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The role of digital twin technology in physiotherapy and rehabilitation practice

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Abstract: Digital twin technology, that creates virtual replicas of physical entities using real-time data and simulation models, has emerged as a transformative innovation across multiple healthcare domains. Its application in physiotherapy and rehabilitation represents a paradigm shift from traditional therapeutic approaches to personalized data-driven interventions that optimize patient outcomes. This narrative review examines the current applications, benefits, challenges, and future prospects of digital twin technology in physiotherapy and rehabilitation, providing a comprehensive analysis of the manner in which this technology is reshaping clinical practice and patient care. A narrative review approach was employed, systematically searching PubMed, IEEE Xplore, Scopus, and Web of Science databases. Studies describing digital twin applications, development methodologies, clinical implementations, and theoretical frameworks in physiotherapy and rehabilitation contexts were included. Digital twin technology demonstrates significant potential in personalizing rehabilitation programs, enabling real-time monitoring of patient progress, predicting treatment outcomes, and facilitating remote therapeutic interventions. Current applications span musculoskeletal rehabilitation, neurological recovery, post-surgical care, and sports injury management. Key benefits include enhanced treatment precision, improved patient engagement, reduced healthcare costs, and accelerated recovery times. However, implementation faces challenges including technological complexity, data privacy concerns, interoperability issues, and the need for substantial infrastructure investment. Digital twin technology represents a promising frontier in physiotherapy and rehabilitation, offering unprecedented opportunities for personalized, efficient, and effective patient care. Successful integration requires addressing the current limitations while fostering interdisciplinary collaboration between clinicians, engineers, and data scientists.

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1 Introduction

The healthcare landscape has undergone a remarkable transformation over the past decade, driven by rapid technological advancements and the increasing availability of sophisticated data analytics tools. Among these innovations, digital twin (DT) technology has emerged as a particularly promising development, offering unprecedented opportunities to revolutionize patient care across multiple clinical domains. Originally conceptualized in the aerospace and manufacturing industries, DTs are virtual replicas of physical entities that use real-time data, machine-learning algorithms, and simulation models to mirror, predict, and optimize the behaviors of their physical counterparts [1]. In healthcare, this technology has found applications ranging from drug discovery and surgical planning to disease prediction and personalized treatment protocols, marking a significant departure from traditional one-size-fits-all therapeutic approaches [2]. Recent comprehensive surveys have demonstrated the integration of DTs with broader healthcare Internet of Things (IoT) ecosystems and generative artificial intelligence (AI) trends, highlighting the evolution of technology from isolated systems to interconnected AI-enhanced platforms capable of comprehensive patient characterization and real-time status reflection [3–5].

Physiotherapy and rehabilitation constitute critical components of modern healthcare systems, serving millions of patients worldwide who require therapeutic interventions following injury, surgery, or illness. Traditional rehabilitation approaches have relied heavily on standardized protocols, subjective clinical assessments, and periodic in-person consultations that, although effective in many cases, often lack the precision and adaptability necessary to optimize individual patient outcomes. The increasing prevalence of chronic musculoskeletal (MSK) conditions, aging global population, and rising burden of neurological disorders have placed unprecedented demands on rehabilitation services, necessitating innovative approaches that can deliver more efficient, accessible, and personalized care. Furthermore, the COVID-19 pandemic has accelerated the adoption of telehealth and remote-monitoring technologies, highlighting both the potential and challenges of delivering rehabilitation services beyond traditional clinical settings.

DT technology addresses many limitations inherent in conventional rehabilitation practices by creating dynamic patient-specific virtual models that integrate diverse data streams including biomechanical measurements, physiological parameters, medical imaging, and patient-reported outcomes [6]. These virtual representations enable clinicians to simulate different therapeutic interventions, predict patient responses, and adjust treatment protocols in real time based on continuous feedback loops [6]. This technology facilitates a shift from reactive to proactive care, allowing healthcare providers to anticipate potential complications, identify optimal intervention windows, and personalize rehabilitation programs according to individual patient characteristics, preferences, and goals. Moreover, DTs can incorporate historical patient data, population-level evidence, and emerging research findings to continuously refine treatment recommendations, thereby bridging the gap between clinical research and practice [1]. Convergence with generative AI enables DTs to automatically create, manipulate, and modify valuable yet diverse data, addressing the challenges of scarce, biased, and noisy data that commonly plague healthcare applications [3].

The convergence of several technological advances has made DT implementation in physiotherapy and rehabilitation increasingly feasible and practical. The proliferation of wearable sensors and IoT devices has enabled continuous unobtrusive monitoring of patient movement patterns, activity levels, and physiological responses during daily activities and therapeutic exercises. Advances in computer vision and motion capture technology allow for the precise quantification of biomechanical parameters without requiring expensive laboratory equipment. The cloud-computing infrastructure provides the necessary computational resources to process large volumes of data and run complex simulation models in real time. However, for latency-sensitive rehabilitation tasks such as real-time gait correction, edge computing architectures have emerged as critical enablers, providing near-instant feedback through distributed processing at network edges closer to the patient [7,8]. These edge-based frameworks support responsive physical-to-virtual twin connectivity, ensuring the continuous maintenance of true replicas of physical twins, while reducing the experienced delay to zero or near-zero levels [7]. AI and machine-learning algorithms can identify patterns in rehabilitation data that may not be apparent to human observers, enabling more accurate outcome predictions and treatment optimizations [2]. Mobile generative AI-driven human digital twins (HDTs) specifically address human-centric applications by providing customized services, user-friendly experiences, context-aware responses, and seamless integration while accommodating uncertain user mobilities, time-varying factors, and unstable network performances [5]. These technological components, when integrated effectively, create a powerful ecosystem for implementing DT solutions in rehabilitation settings.

Despite the considerable promise of DT technology in physiotherapy and rehabilitation, several critical knowledge gaps persist that this review aims to address. First, although individual case studies and pilot implementations exist, a limited comprehensive synthesis remains regarding the manner in which DTs are applied across different rehabilitation contexts, the specific clinical benefits they deliver compared with conventional approaches, and the barriers impeding their widespread adoption in routine clinical practice. Second, the heterogeneity of DT implementations, ranging from simple sensor-based monitoring systems to complex AI-driven predictive models, poses a challenge for clinicians, researchers, and healthcare administrators to distinguish which applications have achieved clinical maturity, which demonstrate the greatest evidence-based promise, and where further technological and clinical development is urgently needed. Third, crucial questions regarding secure bidirectional data transmission, temporal synchronization of heterogeneous sensor data, algorithmic transparency, equitable access across diverse patient populations, and long-term cost-effectiveness remain inadequately addressed in the existing literature. Finally, the guidance on practical implementation pathways is insufficient, including workflow integration strategies, clinician training requirements, and sustainable reimbursement models that could facilitate the successful translation from research prototypes to scalable clinical solutions.

Therefore, this narrative review has three primary objectives: (1) To systematically synthesize current evidence on DT applications across major rehabilitation domains including MSK, neurological, sports, and remote care contexts; (2) to critically evaluate the clinical benefits, technological challenges, and implementation barriers associated with DT technology in physiotherapy practice; and (3) to identify priority areas for future research, development, and policy action that could accelerate evidence-based adoption while ensuring equitable access, patient safety, and clinician empowerment. As illustrated in Figure 1, DT systems integrate heterogeneous data streams into a continuously updated virtual model that informs personalized rehabilitation decisions.

2 Method

2.1 Search strategy

This narrative review employed a comprehensive literature search across multiple electronic databases including PubMed, IEEE Xplore, Scopus, and Web of Science, following the current best practices for

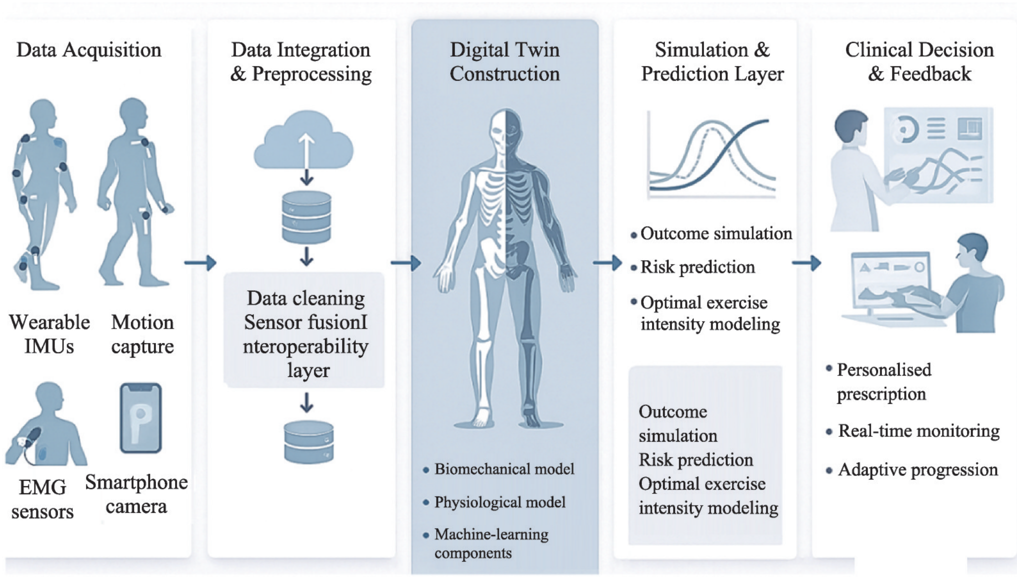

Figure 1 Workflow of a digital twin (DT) system for physiotherapy and rehabilitation. The figure illustrates the sequential integration of multimodal data sources into a dynamic virtual model capable of simulating personalized rehabilitation strategies, predicting outcomes, and enabling real-time clinical decision-making.

narrative and scoping reviews in digital health research. The search was conducted in August 2025 and included publications from January 2018 to June 2025, a period during which DT applications in healthcare experienced substantial growth. The search strategy combined controlled vocabulary terms and keywords related to DT technology and physiotherapy or rehabilitation. Specific search strings included ("digital twin" OR "digital twins" OR "virtual twin" OR "cyber-physical system" OR "human digital twin") AND ("physiotherapy" OR "physical therapy" OR "rehabilitation" OR "musculoskeletal" OR "neurorehabilitation" OR "orthopedic rehabilitation" OR "sports rehabilitation"). Boolean operators were used to combine the search terms, and no language restrictions were applied initially, although only English-language publications were ultimately included in the review.

2.2 Inclusion and exclusion criteria

Studies were included if they (1) described the development, implementation, or evaluation of DT technology in physiotherapy or rehabilitation contexts; (2) discussed theoretical frameworks, methodologies, or technical architectures for DT systems in MSK, neurological, or general rehabilitation; (3) presented clinical applications, case studies, or pilot implementations of DTs for rehabilitation purposes; or (4) examined challenges, opportunities, or future directions for DT technology in physiotherapy practice. The exclusion criteria included (1) studies focusing solely on surgical DTs without rehabilitation components, (2) publications addressing DTs in other medical specialties without relevance to physiotherapy, (3) purely theoretical computer science papers without healthcare applications, and (4) conference abstracts lacking sufficient methodological details or results. Gray literature, including technical reports from healthcare technology companies and white papers from professional organizations, was included when it provided valuable insights into practical implementations or emerging trends.

To ensure methodological rigor, the included studies were assessed using the quality criteria adapted from the Mixed Methods Appraisal Tool (MMAT) for empirical studies and established frameworks for evaluating theoretical and conceptual papers. Studies were categorized as high, moderate, or low quality based on the clarity of aims, appropriateness of methods, transparency of reporting, and validity of conclusions. Although no studies were excluded solely on quality grounds, the quality assessment informed the weight given to the findings during synthesis. Borderline cases, particularly biomechanical simulation studies that exhibited DT characteristics but did not explicitly use digital twin terminology, were resolved through a consensus discussion among the authors, focusing on whether the system demonstrated core DT features: bidirectional data flow, real-time or near-real-time updation, predictive capability, and patient-specific modelling. The studies meeting at least three of these four criteria were included regardless of the terminology used.

2.3 Data extraction and synthesis

Following the database searches, all the identified records were exported to the Zotero reference management software, and the duplicates were removed. The titles and abstracts were screened for relevance according to the inclusion and exclusion criteria, and the full-text articles of potentially relevant studies were retrieved and assessed in detail. Given the narrative nature of this review and the heterogeneity of study designs, methodologies, and outcomes in the included literature, a formal meta-analysis was not appropriate. Instead, data were extracted using a standardized form capturing the information on study characteristics, DT application domains (for example, MSK, neurological, and sports), technological components and architecture, clinical outcomes and benefits, identified challenges and limitations, and recommendations for future development. The extracted data were synthesized narratively, organizing the findings thematically according to the application areas, technological considerations, clinical benefits, and implementation challenges. This approach allowed for a comprehensive examination of the current state of DT technology in physiotherapy and rehabilitation while accommodating the diverse nature of available evidence.

3 Current applications in physiotherapy and rehabilitation

3.1 Musculoskeletal rehabilitation

DT technology has shown significant promise in MSK rehabilitation, particularly in patients recovering from orthopedic injuries and postsurgical procedures. Lower-limb rehabilitation following knee and hip arthroplasty is one of the most mature areas of DT development, with systems combining wearable inertial measurement units (IMUs) and MSK simulation models to monitor gait parameters, joint loading, and movement quality [9]. This enables physiotherapists to quantify subtle compensations and adjust progression based on objective biomechanical feedback, improving the precision of exercise prescriptions [10]. For instance, hybrid MSK DT-integrated surface Electromyography (sEMG) and motion-capture data have been used to monitor real-time muscle activation during rehabilitation [11]. In spinal rehabilitation, DTs have been used to simulate vertebral loading and predict safe movement ranges [12, 13]. For chronic MSK pain management, DTs that integrate data from wearables, activity monitors, and pain questionnaires have been shown to model the correlations between physical activity and symptom severity, allowing the identification of pain-exacerbation triggers [6]. Machine-learning algorithms applied to these longitudinal datasets can predict flare-ups and suggest preemptive modifications, representing a shift from reactive care toward predictive, patient-empowering rehabilitation.

3.2 Neurological rehabilitation

Neurological rehabilitation presents unique challenges owing to motor control deficits, cognitive impairments, and variable recovery trajectories following stroke, traumatic brain injury, and neurodegenerative disorders. DT technology addresses these issues by constructing personalized neuro-MSK models that integrate kinematic limb data, neuroimaging, and functional scales such as the Fugl-Meyer assessment [14]. These models enable the prediction of recovery potential and optimization of therapy dosage based on individual response curves [15]. Gait-rehabilitation DTs employ instrumented walkways and wearable IMUs to quantify spatiotemporal gait parameters and symmetry indices, and integration with neural-control models pinpoints deficits such as reduced ankle dorsiflexion or asymmetrical hip extension [10]. A compensatory movement detection model trained with 1,590 data samples from healthy participants simulating typical compensatory movements achieved 96% accuracy in classifying compensatory movements during biceps curl exercises [14]. The model was subsequently evaluated in a user study with eight stroke patients and six therapists over three weeks, demonstrating its potential for the real-time detection of unnatural supportive movements during rehabilitation exercises. However, this HDT system remains experimental, with automated feedback mechanisms and longitudinal outcome prediction capabilities still undergoing validation in controlled research settings rather than in routine clinical practice. For upper-limb recovery, DTs integrate data from robotic exoskeletons, EMG, and motion sensors to map muscle synergies and forecast individual recovery trajectories. Machine-learning models within these DTs have identified patients at risk of "learned non-use" and recommended optimal task-specific training intensities [9]. Continuous monitoring via wearables provides further insights into real-world limb use, that often diverges from in-clinic performance, helping therapists adjust interventions more precisely [12]. Secure federated multitask learning frameworks have been integrated into HDT connectivity schemes to ensure privacy-preserving model evolution while maintaining accuracy and reducing overall connectivity costs [16].

3.3 Sports rehabilitation and performance optimization

The application of DT technology in sports rehabilitation and performance optimization is expanding rapidly, emphasizing data-driven personalized recovery. Sports rehabilitation DTs combine biomechanical movement data, training-load metrics, heart rate variability, and psychological readiness indicators to generate adaptive return-to-sport protocols [17]. For running-injury prevention, DTs incorporate data from smart footwear and inertial sensors that track gait asymmetry and ground reaction forces. Training-load DTs that integrate weekly mileage and recovery metrics predict the optimal progression rates [17,18]. For team sports, DTs model multidirectional movements and high-impact mechanics using GPS tracking and force-plate data, assisting clinicians in defining quantitative readiness benchmarks for return-to-play decisions [19]. Although promising, direct comparative studies evaluating DT-based decision support against established sports-medicine return-to-play criteria (such as the Sports Medicine Australia Return-to-Play guidelines or Consensus Statement on Return-to-Sport) remain limited. These data-driven approaches mitigate subjective bias and external pressures, thus fostering safer and more objective clinical decision-making.

3.4 Remote and home-based rehabilitation

The COVID-19 pandemic has accelerated the adoption of remote and home-based rehabilitation systems, with DT technology enabling continuous virtual monitoring and adaptive intervention outside the clinic [6]. DTs use data from smartphones, wearable sensors, and home-based IoT devices to create evolving virtual patient models that physiotherapists can access remotely [20]. Smartphone-based systems using computer vision algorithms can capture exercise performance using cameras, estimate joint angles, and evaluate form accuracy, providing immediate visual feedback to patients.

Wearable IMU-based DT systems further quantify arm-use frequency in upper-limb stroke rehabilitation and gait symmetry in lower-limb therapy. These continuous data streams reveal intraday functional fluctuations influenced by factors such as the time of day, medication timing, or fatigue, allowing real-time protocol adjustment. Quality of experience (QoE)-aware resource allocation strategies employing deep reinforcement learning have optimized bandwidth allocation, bit rate, rendering modes, and signal compression to maximize the synchronization between visual and haptic feedback transmissions, enhancing immersive interactions in HDT systems [21]. These systems expand accessibility for patients in remote or mobility-limited contexts, promoting equity and adherence in long-term rehabilitation care. These diverse applications across MSK, neurological, sports, and remote rehabilitation contexts are summarized in Table 1.

Table 1 Key applications of digital twin (DT) technology in physiotherapy and rehabilitation

Application domain	Specific use cases	Data sources	Primary clinical benefits
Musculoskeletal rehabilitation [9,11,12]	Post-surgical knee/hip recovery, shoulder pathologies, spinal conditions, and chronic pain management	Wearable IMUs, EMG sensors, motion capture, pain questionnaires, and activity monitors	Objective movement quantification, early compensation detection, personalized progression, and improved outcomes
Neurological rehabilitation [10,14,15]	Stroke recovery, traumatic brain injury, gait training, and upper-limb rehabilitation	Instrumented walkways, robotic devices, wearable sensors, functional assessments, and neuroimaging	Recovery prediction, targeted intervention selection, real world activity monitoring, and dose optimization
Sports rehabilitation [17–19]	Injury prevention, return-to-sport protocols, running biomechanics, and team sport monitoring	GPS tracking, force plates, smart footwear, training load apps, and biomechanical testing	Injury risk reduction, objective return-to-play decisions, performance optimization, and reinjury prevention
Remote/home based care [20]	Telerehabilitation, exercise monitoring, functional assessment, and patient engagement	Smartphone cameras, consumer wearables, home sensor systems, and patient reported outcomes	Increased access, reduced costs, continuous monitoring, improved adherence, and convenience

4 Clinical benefits and outcomes

4.1 Personalized treatment approaches

One of the most significant benefits of DT technology in physiotherapy lies in its capacity to enable truly personalized rehabilitation programs that account for individual patient characteristics, responses, and preferences. Traditional rehabilitation protocols follow standardized progressions based on the time since injury or surgery, applying uniform interventions to all patients with a given diagnosis. However, these approaches fail to capture substantial inter-individual variability in recovery rates, comorbidities, and baseline functions [10,12]. DT systems overcome this limitation by constructing patient-specific biomechanical and physiological models that update continuously as the rehabilitation progresses. This allows therapy parameters to adapt dynamically based on real-time responses rather than on predetermined timelines [9]. Exercise prescriptions can therefore be tailored to biomechanics of an individual, with DT simulations identifying the optimal movement patterns and loading parameters that maximize therapeutic effects while minimizing strain. For example, simulating knee-joint stress at varying squat depths has been shown to guide safe loading strategies for patellofemoral pain syndrome [11]. Temporal personalization represents an additional dimension of DT-enabled care. DTs that analyze circadian variations in pain and function can identify optimal time windows for challenging exercises, pain management, or rest. The ability to detect recovery readiness through continuous feedback enables precise progression when data indicate tolerance, rather than at arbitrary intervals. Figure 2 outlines the major clinical benefits of integrating DT technology into physiotherapy practice.

4.2 Enhanced monitoring and outcome prediction

DT technology substantially enhances clinical monitoring by integrating multimodal data, such as wearables, EMG, imaging, and self-reports, into a continuously updated representation of patient progress [14, 20]. Traditional physiotherapy relies on periodic evaluations that offer only brief snapshots of recovery, whereas

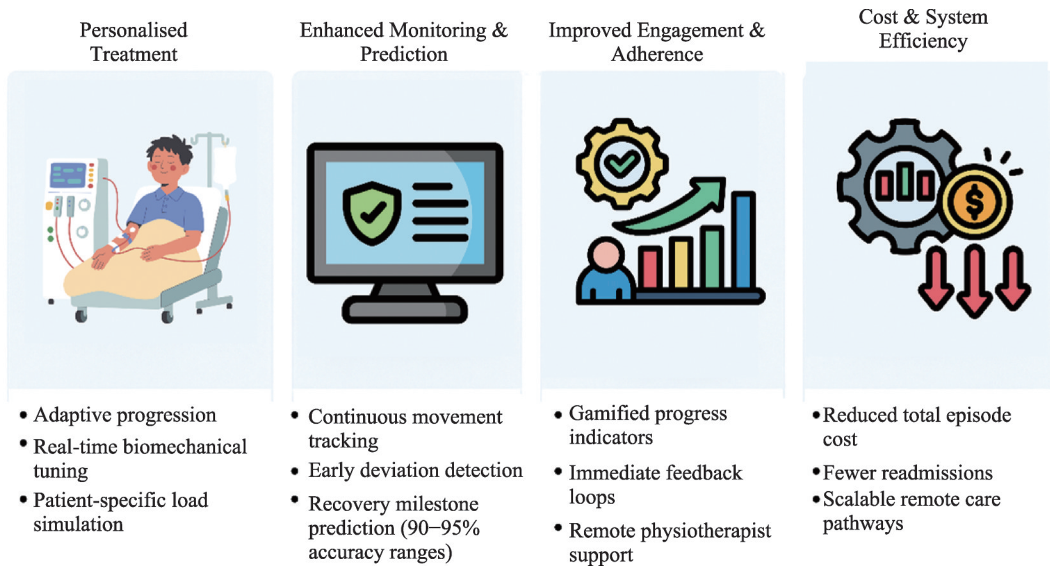

Figure 2 Key clinical benefits associated with DT-enhanced rehabilitation, including personalized therapy, continuous monitoring with predictive analytics, improved patient engagement, and reduced healthcare costs.

DTs maintain longitudinal trajectories of movement quality, muscle function, and adherence, allowing the early identification of regression or abnormal trends [15]. Critical to reliable monitoring is the implementation of time-synchronization mechanisms that address varying sampling rates from heterogeneous sensor sources. Fusion algorithms employing Kalman filtering and timestamp alignment protocols ensure temporal coherence across devices sampling at 50–200 Hz (IMUs), 1–10 Hz (EMG), and variable rates (patient-reported outcomes), while maintaining the data fidelity essential for accurate real-time feedback loops.

Predictive modelling constitutes one of the most transformative aspects of DT-based rehabilitation. Machine-learning algorithms trained on datasets can forecast individual recovery milestones such as gait symmetry restoration or return-to-work timelines. These predictive functions enable clinicians to estimate likely outcomes under different intervention strategies and select resource-intensive modalities, such as robotic therapy or aquatic programs, only for those with the greatest potential benefits [12]. This predictive capacity shifts clinical management from reactive to proactive, as physiotherapists can preempt functional decline or detect early signs of non-response to therapy, thereby optimizing overall treatment efficacy and safety [2].

4.3 Improved patient engagement and adherence

Patient engagement and adherence are critical determinants of rehabilitation success; however, non-adherence rates in outpatient physiotherapy have been reported [22,23]. DT technology helps address this issue through interactive visualization and gamification. Three-dimensional anatomical avatars and progress dashboards allow patients to visualize real-time improvements, reinforcing motivation and accountability [6]. Gamified DT systems that employ feedback badges, milestone tracking, and progress visualization can increase exercise adherence [24]. Continuous monitoring fosters a responsive therapeutic relationship: physiotherapists can review remote performance data, provide tailored encouragement, and adjust prescriptions between visits. Automated alerts notify clinicians of deviations such as missed sessions or declining metrics, facilitating early intervention before the setbacks escalate [12].

However, security vulnerabilities unique to bidirectional data flows in rehabilitation DTs pose significant risks that must be addressed. The real-time transmission of exercise feedback from virtual twins to physical patients creates potential attack surfaces where manipulated data could cause physical harm, such as erroneous resistance settings in robotic-assisted therapy or incorrect movement guidance, leading to biomechanical overload. Implementing end-to-end encryption, authentication protocols, data integrity verification through cryptographic hashing, and anomaly detection algorithm monitoring for unexpected parameter changes are essential safeguards. Additionally, fail-safe mechanisms that default to conservative settings upon detecting transmission anomalies help mitigate the risks of harmful feedback delivery [16]. This enhanced connectivity strengthens the therapeutic alliance and empowers patients through transparency, resulting in increased satisfaction and sustained participation.

4.4 Cost-effectiveness and healthcare system benefits

The economic implications of DT adoption extend beyond direct treatment costs to encompass broader health system efficiency. Although initial infrastructure and training investments are substantial, studies have reported that DT-enabled rehabilitation can reduce total care costs compared with conventional therapy [18]. These savings result from shortened rehabilitation episodes, reduced travel and facility overheads, and improved clinician productivity [18].

Continuous monitoring also prevents expensive secondary interventions and readmissions that account for nearly 15% of physiotherapy-related expenditures in certain health systems [11,17]. Beyond healthcare budgets, improved functional outcomes and reduced disability translate into measurable societal benefits: accelerated return-to-work, enhanced quality of life, and reduced reliance on social-support programs [15]. At the population level, widespread DT deployment could yield significant public-health gains if accessibility and affordability challenges are addressed, thus ensuring equitable benefit distribution across patient populations [25]. Table 2 provides a detailed comparison of traditional rehabilitation approaches with DT-enhanced rehabilitation across key features including treatment personalization, monitoring frequency, outcome prediction, and cost-effectiveness.

Table 2 Comparison of traditional rehabilitation and DT-enhanced rehabilitation

Feature	Traditional rehabilitation	Digital twin-enhanced rehabilitation
Treatment personalization [9,12]	Protocol based, adjusted periodically based on clinical assessment	Continuously adapted based on real-time data and predictive models
Monitoring frequency [10,14]	Intermittent (weekly or less frequent consultations)	Continuous or daily through sensor systems
Outcome prediction [11]	Based on clinician experience and population averages	Data-driven predictions using individual patient characteristics and response patterns
Patient feedback [6]	Subjective self-report during consultations	Objective sensor data plus patient-reported outcomes
Home program adherence [17,20]	Self-reported, limited verification possible	Objectively monitored through sensor systems and applications
Therapeutic relationship [15]	Primarily in-person interactions	Hybrid model with in-person and technology-mediated interactions
Decision support [10,19]	Clinical reasoning based on periodic assessments	AI-assisted recommendations based on continuous data analysis
Cost per patient episode [11,25]	Moderate to high facility and therapist time costs	Lower through remote monitoring and optimized care pathways

5 Challenges and barriers to implementation

5.1 Technological and infrastructure challenges

Despite its substantial promise, numerous technological barriers continue to limit the large-scale deployment of DT technology in physiotherapy and rehabilitation. Consumer-grade sensors and wearable devices vary widely in measurement accuracy, with error margins compared with laboratory-grade motion-capture systems [26]. Although research-grade platforms such as optical motion capture and force plates achieve high precision, their cost and maintenance requirements make them impractical for most outpatient clinics.

The principal challenge lies in developing cost-effective and clinically validated sensor ecosystems that balance accuracy, affordability, and user-friendliness. Interoperability also remains a critical issue because DT systems must aggregate data from diverse sources, such as electronic health records, imaging repositories, and wearable devices, that are often formatted under incompatible standards. In addition, computational demands are substantial when running real-time biomechanical models, finite-element simulations, or large-scale machine-learning algorithms.

Although cloud computing provides scalable processing power, latency-sensitive rehabilitation tasks (for example, real-time gait correction) often require edge computing for near-instant feedback. Dynamic deployment strategies employing two-timescale online optimization frameworks can maximize task execution accuracy while stringently constraining energy consumption and delay, balancing virtual twin construction between edge servers and cloud resources based on evolving patient status and mobility patterns [8]. Achieving optimal trade-offs between computational complexity and responsiveness remains a pressing research priority. Finally, maintaining reliability requires redundant backup servers, cybersecurity protocols, and technical support capacity that are often lacking in smaller rehabilitation centers.

5.2 Data privacy, security, and ethical considerations

DTs generate vast amounts of sensitive health data, creating challenges in terms of privacy, security, and ethics. These datasets fall under stringent frameworks, such as the General Data Protection Regulation (GDPR) in Europe and Health Insurance Portability and Accountability Act (HIPAA) in the United States, mandating encryption, authentication, and access control.

However, DT architectures that span wearables, smartphones, cloud servers, and clinician interfaces can create multiple potential breach points [27]. Differentially private federated multi-task learning frameworks offer promising solutions, enabling secure, privacy-preserving connectivity schemes that accelerate learning processes without sacrificing accuracy, privacy, and communication costs, that are non-negotiable requirements for HDT networks. Blockchain-based validation processes during federated learning can guarantee accurate and authorized model evolution while maintaining data sovereignty [28]. Beyond technical security, ethical concerns include data ownership, consent, and secondary use. Continuous passive data capture blurs the boundaries of ongoing informed consent, and a legitimate fear that employers or insurers might seek to exploit health data for discriminatory purposes, exists.

AI introduces an additional risk of algorithmic bias. Models trained on non-representative data may yield fewer effective recommendations for underrepresented groups [2]. Calls for Explainable AI (XAI) frameworks have intensified, with proposals for clinician oversight protocols that ensure transparency and accountability [29].

5.3 Clinical integration and workflow challenges

Integrating DTs into clinical physiotherapy workflows requires major organizational, educational, and cultural changes. Resistance often stems from concerns about technology supplanting clinical expertise or from perceived increases in the documentation workload [6]. Workflow redesign is crucial to prevent alert fatigue and streamline data review, ensuring that DT systems enhance rather than hinder efficiency [10]. Financial structures have also impeded this integration. Traditional fee-for-service reimbursement models compensate only for face-to-face sessions, neglecting continuous monitoring that is central to DT-based care. Value-based care frameworks that reward outcomes align more naturally with DT capabilities; however, policy adoption remains uneven. These frameworks are implemented fully in only nine of 38 OECD nations. Sustainable uptake thus depends on policy reform recognizing the technology-enabled intervention value and reimbursing clinicians for remote contributions.

5.4 Validation and evidence-based limitations

Although the empirical support for DTs in healthcare is increasing, robust clinical validation remains limited. Most published studies describe pilot implementations or proof-of-concept demonstrations rather than Randomized Controlled Trials (RCTs) that assess functional outcomes or cost-effectiveness [9]. Moreover, long-term effects of DT-guided rehabilitation remain unclear. Potential psychosocial disadvantages, such as data anxiety or overemphasis on quantitative metrics at the expense of holistic care, are rarely investigated. Algorithm validation also poses major challenges. Many machine-learning models are trained on single-institution datasets, limiting generalizability across demographic and clinical contexts [12]. Federated DT construction via distributed sensing under edge-cloud collaboration offers potential solutions, enabling AI model validation across heterogeneous populations while preserving data privacy. Game-theoretic online optimization with overlapping coalitions can jointly optimize partial-DT assignments, edge-server associations, and resource allocations to maximize model quality while minimizing configuration costs in long-run deployments [30]. Establishing continuous-validation frameworks to monitor algorithm drift, retrain models, and audit performance will be crucial as DT systems evolve dynamically over time.

6 Future directions and opportunities

6.1 Standardization and interoperability

To realize the full potential of DT technology in physiotherapy and rehabilitation, international standards for data exchange, model validation, and interoperability must be established. Current DT implementations remain fragmented, with varying sensor platforms, data formats, and simulation architectures hindering scalability and reproducibility [25]. Initiatives such as the ISO/IEC 30173:2023 standard on DT frameworks mark important progress, providing guidelines for system modelling and interoperability [31].

Specifically, clauses 6.2 (Data Exchange Protocols) and 7.3 (Semantic Interoperability Requirements) of ISO/IEC 30173: 2023 are particularly applicable to heterogeneous physiotherapy data types. Clause 6.2 specifies the mechanisms for real-time synchronization of multimodal sensor streams, addressing the challenge of integrating wearable IMUs (50–200 Hz), EMG sensors (1–10 kHz), force plates (100–1000 Hz), and patient-reported outcomes (variable temporal resolution). Clause 7.3 establishes semantic frameworks using standardized ontologies such as SNOMED CT for clinical terminology and LOINC for observational data, enabling the unambiguous interpretation of rehabilitation metrics across platforms. Implementing these clauses requires developers to adopt Health Level 7 Fast Healthcare Interoperability Resources (HL7 FHIR) standards for health data exchange, employ IEEE 11073 Personal Health Device standards for wearable sensor communication, and utilize Industry Foundation Classes (IFC) adapted for biomechanical models to ensure cross-vendor compatibility [31].

Developing shared ontologies and data schemas will facilitate seamless integration across different rehabilitation platforms, enabling the pooling of multimodal datasets from wearables, imaging, and clinical assessments. Cloud-based interoperability frameworks could allow real-time data synchronization between rehabilitation facilities, thus improving the continuity of care [27,28]. Future research should focus on opensource DT architectures that support cross-vendor compatibility and foster collaborative innovation, while maintaining data security.

6.2 Advances in artificial intelligence and predictive analytics

AI-driven DTs will continue to evolve from descriptive models into autonomous decision-support systems capable of adaptive reasoning and real-time therapeutic adjustment. Recent developments in deep reinforcement learning have enabled DTs to self-optimize treatment parameters based on simulated outcomes, thereby reducing manual therapist input while maintaining safety thresholds [14]. Generative AI-aided QoE maximization approaches employing prompt-guided decision transformers integrated with zero-forcing optimization (PG-ZFO) can address the uncertain evolution of DT models across various rehabilitation scenes, constantly resolving scene-specific optimization problems as models evolve without requiring complete re-solving [32].

As algorithm transparency remains a priority, the integration of XAI and causal inference frameworks will help clinicians understand model recommendations, fostering trust and accountability [2]. Federated learning allowing AI models to learn from distributed datasets without transferring sensitive patient information will be crucial for addressing privacy concerns while ensuring generalizability. Differentially private mechanisms combined with blockchain validation can further enhance the security and model integrity. Future DT systems will likely incorporate multimodal fusion, combining biomechanical, electrophysiological, and psychosocial data for richer patient modelling. DTs integrating visual, haptic, and proprioceptive feedback with adaptive data compression can improve prediction accuracy by 25%–40% compared with single-modality systems, while maximizing QoE through dynamic bandwidth allocation and rendering optimization [11,21].

6.3 Integration with extended reality and robotics

The convergence of DTs, extended reality (XR), and rehabilitation robotics represents a transformative frontier. Virtual reality (VR) and augmented reality (AR) interfaces can visualize DT outputs, enabling immersive feedback environments in which patients interactively engage with their digital replicas. Combining DT-guided modelling with robotic-assisted rehabilitation enhances the precision and reproducibility of movement training. The integration of haptic feedback further improves proprioception and engagement, making XR-driven DT systems particularly effective for neurological rehabilitation. Future systems could employ bidirectional communication between DTs and robotic actuators through prediction-enhanced physical-to-virtual twin connectivity frameworks, allowing the virtual twin to continuously optimize mechanical assistance levels based on evolving patient performance, while maintaining security and privacy through federated learning architectures [7,12].

6.4 Ethical governance, equity, and human-centered design

As DTs become embedded in clinical workflows, ethical governance must evolve to ensure transparency, inclusivity, and fairness. Ethical frameworks should require the validation of AI models across diverse demographic and clinical populations, addressing disparities observed in existing digital health systems [15]. Human-centered design (HCD) approaches, engaging clinicians and patients in co-design processes, will be essential to ensure usability and trust [2]. Equitable access also demands attention. Low- and middle-income countries face barriers related to infrastructure, connectivity, and affordability. Federated DT construction frameworks leveraging distributed sensing and edge-cloud collaboration could help reduce cost barriers by optimizing resource allocation and minimizing configuration overhead while maintaining model quality [30]. Cloud-based and mobile DT implementations could further reduce infrastructure requirements; however, partnerships with public health organizations will be key to sustainable scaling.

6.5 Translational research and clinical implementation

To bridge the gap between research and practice, future efforts should prioritize multicenter clinical trials that evaluate DT-guided rehabilitation outcomes, cost-effectiveness, and patient satisfaction. Developing translational frameworks that integrate clinicians, engineers, and policymakers can accelerate real-world adoption through multi-user computation offloading schemes and transmission scheduling mechanisms designed specifically for delay-sensitive rehabilitation applications [12,33,34]. Academic–industry partnerships exemplify the collaborative models driving DT innovation from laboratory prototypes to clinical deployment. Ultimately, establishing national Digital Twin Repositories could enable evidence-based benchmarking of rehabilitation outcomes and support AI model validation across populations.

7 Limitations of the review

This narrative review has several limitations that should be acknowledged when interpreting its findings and implications. As this was a narrative rather than a systematic review, the literature search and synthesis were not exhaustive, and relevant studies may have been inadvertently omitted. Narrative reviews are subject to selection bias in the studies included and potential overemphasis of findings that align with the perspectives of the authors. The rapidly evolving nature of DT technology means that recent developments and emerging applications may not yet be represented in peer-reviewed literature, potentially limiting the comprehensiveness of this review. Gray literature and technical reports were included to capture practical implementation insights. However, these sources have not undergone peer review, and their quality varies.

The heterogeneity of DT implementations described in the reviewed literature created challenges in synthesizing findings and drawing definitive conclusions about technology effectiveness. Differences in sensor systems, algorithms, clinical protocols, patient populations, outcome measures, and implementation contexts limited the generalizability of findings from individual studies. Many reviewed studies were pilot implementations or proof-of-concept demonstrations with small sample sizes, limiting the strength of the evidence regarding clinical effectiveness and patient outcomes. The preponderance of studies from high-income countries and well-resourced healthcare settings meant that the findings might not be generalized to resource-limited contexts in which implementation challenges and priorities differed.

Publication bias likely influences the available literature because studies demonstrating positive results or successful implementations are more likely to be published than those reporting negative findings or unsuccessful technology deployments. This bias may lead to overly optimistic assessments of DT effectiveness and an underestimation of implementation challenges. Limited information on technology failures, discontinued projects, or implementations that did not achieve the anticipated benefits constrains the understanding of the factors that impede success. The review relied on published literature and could not capture the tacit knowledge held by developers and clinicians working with DT systems but not yet disseminated through formal publications. Finally, although the review involved multiple authors for consensus resolution of borderline inclusion cases and quality assessment, primary screening and data extraction were conducted by a single reviewer; this may have introduced errors or biases not present in reviews employing fully independent dual screening.

8 Conclusion

DT technology represents a transformative innovation in physiotherapy and rehabilitation, offering unprecedented capabilities for personalizing treatments, predicting outcomes, monitoring progress, and optimizing therapeutic interventions. The convergence of wearable sensors, machine-learning algorithms, biomechanical modelling, and cloud computing infrastructures has made it feasible to create dynamic, patient-specific virtual models that continuously update based on real-time data and provide actionable insights to guide clinical decision-making. Current applications span MSK rehabilitation, neurological recovery, sports injury management, and remote care delivery, demonstrating benefits including enhanced treatment precision, improved patient engagement, accelerated recovery, and reduced healthcare costs. Despite its considerable promise, significant challenges must be addressed to achieve widespread clinical adoption of DT technology. Technological barriers including sensor accuracy limitations, interoperability challenges, and computational demands require ongoing innovation and standardization efforts, whereas privacy, security, and ethical considerations necessitate robust safeguards and clear policies governing data use and algorithmic decision making. Clinical integration demands substantial changes in workflows, professional competencies, and organizational cultures, supported by adequate training, technical support, and appropriate reimbursement models; strengthening the evidence base through rigorous clinical trials, long-term outcome studies, and external validation of predictive models remains essential.

The future of DT technology in physiotherapy and rehabilitation appears promising with advancing sensor capabilities, increasingly sophisticated AI methods, and expanding clinical applications poised to enhance the scope and impact of DT systems. Integration with complementary technologies including VR, robotics, and genomics will create synergistic capabilities that further personalize and optimize rehabilitation care. The technology holds substantial potential as a research tool, enabling the generation of real-world evidence and facilitating pragmatic trials. As healthcare systems worldwide face growing demand for rehabilitation services amid resource constraints, DT technology offers a pathway to deliver more effective, efficient, and accessible care. Success in implementing these technologies requires not only technological sophistication but also thoughtful attention to human factors, ethical considerations, and the practical realities of clinical practice. By maintaining focus on improving patient outcomes while addressing legitimate concerns regarding the role of technology in care delivery, the field can harness the considerable potential of DTs to advance the practice of physiotherapy and enhance the lives of individuals recovering from injuries, illnesses, and disabilities.

Declaration of competing interest

We declare that we have no conflict of interest.

CRediT authorship contributions statement

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