driven tripartite classification for optimizing wearable bioelectronics in depression management. *Sci. Adv.* **2026**, *12*, eaec9837. [CrossRef] [PubMed]

132. Jin, G.Z. Exercise-Based Mechanotherapy: From Biomechanical Principles and Mechanotransduction to Precision Regenerative Rehabilitation. *Int. J. Mol. Sci.* **2026**, *27*, 694. [CrossRef] [PubMed]
133. Li, Q. AI-driven communication networks for real-time sports analytics and fan engagement in edge-IoT environments. *Int. J. Inf. Commun. Technol.* **2026**, *27*, 66–87. [CrossRef]
134. Schadd, M.P.; Berman, D.S.; Chen, C.; Cohen, M.; Dorsch, J.; Gegov, A.; Rempel, M. Reinforcement Learning for decision support in defense and security: A systematic review. *Ann. Oper. Res.* **2026**, 1–66. [CrossRef]
135. Sondej, T.; Zawadzka, S. Influence of cuff pressures of automatic sphygmomanometers on pulse oximetry measurements. *Measurement* **2022**, *187*, 110329. [CrossRef] [PubMed]
136. Bistroń, M.; Piotrowski, Z. Comparison of Machine Learning Algorithms Used for Skin Cancer Diagnosis. *Appl. Sci.* **2022**, *12*, 9960. [CrossRef]
137. Sawicki, K.; Piotrowski, Z. The proposal of IEEE 802.11 network access point authentication mechanism using a covert channel. In *2012 19th International Conference on Microwaves, Radar & Wireless Communications*; IEEE: Piscataway, NJ, USA, 2012; Volumes 1–2, pp. 656–659.
138. Chopra, L.; Chohan, J.S.; Sharma, S.; Pelc, M.; Kawala-Sterniuk, A. Multifunctional Modified Chitosan Biopolymers for Dual Applications in Biomedical and Industrial Field: Synthesis and Evaluation of Thermal, Chemical, Morphological, Structural, In Vitro Drug-Release Rate, Swelling and Metal Uptake Studies. *Sensors* **2022**, *22*, 3454. [CrossRef] [PubMed]
139. Recmanik, M.; Martinek, R.; Nedoma, J.; Jaros, R.; Pelc, M.; Hajovsky, R.; Velicka, J.; Pies, M.; Sevcakova, M.; Kawala-Sterniuk, A. A Review of Patient Bed Sensors for Monitoring of Vital Signs. *Sensors* **2024**, *24*, 4767. [CrossRef] [PubMed]
140. Dobrosielski, W.T.; Czerniak, J.M.; Szczepanski, J.; Zarzycki, H. Two New Defuzzification Methods Useful for Different Fuzzy Arithmetics. In *Uncertainty and Imprecision in Decision Making and Decision Support: Cross-Fertilization, New Models, and Applications*; Atanassov, K.T., Kacprzyk, J., Kaluszko, A., Krawczak, M., Owsinski, J., Sotirov, S., Sotirova, E., Szmidt, E., Zadrozny, S., Eds.; Series Advances in Intelligent Systems and Computing; Springer: Cham, Switzerland, 2018; pp. 83–101. [CrossRef]
141. Czerniak, J.M.; Dobrosielski, W.T.; Apiecionek, L.; Ewald, D.; Paprzycki, M. Practical Application of OFN Arithmetics in a Crisis Control Center Monitoring. In *Recent Advances in Computational Optimization. In Workshop on Computational Optimization (WCO)*; Fidanova, S., Ed.; Series Studies in Computational Intelligence; Springer: Cham, Switzerland, 2016; Volume 655, pp. 13–16. [CrossRef]
142. Heinrichs, H.; Kies, A.; Nagel, S.K.; Kiessling, F. Physicians' Attitudes Toward Artificial Intelligence in Medicine: Mixed Methods Survey and Interview Study. *J. Med. Internet Res.* **2025**, *27*, e74187. [CrossRef] [PubMed]
143. Page, M.J.; McKenzie, J.E.; Bossuyt, P.M.; Boutron, I.; Hoffmann, T.C.; Mulrow, C.D.; Shamseer, L.; Tetzlaff, J.M.; Akl, E.A.; Brennan, S.E.; et al. The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ* **2021**, *372*, n71. [CrossRef] [PubMed]