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Review

Applications of Artificial Intelligence-Based Patient Digital Twins in Decision Support in Rehabilitation and Physical Therapy

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Abstract: Artificial intelligence (AI)-based digital patient twins have the potential to make breakthroughs in research and clinical practices in rehabilitation. They make it possible to personalise treatment plans by simulating different rehabilitation scenarios and predicting patient-specific outcomes. DTs can continuously monitor a patient's progress, adjusting therapy in real time to optimise recovery. They also facilitate remote rehabilitation by providing virtual models that therapists can use to guide patients without having to be physically present. Digital twins (DTs) can help identify potential complications or failures at an early stage, enabling proactive interventions. They also support the training of rehabilitation professionals by offering realistic simulations of different patient conditions. They can also increase patient engagement by visualising progress and potential future outcomes, motivating adherence to therapy. They enable the integration of multidisciplinary care, providing a common platform for different professionals to collaborate and improve rehabilitation strategies. The article aims to trace the current state of knowledge, research priorities, and research gaps in order to properly guide further research and shape decision support in rehabilitation.

Keywords: rehabilitation; physiotherapy; digital twin; therapy planning; artificial intelligence; machine learning; health status prediction

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1. Introduction

Digital twins (DTs) of patients supported by artificial intelligence (AI) have the potential to revolutionise clinical practice and rehabilitation research and practice. These virtual representations of patients enable personalised treatment plans by simulating different rehabilitation scenarios and predicting individual patient outcomes [1]. Using real-time data, DTs can continuously monitor a patient's progress, adjusting therapy as necessary to optimise recovery. This dynamic feedback loop ensures that therapy remains responsive and effective throughout the rehabilitation process [1]. We add logic and eliminate overlaps, separating the broad applications of DTs in medicine from the niche applications in rehabilitation and physical therapy. While DTs are widely studied in medicine, there is a lack of tailored models that specifically address the unique biomechanical, neurological, and functional aspects of rehabilitation and physical therapy. Existing research often fails to develop AI-based DTs capable of adapting treatment plans in real-time based on ever-evolving patient-specific data, which is crucial for personalised rehabilitation. The effectiveness of DTs in rehabilitation remains under-evidenced, with limited evidence on their ability to improve both short-term clinical outcomes, such as recovery rates, and long-term functional independence compared to traditional methods. Clinician usability and workflow integration: Studies rarely address how DTs can seamlessly integrate into

rehabilitation workflows, leaving gaps in understanding how these tools can increase decision-making efficiency without adding complexity to observations. Targeted research is needed to address ethical and data management issues specific to rehabilitation, where confidential patient data must be used securely and transparently to build trust between patients and service providers. Additionally, DTs facilitate remote rehabilitation, allowing therapists to monitor a patient's progress and make adjustments without being physically present. This capability is particularly valuable in areas where access to in-person care may be limited, such as rural or underserved areas. By identifying potential complications or treatment failures early, DTs enable timely and proactive interventions, potentially reducing the likelihood of patient recovery failure [1,2]. In addition to supporting patient care, DTs offer a valuable tool for training rehabilitation and physiotherapy professionals, providing realistic simulations of different patient conditions and responses to treatment, thereby improving methods, their use, and the clinical decision-making process [3–5]. These simulations help professionals hone their skills and gain experience in managing complex rehabilitation cases. DTs can also increase patient engagement by providing clear visualisations of progress and possible future outcomes, motivating patients to adhere to treatment programmes [6,7]. The collaborative nature of DT platforms enables the integration of multidisciplinary care, bringing together doctors, therapists, and other medical professionals to create more effective, coordinated rehabilitation strategies. The ability to simulate and test different approaches can also drive innovation in treatment methods, ultimately improving patient outcomes [8,9]. This article aims to map the current state of knowledge on DTs in rehabilitation and physical therapy, identifying research priorities and identifying existing gaps to better guide future research efforts. We will also explore how DTs can shape decision support systems in rehabilitation, improving both clinical and operational outcomes [8–10], taking into consideration observed research gaps (Table 1) and DT technology limitations (Figure 1).

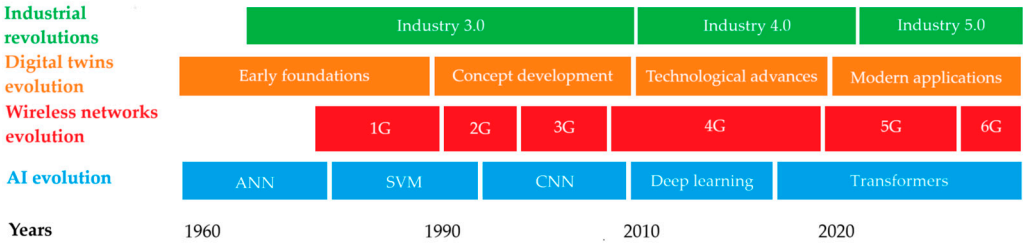

Figure 1. DTs emerging against the backdrop of AI/ML developments (own version). Abbreviations: 1G–6G—first generation—sixth generation; ANN—artificial neural network; SVM—support vector machine; CNN—convolutional neural network.

Table 1. Research gaps observed in state-of-the-art AI-based DTs for supporting decision-making in rehabilitation and physical therapy (Table 1).

Area	Detailed Gap(s)
Integration	Current research on AI-based DTs in rehabilitation lacks a solid framework for integrating multimodal data such as biomechanical, physiological, and patient-reported outcomes, which are crucial for accurately modelling individual patient responses to therapy.
Personalisation and Adaptation	There is a significant gap in developing adaptive AI algorithms capable of updating DTs in real time based on patient progress, limiting the ability to provide personalised and dynamic decision support for rehabilitation plans.

Table 1. *Cont.*

Area	Detailed Gap(s)
Clinical Validation and Adoption	Despite growing interest, few studies rigorously validate the effectiveness of DTs in real-world clinical settings, creating barriers to their adoption by clinicians who need evidence of tangible improvements in outcomes and efficiency.
Interdisciplinary Collaboration	Research is often conducted in silos, with insufficient collaboration between AI developers, rehabilitation professionals, and healthcare stakeholders, which hinders the development of practical, user-friendly DT systems tailored to clinical needs.
Operational outcomes and scalability	Most studies focus on clinical outcomes while neglecting operational impacts such as workflow integration and resource optimisation, leaving a gap in understanding how DTs can holistically improve rehabilitation programs at an organisational level.
Ethical and privacy concerns	There is limited exploration of ethical issues related to the use of confidential patient data in AI-powered DTs, as well as mechanisms to ensure data privacy and compliance with health regulations, which may hinder their implementation.

AI-based data analysis for DT is already being used in healthcare (Figure 2), but it has not yet reached all medical specialities, and not all AI methods have been tested in this group of applications. This article attempts to take a comprehensive approach to the topic of DT use in rehabilitation and physiotherapy, with a particular focus on AI-based DT, by revisiting, analysing, and systematising previous research, its strengths and limitations, and identifying future research directions and associated risks (including those covered by the General Data Protection Regulation (GDPR) and the AI Act).

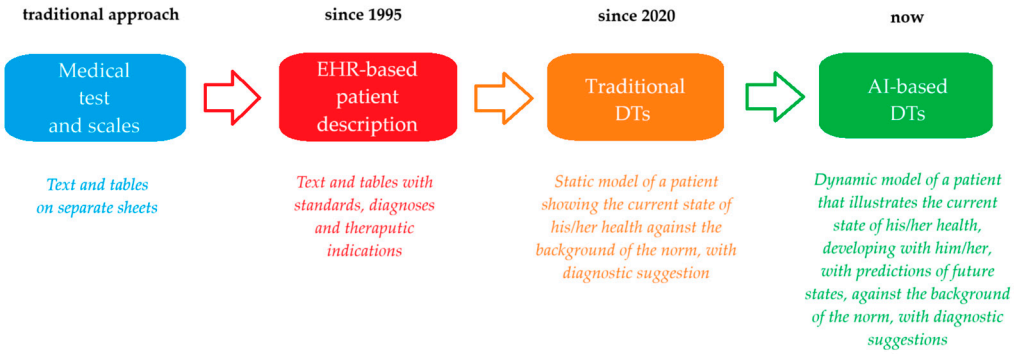

Figure 2. Evolution of DTs in rehabilitation and physiotherapy (own version). To date, all four approaches are being used.

Their novelty lies in their ability to predict the outcome of interventions, optimising the effectiveness of therapies, and reducing trial-and-error methods. They contribute to improving patient outcomes by adapting rehabilitation protocols based on constantly updated, multimodal patient data. Using AI, DTs facilitate early detection of complications, improve adaptive therapeutic strategies, and improve resource allocation. This innovation represents a significant step towards personalised and efficient healthcare, redefining standards in rehabilitation practice.

2. Materials and Methods

2.1. Data Set

This bibliometric analysis explores the research landscape on DT planning and implementation in rehabilitation and physiotherapy, with a particular focus on those based on AI. To conduct this study, we use bibliometric methods to analyse scientific publications in the field. Our approach involves formulating research questions to identify key areas such as the evolution of research topics, the origin of publications, and the most influential authors and articles. Gaining a comprehensive understanding of current research and industry trends in sustainable energy solutions is essential. By interpreting bibliometric data, this study aims to enrich ongoing discussions and establish a solid foundation for future research.

2.2. Methods

This study used the bibliographic databases Web of Science (WoS, Clarivate Plc, Philadelphia, PA, USA), Scopus (Elsevier, Amsterdam, The Netherlands), and PubMed (National Center for Biotechnology Information (NCBI), at the U.S. National Library of Medicine (NLM), located at the National Institutes of Health (NIH), Bethesda, MD, USA), selected for their wide range of studies and rich citation data that support accurate bibliometric analysis (Figure 3). To focus on the relevant literature, we applied filters, narrowing the scope to original articles in English. After filtering, we conducted a manual review of each article to ensure compliance with our study criteria, which determined the final sample size. We then analysed the main features of the dataset, including known authors, research groups/institutions, thematic clusters, and emerging trends. This allowed us to map the evolution of key terminology and major research developments in the field. Where possible, we followed temporal trends to monitor changes in research focus over time and grouped publications into thematic clusters, revealing relationships between different research areas. This process highlights important themes and subfields within the study. In addition, we analysed indicators such as years of publication and authorship patterns to provide a quantitative overview.

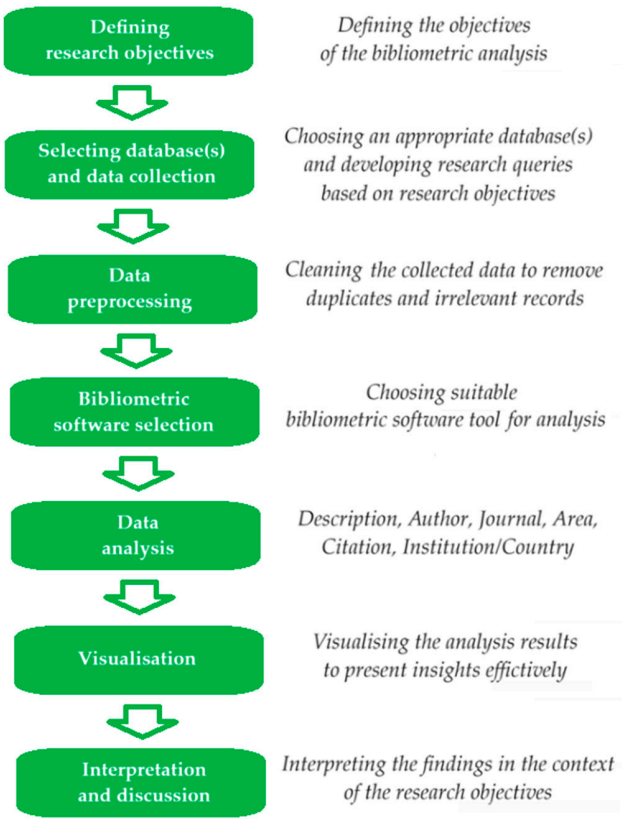

Figure 3. Bibliometric analysis procedure (own approach).

This study followed specific elements of the PRISMA 2020 guidelines for bibliographic reviews, focusing on aspects such as the 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). For bibliometric analysis, we used tools embedded in the Web of Science (WoS), Scopus, and PubMed databases, as well as the Biblioshiny tool from the Bibliometrix 4.0.1 (GNU). This methodology supports bibliometric and scientometric studies, often allowing for refined categorisation by conceptual structures, research areas, authors, documents, and sources. The results are presented using tables that allow for flexible analysis and visualisation options. Given the interdisciplinary scope and complexity of the topic, we have consolidated the key results of the review in a summary table.

3. Results

3.1. Data Sources

To refine our search to suit our research objectives, we used advanced filtered queries, limiting results to English-language articles. In WoS, searches were performed using the "Subject" field (consisting of title, abstract, keyword plus, and other keywords); in Scopus, using article title, abstract, and keywords; and in PubMed, using manual keyword sets. The databases were searched for articles using keywords such as "artificial intelligence" or "machine learning", "digital twin", and "rehabilitation" or "physiotherapy" (Table 2).

Table 2. Detail search query over databases.

Parameter	Description
Inclusion criteria	Articles (original, reviews, communications, and editorials) and chapters, including conference proceedings, in English
Exclusion criteria	Books older than 10 years, letters, conference abstracts without full text, other languages than English
Keywords used	artificial intelligence, machine learning, digital twin, rehabilitation, physiotherapy, physical therapy
Used field codes (WoS)	"Subject" field (consisting of title, abstract, keyword plus, and other keywords)
Used field codes (Scopus)	article title, abstract, and keywords
Used field codes (PubMed)	manually
Boolean operators used	Yes, e.g., "digital twin" AND ("artificial intelligence" OR "machine learning") AND rehabilitation
Applied filters	Results refined by publication year, document type (e.g., articles, reviews), and subject area (e.g., healthcare, engineering).
Iteration and validation options	Query run iteratively, refinement based on the results, and validation by ensuring relevant articles appear among the top hits
Leverage truncation and wildcards used	Used symbols like * for word variations (e.g., "rehabilitat*") and ? for alternative spellings (e.g., "optimis?ation", "physiotherapy", and "physicial therapy")

The selected publications were then further refined (see Figure 4) by manually reviewing articles and removing irrelevant items and duplicates, which resulted in our final sample size.

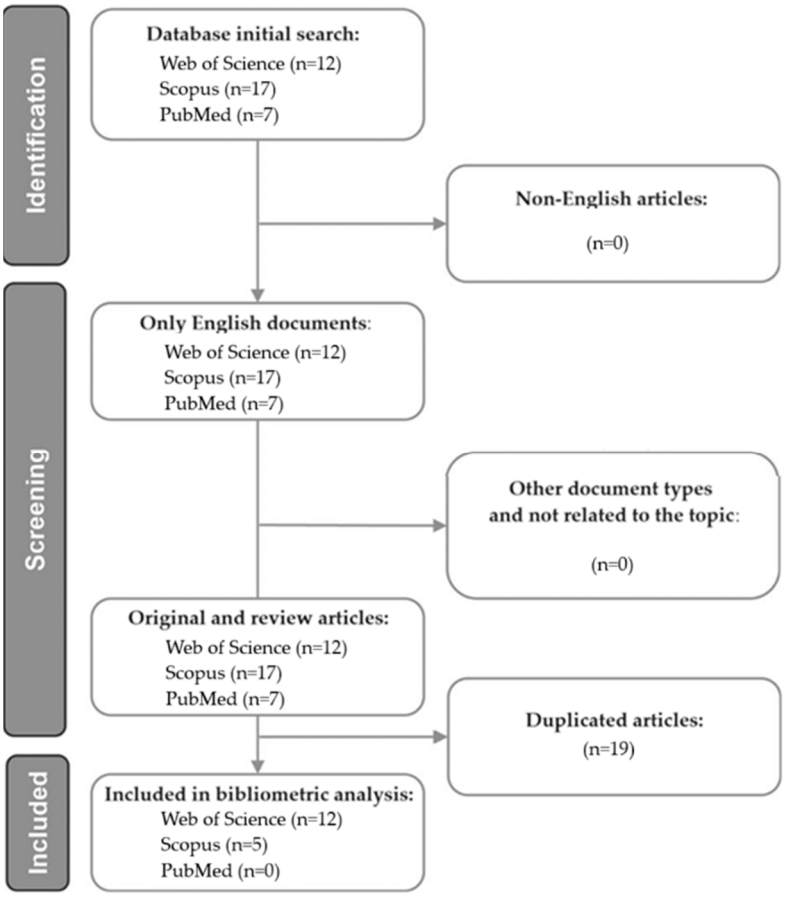

Figure 4. A PRISMA flow diagram of the review process using selected PRISMA 2020 guidelines.

The summary of the bibliographic analysis results is presented in Table 3. Seventeen articles (2020–2024) were included in the review. Fourteen of them were published in the last three years.

Table 3. Summary of results of bibliographic analysis (WoS, Scopus, PubMed).

Parameter/Feature	Value
Leading types of publication	Article (23.5%), conference paper (23.5%), review (23.5%), conference review (23.5%), editorial (5.9%)
Leading areas of science	Computer science (27.0%), Engineering (21.6%), Medicine (10.8%), Biochemistry (5.4%), Chemistry (5.4%), Mathematics (5.4%), Physics and Astronomy (5.4%)
Leading topics	Industrial: Design and Manufacturing, Telecommunication, Transportation, Safety and Maintenance, Human–Computer Interaction, Industry 4.0, Augmented reality
	Medical: Gait and Posture, Neuromuscular disorders, Neurodegenerative diseases, Multiple sclerosis, Essential tremor, Stroke rehabilitation,

Table 3. *Cont.*

Parameter/Feature	Value
Leading countries	China, Australia, Canada, Italy
Leading scientists	Chen, J.; Yi, C.
Leading affiliations	Nanjing University of Aeronautics and Astronautics
Leading funders (where information is available)	National Natural Science Foundation of China, Ministry of Science and Technology of China, National Natural Science Foundation of China, Natural Sciences and Engineering Council of Canada
Sustainable development goals	Industry Innovation and Infrastructure, Good Health and Well-Being, Responsible Consumption and Production, Sustainable Cities and Communities, Partnership for the Goals

3.2. Environmental Mechanisms

The concept of DTs in rehabilitation and physical therapy began with the broader adoption of digital modeling technologies in industries such as aerospace and manufacturing, where virtual representations of physical systems enabled monitoring, simulation, and predictive maintenance [10–12]. The idea was adapted to healthcare as the technology matured, allowing medical professionals to create virtual models of patients, tracking their physical condition and progress in real-time. Advances in motion capture, wearable sensors, and AI have enabled the collection of detailed biomechanical data, allowing DTs to model human movement and physical conditions with increasing accuracy. In rehabilitation, DTs have offered personalized treatment plans that are dynamically adjusted as the twin develops based on patient outcomes and feedback [13,14]. Early adoption occurred in physical therapy for conditions such as musculoskeletal injuries, stroke recovery, and post-operative rehabilitation, where monitoring progress is critical. These virtual replicas provide medical professionals with continuous data, enabling more accurate assessments of patient improvement and predictions of recovery outcomes [1,2]. AI plays a key role in analyzing this data, providing recommendations for adjustments to exercise programs or therapy intensity. With the advancement of 3D modelling and simulation technologies, DTs have become more accessible in clinical settings, offering remote monitoring and improving telehealth services [15,16]. By simulating different therapeutic interventions on a DT of a patient, therapists can predict potential outcomes and optimize treatment plans without the trial and error of a real patient. The implementation of DTs in rehabilitation has shifted the field toward more data-driven, precise, and personalized healthcare, promising better outcomes and patient engagement [17].

To sum up, DTs in rehabilitation and physical therapy are virtual representations of a patient's anatomy, physiology, and functional capacity used to simulate and analyze treatment outcomes in a secure, adaptable digital environment. They provide personalized care by integrating patient-specific data, including medical imaging, biomechanics, and real-time monitoring, enabling tailored rehabilitation strategies. By combining data from wearable devices, sensors, and electronic health records, DTs provide a comprehensive picture of a patient's condition and progress. Real-time data updates allow therapists to dynamically adjust rehabilitation plans, ensuring that treatment is responsive to the patient's current condition. DTs enable the simulation of different rehabilitation techniques and their outcomes, reducing trial and error in selecting effective interventions. These models predict recovery trajectories based on individual patient data, helping clinicians set realistic goals and timelines. When combined with telemedicine technologies, DTs support remote monitoring and virtual rehabilitation sessions, making therapy accessible to patients

in remote locations. They provide measurable measures of functional recovery, increasing the objectivity and accuracy of rehabilitation assessments. With immersive technologies such as augmented and virtual reality (AR and VR, respectively) combined with DTs, rehabilitation exercises can be gamified to increase patient engagement and compliance. DTs enable noninvasive testing of high-risk interventions, minimising potential harm to patients during their recovery. By improving diagnostic accuracy and reducing the need for repeat interventions, DTs can reduce the overall cost of rehabilitation care. DTs serve as educational tools for therapists, allowing them to visualise complex cases and co-design rehabilitation strategies. The incorporation of AI enhances the decision-making capabilities of DTs, offering deeper insights and suggestions based on large data sets. Advances in computing power and machine learning promise more accurate and dynamic DTs, potentially encompassing aspects of cognitive and emotional recovery in addition to physical rehabilitation.

3.3. The Specificity of Using Digital Twins to Support Decisions in Rehabilitation and Physical Therapy

Rehabilitation and physical therapy processes often take months or even years to complete, which distinguishes them from many clinical areas where treatment durations are typically shorter, requiring DTs to maintain long-term modelling and adaptive capabilities. Unlike other clinical applications, rehabilitation relies on a broader spectrum of devices, such as wearables, biomechanical sensors, and assistive technologies, requiring DTs to integrate different data streams. The expanded role of therapists in rehabilitation includes shared decision-making, where DTs serve as adjuncts rather than final tools in adapting treatment plans. Rehabilitation requires the active cooperation of patients and their families, as their participation in exercise, lifestyle changes, and monitoring has a major impact on outcomes, making DTs more interactive and user-centric. In some cases, such as degenerative diseases or chronic disabilities, the goal of rehabilitation is not to restore health but to maintain the current state or slow decline, requiring DTs to focus on stabilisation rather than improvement. Rehabilitation involves continuous adjustments based on patient progress or setbacks, which distinguishes it from more static treatment plans in other clinical areas where decision points are often more discrete. Emotional and motivational factors are more prominent in rehabilitation, requiring DTs to incorporate patient engagement strategies such as gamification or visualisation of progress to encourage compliance. The biomechanical emphasis in physical therapy requires DTs to simulate complex movement patterns and analyse functional performance, a requirement that is less critical in many other clinical applications. Therapists often must balance medical recommendations with practical considerations such as the patient's daily life and resource availability, which DTs must incorporate into their predictive models. Unlike acute clinical interventions, rehabilitation success depends on gradual progress, making long-term tracking and nuanced reporting integral to DTs in this field.

Therefore, technologically, such DTs will be more similar to solutions in medium- and long-term therapy and care than in acute care. They will also more often combine hospital with outpatient and home (hybrid) therapy, which will increase the emphasis on the patient's independence and compliance with recommendations, as well as objective monitoring of his/her behaviour in order to predict the results of rehabilitation.

3.4. Source of Data Set for Digital Twins for Decision Support in Rehabilitation

DTs in rehabilitation and physical therapy rely on diverse data sets that simulate real-time patient conditions and treatment outcomes [1,2]. Primary data sources include clinical records, which provide detailed information on patient demographics, medical history, and details of specific injuries or conditions [15–18]. Motion capture systems, such as 3D cameras and wearable sensors, track and record patient movements, allowing DTs to model the biomechanics of individual joints and muscles. Additionally, wearable devices such as smartwatches and fitness trackers continuously collect basic vital signs (e.g., heart rate,

oxygen saturation, activity level) and patient behaviour (e.g., daily step count), which are key to assessing rehabilitation progress. EMG (electromyography) sensors measure muscle activation patterns, providing data on muscle function and exertion during exercise, which are essential for personalised physical therapy interventions. Imaging data from MRI, CT scans, and ultrasound provide high-resolution insight into anatomy, helping DTs accurately represent tissue structures, injuries, or surgical modifications. Clinical assessment tools such as gait analysis labs collect spatial-temporal data on walking patterns and postural control, allowing DTs to simulate mobility issues and balance-related therapies.In addition to patient-specific data, anonymised population data from rehabilitation clinics offers insight into typical patterns of injury recovery and treatment response across age and demographic groups. Environmental sensors (such as temperature, humidity, and air quality monitors) contextualise data from environmental conditions that may impact patient comfort and therapy effectiveness. Data from therapy equipment, such as resistance bands and treadmills equipped with force and pressure sensors, add insight into exercise effort and response under controlled conditions. Patient feedback, including pain levels and perceived exertion, collected via mobile apps or self-assessment surveys, enables subjective data integration with DT models. In some cases, genetic data can be used to tailor DTs to individuals whose recovery may be genetically predisposed, helping to identify tailored intervention strategies. AI-based video analysis tools extract movement quality data, such as joint angles and stability during exercise, providing an objective measure of technique that guides therapeutic adjustments. Data from VR/AR rehabilitation platforms capture interactions in virtual environments, giving DTs insight into cognitive engagement and hand-eye coordination exercises. Cognitive assessments and brain imaging data (e.g., fMRI or EEG) provide insights when cognitive rehabilitation is involved, particularly in cases of neurological injuries or conditions such as stroke. Finally, machine learning algorithms analyse patterns in these different data sources, enabling the DTs to predict and recommend optimised interventions for future rehabilitation sessions. Together, these data sources enable the DTs to serve as accurate, personalised decision-support tools, adapting to the unique needs of each patient and optimising treatment outcomes [18–22].

3.5. Environments and Mechanisms of Building DTs for Rehabilitation and Physiotherapy Purposes

Creating DTs for rehabilitation and physical therapy requires environments that integrate physical, virtual, and real-time data processing, providing the basis for personalised therapy models [1,2,23,24]. The underlying environment often includes a virtual modelling platform where patients' anatomical and physiological data are structured as digital avatars to accurately replicate their physical state [1,2,25]. Real-time data acquisition setups, such as motion capture rooms with high-resolution 3D cameras and sensors, capture patients' movements during therapeutic exercises to refine the precision of the DT. Wearable sensor systems are key mechanisms, collecting continuous data on patient posture, joint movement, and muscle activation, which are then fed back to the DT to dynamically adjust therapy protocols. Cloud-based infrastructure enables large-scale data storage and facilitates real-time processing, enabling continuous updates to the DT based on patient progress and clinician input [26,27]. AI and machine learning algorithms act as the "brains" of the system, analysing patterns from patient data to model likely outcomes and recommend tailored interventions. Simulated environments, such as virtual reality (VR) spaces, are integrated with DTs to provide immersive, guided therapy sessions where patients can perform exercises while their DTs reflect responses in real-time. Augmented reality (AR) interfaces, which overlay visual feedback on patient movements, act as mechanisms to improve movement accuracy by showing patients real-time corrections. In the case of DTs focused on recovery tracking, the system often includes biomechanics simulators that model joint kinetics and dynamics at different levels of exertion, predicting recovery timelines. Collaborative environments allow clinicians to interact directly with DTs via user interfaces, allowing manual adjustments to reflect new medical assessments or modifi-

cations to treatment goals. In rehabilitation scenarios, simulation software is a fundamental element, allowing DTs to "test" different treatment approaches and predict which ones might be most effective before implementing them in the real world. Cloud-based environments provide the bandwidth to integrate data from multiple sources, such as medical records, sensor data, and environmental inputs, creating comprehensive patient models. Mobile applications serve as a patient input mechanism, capturing real-time feedback on pain and progress, which is then analysed and reflected in the DT. Through IoT (Internet of Things) connectivity, the DT receives real-time updates from rehabilitation equipment (e.g., smart exercise machines) to dynamically adjust workloads and exercise parameters. Data security environments protect sensitive patient data, ensuring that each DT complies with healthcare data regulations and remains confidential. Feedback loops enhanced by machine learning tailor the DT's response to each patient's specific biomechanics, making rehabilitation programs adaptive over time. Overall, these environments and mechanisms work together to create a responsive, data-driven DT system that continually learns from each patient, guiding them through personalised, optimised rehabilitation pathways [27–29].

3.6. Operation of DTs in Rehabilitation and Physiotherapy

DT in rehabilitation and physical therapy involve structured rules and stages designed to create personalised and adaptive therapy for patients. The initial baseline assessment stage collects comprehensive patient data, including medical history, injury details, movement patterns, and any imaging or physiological data needed to build a detailed digital model. Patient consent and data privacy principles are strictly adhered to during this stage to ensure patient information is secure and healthcare regulatory compliant. The second stage, calibration, involves adapting the DT to the patient's specific biomechanics by using real-time sensor data from wearable devices or motion capture systems and fine-tuning the model to accurately reflect physical parameters. During the simulation stage, the DT runs virtual scenarios to predict how different exercises, intensities, or movements will affect the patient, offering insight into safe and effective treatment approaches. During this stage, the principles dictate that simulations avoid excessively strenuous or unsafe movements, focusing only on clinically proven techniques. In the intervention phase, the DT recommends personalised exercises and tracks patient progress by comparing actual movement data with simulated results, helping therapists monitor adherence and adjust routines as needed. The feedback loop rule requires the DT to continuously consider real-time data, refining predictions and responses to accurately reflect patient progress or failure. Adaptive learning algorithms, governed by preset treatment goals and safety thresholds, adjust the DT's recommendations based on the patient's rate of recovery, responding to daily changes in strength or mobility. The monitoring phase includes rules to check movement accuracy and exercise adherence, using alerts to clinicians when deviations from prescribed movements or errors in execution are detected. The analysis phase allows clinicians to review performance data and predicted recovery timelines, adjusting the treatment plan based on quantitative insights from the DT. Patient engagement rules allow patients to access visualisations of their progress, encouraging motivation and adherence by showing milestones in recovery and improvements. At each stage, supervision by a medical professional is crucial. Clinicians have the right to ignore DT suggestions or modify parameters to reflect any new medical findings or changes in patient goals. DT operates in accordance with safety protocols, alerting patients or therapists if risky or high-stress movements are detected during real-time exercises. The reassessment principle allows for periodic assessments that check the fit of DT with patient progress, ensuring that the model predictions remain relevant to current needs. Finally, there is a discharge phase when the DT indicates that recovery goals have been achieved, offering a long-term maintenance exercise plan and any further recommendations. These stages and rules are subject to adaptation depending on the technologies used and the specifics of the patients (age, type of conditions, stage of rehabilitation: acute, post-acute, long-term) and healthcare facilities (hospital clinics and wards, rehabilitation centres, outpatient clinics, and rehabilitation facilities) [1,2,28,29].

3.7. Data Update for DTs in Rehabilitation and Physiotherapy

Data updates for DTs in rehabilitation and physical therapy involve systematic procedures to ensure that the models remain accurate and reflect patient progress. First, a real-time data streaming engine from wearable sensors, motion capture systems, and smart devices sends continuous updates on patient movement, vital signs, and environmental factors to the DT. Data preprocessing occurs immediately to filter out noise and irrelevant data, ensuring that only high-quality information updates the model. A time-synchronised engine coordinates data from multiple sources, such as EMG signals, heart rate monitors, and motion sensors, matching inputs to avoid discrepancies in interpretation. Periodic calibration procedures compare actual patient metrics to the current state of the DT, automatically adjusting model parameters to account for any physical or performance changes. Feedback loops integrate patient-reported data—such as pain level, fatigue, or perceived exertion—with the DT, providing subjective context that complements objective sensor data. Adaptive algorithms within DT continually learn from new data points, modifying exercise prescriptions or intensity levels based on updated patient response patterns. Scheduled reassessment routines, such as weekly or monthly assessments, incorporate clinician observations and any new medical data (e.g., imaging or test results), adapting DT to the patient's current status. Security protocols ensure that data updates are encrypted and access-controlled, protecting patient privacy during each update cycle. Patient progress reports, generated through data analysis, provide clinicians and patients with insight into recovery trends, helping to decide if any changes to therapy are necessary. Environmental update mechanisms enable DT to modify exercises based on contextual changes, such as room temperature, humidity, or spatial constraints that may impact exercise safety or comfort. A backup and logging system tracks all updates, allowing clinicians to review previous modifications and data entries to understand therapy progress over time. Finally, clinicians have the ability to manually overwrite, allowing them to make changes directly to the DT, which is particularly useful for incorporating any new, nuanced patient insights that may not be captured by the sensors. Taken together, these procedures and mechanisms ensure that the DT for rehabilitation and physical therapy remains highly accurate, responsive, and personalised throughout the rehabilitation period [1,2,28,29].

3.8. Data Security in DTs in Rehabilitation and Physiotherapy

As DTs become more widespread, concerns about data security, patient consent, and equitable access to the technology must be addressed to ensure widespread adoption and confidence in their use. Data security for DTs in rehabilitation and physical therapy is paramount, given the sensitive patient information. One of the basic procedures is data encryption, which protects patient information both in transit and at rest, ensuring that only authorised individuals can access or interpret the data. Blockchain technology adds another layer of security through decentralised and immutable data logging, allowing for secure recording, verification, and timestamping of every data update or access event. This blockchain logging mechanism prevents tampering and unauthorised changes, creating an audit trail to track all DT-related activities. AI-based anomaly detection is used to monitor suspicious patterns or potential breaches, flagging irregular access attempts or unauthorised modifications to data in real-time. Advanced access control protocols use multi-factor authentication and role-based access, ensuring that only verified users, such as physicians and authorised administrators, can access or update DT data. Quantum computing, a potential threat to traditional encryption, is mitigated by the integration of post-quantum cryptographic techniques that ensure data security even in the face of advanced computational attacks. Blockchain smart contracts enable secure, conditional data sharing between DT systems and third-party systems, enforcing policies that limit data exposure to only necessary information and only when legally permitted. Regular security audits and penetration tests identify vulnerabilities in the DT system, enabling proactive updates to security protocols and encryption methods. Differential privacy algorithms in AI modules protect patient data by adding statistical noise, preventing individual

identification while maintaining the accuracy of predictive models. Data minimisation practices ensure that only necessary information is collected and stored, reducing the risk associated with data breaches. Real-time backup mechanisms combined with blockchain ledger functionality provide reliable data recovery options in the event of data corruption or loss. Finally, AI-based risk assessment models continuously evaluate the security posture of the DT system, dynamically updating security settings to adapt to emerging cyber threats. Together, these procedures and mechanisms create a solid security framework for data processing in rehabilitation and physical therapy, addressing current and future data protection challenges.

In the case of rehabilitation and physical therapy DTs, edge computing and federated learning are key to data anonymisation and cybersecurity. Edge computing processes data locally on devices near the patient, such as wearables or on-site servers, minimising the need to transmit sensitive data to central servers and thus reducing the risk of exposure. Anonymisation techniques such as data masking and tokenisation are applied directly at the edge, ensuring that personal identifiers are removed before the data leaves the local device. Federated learning further enhances data privacy by training machine learning models on decentralised devices rather than centralising the data; in this way, DTs can improve their intelligence and accuracy without the raw patient data leaving the device. Only model updates, not the patient data, are shared with the central system, reducing the risk of a data breach. AI algorithms at the edge detect and respond to any cybersecurity threats in real time, blocking or flagging suspicious activity and securing the data locally before it reaches the network. Secure aggregation protocols in federated learning enable encrypted model updates, ensuring that the central server receives only aggregated information without visibility into individual patient data, preserving anonymity. Edge devices use secure, lightweight encryption methods that prevent unauthorised access while maintaining the fast processing speeds necessary for real-time data updates in the DT. Differential privacy mechanisms add statistical noise to data updates at the edge, increasing anonymity by preventing data from being traced back to individual patients. Federated learning uses multi-party computation (MPC) techniques to securely combine model updates from multiple sources, ensuring that data from one device remains inaccessible to others, even in collaborative learning environments. Both edge computing and federated learning implement local data retention policies, storing patient data only as long as needed for analysis, limiting time exposure. Blockchain can also be incorporated to track all data access transactions and model updates securely at the edge, providing an immutable record and strengthening accountability in federated learning networks. Finally, routine AI-driven audits assess DT security and anonymisation processes, detecting any gaps and strengthening local encryption and federation protocols in response to emerging cyber threats. Together, edge computing and federated learning create a secure, privacy-preserving environment for DT, ensuring that sensitive patient data remains anonymous and protected at all times.

3.9. Distinctive Role of Rehabilitation and Physiotherapy in Preventive Medicine and Early Diagnosis

DTs are playing an increasingly valuable role in preventive medicine and wellness, shifting the focus from reactive treatment to proactive health management in rehabilitation and physical therapy. Initially, DTs collect baseline data on individuals, such as fitness levels, movement patterns, and lifestyle factors, allowing for the creation of personalised health profiles that identify potential risks before they manifest [27–29]. This early profiling allows DTs to simulate possible future health scenarios, predicting the likelihood of injury or musculoskeletal problems based on current habits, posture, or physical stressors. For those at risk of injury, DTs provide tailored exercise and movement recommendations to strengthen vulnerable areas, correcting imbalances or weaknesses before they become problems [30]. Continuous monitoring of biomechanical data via wearable devices and sensor-based feedback allows DTs to detect even subtle deviations in movement quality,

alerting users to make real-time corrections that help prevent overuse or injury [31,32]. In the case of sedentary lifestyles, DTs can encourage users to use personalised routines that promote regular activity, preventing inactivity-related issues such as muscle atrophy, poor posture, or joint stiffness. DTs can also provide feedback on ergonomic improvements, suggesting better positioning or techniques during daily activities such as sitting, lifting, or working, which are common contributors to physical discomfort or injury [33]. For athletes or highly active individuals, DTs assess performance metrics to identify optimal training loads, thereby reducing the risk of overtraining, burnout, or repetitive stress injuries [34,35]. By continually assessing changes in body metrics and lifestyle factors, DTs dynamically adjust preventive recommendations, ensuring that advice remains relevant as an individual's condition evolves over time. Another important role of DTs is to educate users on the importance of gradual progression in exercise, avoiding the common trap of sudden, intense bursts of activity that can lead to injury. Integrated with AI, DTs can analyse historical health and fitness data to identify emerging patterns or behaviours that increase the risk of injury, leading to preventive changes to activity levels or routines [36,37]. Additionally, DTs can suggest restorative activities such as stretching or relaxation techniques, promoting holistic well-being by maintaining flexibility, circulation, and mental resilience [38]. Preventive DTs work with physical therapists to identify early warning signs of injury or misalignment, allowing for minor interventions that avoid the need for full-blown therapy later on. DTs also provide users with personalised insights on nutrition, hydration, and lifestyle changes that support musculoskeletal health, preventing deficiencies that can exacerbate physical strain [39]. They help educate users on safe movement practices at work and in everyday life, thereby reducing exposure to risky, repetitive movements. Regular reports from DTs keep users engaged in their health, increasing self-awareness and motivating them to follow preventive practices [40,41]. DTs ultimately promote a "prevention is better than cure" mindset, helping people maintain their well-being and avoid the physical and financial costs of extensive rehabilitation. In summary, DTs act as intelligent, proactive health companions, supporting an innovative, prevention-focused approach to rehabilitation and physical therapy [42].

4. Discussion

AI-based patient DTs offer transformative applications in decision support for rehabilitation and physiotherapy by enabling highly personalised care [43]. These virtual models replicate the patient's musculoskeletal and neurological systems, allowing clinicians to simulate different therapeutic interventions and/or predict their outcomes (Table 4). By integrating real-time data from wearables and medical records, DTs can adjust physiotherapy treatments dynamically based on the patient's progress [44]. They enhance decision-making by predicting recovery timelines and identifying the most effective exercises or treatments tailored to the individual [45–47]. AI-driven insights also help in preventing injury recurrence by simulating stress on muscles and joints during therapy. These models enable continuous monitoring, making it easier to adjust plans proactively and reducing trial-and-error in treatment approaches [48,49]. Overall, AI DTs optimise patient outcomes by enhancing precision and efficiency in rehabilitation and physiotherapy [50].

Table 4. Studies on AI-based DT applications in rehabilitation and physical therapy.

Study	Results
Young et al., 2024 [51]	Exercise-aware decision support system that uses DTs to provide personalised recommendations that help people with type 1 diabetes maintain safe glucose levels and avoid low glucose levels during and after exercise.

Table 4. *Cont.*

Study	Results
Lloyd et al., 2023 [52]	Laboratory-quality biomechanical measurements and modelling can be performed outside the lab using wearable sensors or computer vision. The next step is to combine these technologies into easy-to-use products.
Zhou et al., 2022 [53]	The development of data science, virtual reality, AI, and DTs, and the introduction of the metaverse concept to medicine have brought alternative and complementary intervention strategies.
Gamez Diaz et al., 2020 [54]	The DT ecosystem shows the interactions and flow of information and the concept of a DT ecosystem for tracking team sports athletes.
Calderita et al., 2020 [55]	The CPS-AAL presented in this work uses a DT world with information acquired by all connected devices. The basis of this DT world is the CORTEX cognitive architecture, a set of software agents communicating via a Deep State Representation (DSR) that stores the information shared between them.

4.1. Current Limitations

AI-based patient DTs have great potential to support decision-making in rehabilitation, but they face several limitations. DTs rely on accurate, high-quality patient data, but many healthcare systems do not collect comprehensive data, leading to incomplete models [56]. Personal health data are sensitive, and ensuring privacy when developing and using DTs can be challenging due to the need for extensive, detailed information [57,58]. Implementing DTs into everyday clinical practice requires seamless integration, but many healthcare systems are not prepared for this, causing disruptions in workflow. DTs often require data from multiple systems (e.g., EHRs, wearable devices), and many systems are not interoperable, making data exchange difficult. Developing and maintaining AI-based DTs is cost-intensive, requiring significant investments in technology, expertise, and infrastructure [59]. Patient DTs are typically based on specific populations or conditions, making it difficult to generalise findings to broader or more diverse patient groups [60–62]. AI algorithms can inherit bias from training data, leading to unfair or inaccurate predictions for certain patient groups, especially minority or under-represented populations [62]. Ensuring the reliability and clinical validity of DT models is challenging because they require extensive testing in real-world settings before they can be trusted for critical decisions [63]. Patients' health status can change rapidly, and DTs can struggle to update quickly enough to reflect these changes in real-time [64]. Despite advances in AI, fully capturing the complexity of human biology and its response to rehabilitation remains a major hurdle for DTs [65,66]. Regulatory approval of AI-based DTs is complex because health authorities require solid evidence of safety, efficacy, and reliability, which slows adoption [67]. AI-based DTs in rehabilitation and physical therapy raise important moral and regulatory challenges, particularly regarding patient consent and data use. Obtaining informed and voluntary consent for the use of sensitive health data in DT can be complicated by patients' limited understanding of AI technologies. There are also privacy concerns as the aggregation and processing of detailed personal data expose patients to the risk of breach or unauthorised use. The regulatory framework may struggle to keep pace with the rapid development of DT, leading to gaps in oversight and inconsistencies in data protection standards. There are ethical concerns about the potential for bias in the algorithms driving DT, which may result in unfair treatment outcomes for marginalised groups. In addition, accountability for

errors or adverse outcomes in decision-making involving DT remains ambiguous, raising questions about accountability in clinical practice. Medical professionals can have difficulty trusting or interpreting recommendations about DTs, especially when the decision-making process is unclear or difficult to understand [68,69]. While DTs aim to create personalised models, achieving true personalisation in all aspects of a patient's rehabilitation is still far from reality [70]. DTs often rely on real-time data from wearable devices, but not all patients have access to these technologies or can consistently use them. Despite promising achievements, long-term studies are needed to show that the use of AI-based DTs leads to better rehabilitation outcomes compared to traditional methods [71,72]. These limitations must be addressed for AI-based DTs to become a reliable tool for rehabilitation decision support [73,74].

4.2. Directions for Further Studies

Further research on AI-based patient DTs for rehabilitation decision support should address several key directions. Research should focus on developing robust frameworks that integrate multiple data sources, including electronic health records (EHRs), wearable devices, and imaging, to build more comprehensive and accurate digital twin models [75,76]. Research should also explore ways to increase the personalisation of DTs by improving AI algorithms to better capture individual variability, including genetic, lifestyle, and environmental factors [77]. Future research should aim to develop DTs that can automatically adapt in real-time to changes in patient conditions, enabling dynamic and timely decision support during rehabilitation [78]. Research is needed to address the problem of algorithmic bias, ensuring that DTs provide equitable and accurate recommendations for all patient populations, especially those from under-represented or minority groups. Developing explainable AI (XAI) techniques for DTs is critical to ensuring that clinicians can understand and trust the decision-making processes in the model, which will promote greater adoption in clinical practice [79,80]. Rigorous clinical trials are essential to validate the efficacy and safety of digital twin-based decision support systems, with particular attention to different rehabilitation contexts and patient populations. Further research should develop ethical guidelines and regulatory standards for the use of DTs in healthcare, ensuring patient privacy, security, and data protection [81]. Research should explore the integration of multimodal data, such as combining physiological signals, biomechanics, and patient-reported outcomes, to create a more holistic picture of a patient's progress in rehabilitation [82]. Promoting collaboration between AI experts, medical specialists, data scientists, and ethicists is essential to ensure that digital twin models address both technical and clinical challenges in rehabilitation. AI-based patient DTs embody interdisciplinarity, combining informatics, medicine, and physiotherapy to revolutionise decision support in rehabilitation. Computer science contributes to the development of advanced AI algorithms and simulation models that power virtual replicas. Medicine provides the basic knowledge of human anatomy, pathophysiology, and clinical workflows necessary to ensure that the DT reflects the real-world dynamics of the patient. Physical therapy adds expertise in therapeutic interventions and functional assessments, ensuring that the models address practical rehabilitation goals. This collaborative framework fosters innovative solutions, enabling personalised and predictive care that adapts to individual patient needs. The seamless integration of these disciplines highlights the breadth of the DTs, developing innovations in healthcare while bridging technical and clinical disciplines. Research should focus on developing systems that can collect and analyse longitudinal patient data, enabling DTs to offer insight into long-term rehabilitation outcomes and interventions [83]. Future research could explore the role of DTs in supporting remote or telerehabilitation (within smart cities and smart territories), enabling healthcare professionals to monitor and adjust treatment plans based on real-time data from patients at home [84]. Further research is needed to improve the computational efficiency of digital twin models, making them more accessible and easier to implement in real-world clinical settings with limited resources [85]. Research should also include the creation of interoperable digital twin platforms that can seamlessly

integrate with different healthcare systems, devices, and rehabilitation technologies [86]. Future research should emphasise designing digital twin interfaces that are intuitive for both clinicians and patients, improving usability and engagement in rehabilitation settings [87]. Exploring the combination of AI with other computational techniques, such as physics-based models or biomechanical simulations, can improve the accuracy and robustness of DTs in supporting rehabilitation decisions. These research directions aim to overcome current limitations and pave the way for broader, more effective use of AI-based patient DTs in rehabilitation [88,89].

5. Conclusions

AI-based patient DTs offer significant potential for decision support in rehabilitation, enabling personalised treatment planning. As digital models, they simulate patient physiology and pathological changes, enabling medical professionals to predict the outcome of different intervention scenarios without risk to patients and the real-world healthcare system. Through real-time monitoring and data integration, they help identify optimal rehabilitation and physical therapy methods, dynamically adjust treatment, and reduce recovery time. They can also assess the impact of different rehabilitation strategies, ensuring that interventions are tailored to the individual. This personalised approach reduces trial and error and improves the accuracy of decision-making within the evidence-based medicine (EBM) paradigm. Using predictive analytics, DTs help healthcare professionals predict complications and optimise long-term outcomes, increasing the effectiveness of rehabilitation and patient-centred care.

AI-based DTs rely on large datasets for accurate simulations, but limitations in data quality, such as missing or biased data, can compromise their effectiveness in personalising rehabilitation protocols. The high computational power required to create detailed real-time digital replicas of human physiology can be prohibitive, especially in resource-limited clinical settings. Current AI models may struggle to fully capture the nuances of individual variability in anatomy, biomechanics, and response to therapy, reducing their effectiveness in some patients. The collection, storage, and processing of sensitive health data to create DTs raises concerns about data security, privacy, and informed consent. The seamless integration of AI-based DTs into existing healthcare systems, workflows, and physician training can be challenging, potentially hindering widespread adoption in rehabilitation and physical therapy.

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