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Enabling remote rehabilitation through human digital twins: A technological perspective

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ABSTRACT

Remote rehabilitation, or telerehabilitation, has emerged as a scalable modality for delivering rehabilitative care outside clinical settings. Human Digital Twin (HDT) offers a promising paradigm for enabling personalized and adaptive telerehabilitation by continuously representing a patient's functional condition through digital technologies. Despite the growing interest in this field, current research still lacks a comprehensive understanding of how enabling technologies contribute to HDT-based telerehabilitation. This systematic review provides a technological perspective on telerehabilitation with the aim of identifying recurring architectural patterns, analyzing current technological limitations, and deriving design guidelines for future HDT-based rehabilitation systems. Following the PRISMA methodology, fifty-four studies published between 2021 and 2026 were retrieved from Scopus, ScienceDirect, and PubMed and analyzed according to six dimensions: clinical domain, type of Extended Reality (XR) technology, integration of Internet of Medical Things (IoMT) devices, Artificial Intelligence (AI) task, HDT implementation level, and study maturity level. Across the reviewed studies, a common technological workflow emerged in which sensing technologies, AI models, XR interfaces, and network infrastructures jointly support remote monitoring, rehabilitation assessment, and clinical supervision. To translate these findings into actionable recommendations, a Quality Function Deployment (QFD) analysis was conducted to map clinical and operational requirements to technological features. Based on the QFD analysis, a set of guidelines is proposed to translate the identified technological priorities into practical design principles for future research and the development of integrated, scalable, and clinically deployable telerehabilitation frameworks.

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1. Introduction

In recent years, remote rehabilitation, commonly referred to as telerehabilitation, has emerged as an innovative modality for delivering rehabilitative care, enabling supervision, monitoring, and dynamic adaptation of therapeutic programs through digital technologies [1]. Telerehabilitation can be defined as a set of rehabilitation interventions delivered via telemedicine tools that support both synchronous and asynchronous interactions between patients and healthcare professionals, encompassing assessment [2], functional diagnosis [3], monitoring [4], and personalized treatment [5]. The COVID-19 pandemic significantly accelerated research activity in this field [6], leading to the development and optimization of many telerehabilitation solutions [1]. Beyond the pandemic context, broader demographic and epidemiological trends, particularly the progressive aging of the global population and the increasing prevalence of chronic musculoskeletal and neurological disorders, further underscore the urgency of innovating rehabilitation service delivery, thereby highlighting the need for scalable, sustainable, and personalized rehabilitation models [7]. Evidence from the studies of Suhr et al. [8] and Amin et al. [9] indicates that such approaches can achieve outcomes comparable to in-person rehabilitation in terms of pain reduction, functional improvement, and patient satisfaction.

Growing scientific attention has been directed toward the concept of Digital Twin (DT), defined as a dynamic virtual replica of a physical system [10]. In healthcare applications, this concept has evolved into the Human Digital Twin (HDT), which links a patient, the Physical Twin (PT), with a patient-specific digital representation, the Virtual Twin (VT) [11,12]. A key feature of a HDT is the continuous or periodic synchronization between the PT and VT. Patient data are used to update the VT over time, enabling it to reflect changes in the patient's state rather than providing a static representation. The updated VT can then support patient-specific predictions, feedback, or adaptation of the rehabilitation process [11]. Moreover, the VT should provide a sufficiently comprehensive representation of the patient: models limited to a single organ, function, or isolated physiological process are therefore better regarded as components of a HDT rather than complete HDT implementations [12]. These systems constitute a valuable tool for the design and implementation of advanced telerehabilitation solutions, as they enable the integration of real-time data acquisition, personalized modeling, and adaptive therapeutic control.

HDTs development is closely linked to ongoing technological advancements, particularly in the domains of Artificial Intelligence (AI), Extended Reality (XR), and sensing systems.

AI contributes to the creation and continuous updating of the HDT by enabling the extraction of meaningful information from heterogeneous data sources, including images, videos, and sensor data. Through advanced data processing and learning algorithms, AI can support tasks such as human movement analysis, body pose estimation, and the reconstruction of kinematic and postural information without requiring wearable markers [6]. These capabilities facilitate remote assessment of motor performance, gait analysis, and home-based rehabilitation exercises [13]. Beyond data interpretation, AI enables predictive analytics, adaptive decision-making, and personalized rehabilitation planning. By modeling patient-specific conditions and forecasting functional outcomes, AI allows the HDT to evolve from a static representation into a dynamic and predictive model capable of supporting clinical decision-making and treatment adaptation.

XR technologies act as the primary interface between users and the HDT, enabling immersive visualization, interaction, and feedback throughout the rehabilitation process. Depending on the level of immersion, XR includes Augmented Reality (AR), which overlays digital content onto the physical environment [14]; Virtual Reality (VR), which provides fully synthetic environments [15]; and non-immersive Virtual Reality (NIVR), which supports interaction through conventional devices such as monitors, keyboards, and mouses [16]. These technologies have shown significant potential for improving engagement, adherence, and data collection, particularly when combined with gamified rehabilitation approaches [17].

Finally, sensing systems, including wearable devices and Internet of Medical Things (IoMT) technologies, provide continuous physiological, biomechanical, and contextual data streams that keep the HDT synchronized with the individual's real-world condition [18], thus enabling dynamic updates and supporting accurate, personalized patient representations over time [19].

In the present literature, telerehabilitation topics have been extensively explored, often comparing emerging technological solutions with traditional rehabilitation approaches. Overall, these studies suggest that telerehabilitation can achieve outcomes comparable to in-person therapy across musculoskeletal, neurological, and cardiovascular conditions, while potentially improving treatment accessibility and adherence by reducing geographical barriers and travel costs [1,6,8]. However, the available evidence is still often based on relatively small patient cohorts [8].

Several reviews have examined the technological development of telerehabilitation, but generally from a specific perspective. Some focus on individual enabling technologies, including computer vision and AI [7], sensing technologies [6], or XR [17,20]. Others address specific clinical conditions, such as stroke [21], Parkinson's disease [22], and inflammatory arthritis [23]. While these studies provide valuable insights into individual technologies or application domains, they do not offer an integrated analysis of the technological components involved in HDT-based telerehabilitation. The review by Mikołajewska et al. [24] is more closely related to the present work, as it explicitly addresses HDTs in rehabilitation. However, its analysis primarily focuses on the role of AI in developing and updating the digital twin, without systematically examining XR, IoMT, and connectivity as complementary dimensions of an HDT-based telerehabilitation system.

Therefore, despite the growing body of research on telerehabilitation and its enabling technologies, the literature remains fragmented across individual technologies and clinical domains, and an integrated technological perspective on HDT-based telerehabilitation is still lacking. This fragmentation also limits the definition of common architectural principles and design recommendations for the development of integrated systems.

The present review provides a comprehensive and systematic analysis of remote rehabilitation solutions, examining shared strengths and recurrent technological limitations, with the aim of providing integrated design guidelines for a HDT framework specifically tailored to telerehabilitation applications. Unlike previous reviews, the present

work jointly considers AI, XR, IoMT, and connectivity to investigate how these technologies contribute to HDT-based telerehabilitation. In light of these considerations, the objectives of the present systematic review are articulated through the following research questions:

- RQ1: How is remote rehabilitation currently implemented across different clinical applications?
- RQ2: What role do digital technologies, particularly XR, AI, and IoMT, play in enabling the development of Human Digital Twins for telerehabilitation?
- RQ3: What technological limitations and open challenges currently hinder the effectiveness, scalability, and clinical integration of remote rehabilitation systems?

Based on the evidence collected through these research questions, the identified technological components and their interactions are synthesized into an HDT-oriented reference architecture for telerehabilitation. A Quality Function Deployment (QFD) analysis is then used to relate the requirements emerging from the literature to the identified technical features and to support their prioritization. This process ultimately informs the definition of operational design guidelines for the development of HDT-based telerehabilitation systems, while highlighting relevant directions for future research and clinical integration.

This paper is organized as follows: Section 2 describes the literature search strategy, while the selected studies are analyzed in Section 3. Section 4 discusses the main findings of the review and outlines the proposed design guidelines for the development of HDT-based telerehabilitation frameworks. Finally, the conclusions are presented in Section 5.

2. Materials and methods

The objective of this methodological analysis is to identify and define design guidelines to support the implementation of a HDT framework for telerehabilitation.

A data collection procedure has been designed to select relevant studies addressing technological solutions for telerehabilitation, with the aim of ensuring a comprehensive overview of existing approaches and their underlying technological architectures. The literature search was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [25] from November 1, 2025, to January 31, 2026, on the Scopus, ScienceDirect, and PubMed online databases. Only English-language original research articles and conference papers published between 2021 and 2026 were considered for inclusion, while reviews, editorials, book chapters, theses, and other non-peer-reviewed publications were excluded. The temporal restriction was motivated by three major technological and contextual developments, namely the rapid expansion of telehealth adoption following the COVID-19 pandemic [1], recent advancements in 5G and 6G technologies enabling the effective management of the large volumes of data generated by medical and wearable devices and thereby supporting the feasibility of advanced digital healthcare architectures [13], and the commercial availability of advanced XR devices and depth-sensing technologies, which facilitate the development of scalable remote rehabilitation solutions [17].

The search strategy was structured around three conceptual macro-areas aligned with the objectives of the work. The first area addressed telerehabilitation and the HDT domain, including terms related to telemedicine, remote care, and patient-specific digital modeling. The second area focused on the technological domain, comprising keywords associated with AI, XR, and IoMT technologies. The third area targeted the clinical domain, encompassing terms related to physical rehabilitation, physiatry, physiotherapy, and orthopedics. Based on these areas, the search query was organized into three corresponding groups of terms. Keywords within each group were combined using the Boolean operator OR, while the three groups were connected using the Boolean operator AND:

- Telerehabilitation and HDT-related keywords: human digital twin, home-based treatment, telemonitoring, telehealth, telemedicine, teleconsultation, telecollaboration, out-of-hospital care, virtual care, patient digital twin, digital human model, patient-specific digital model;
- Technology-related keywords: artificial intelligence, machine learning, deep learning, computer vision, extended reality, virtual reality, mixed reality, augmented reality, motion tracking, movement analysis, movement recognition, pose estimation, IoMT, internet of medical things;
- Clinical-related keywords: physiatry, physiotherapy, orthopedics, physical rehabilitation, physical therapy.

The full literature search process is illustrated in Fig. 1.

As shown in Fig. 1, a total of four hundred ninety-two (n=492) records were initially identified. Among these, thirty-nine (n=39) duplicate records were detected and removed from the collected results across the searched databases.

The retrieved articles were initially filtered according to the predefined inclusion and exclusion criteria. Based on these criteria, two hundred twenty-nine records (n=229) were excluded due to publication type, twelve (n=12) due to language restrictions, ninety-one (n=91) due to being published outside the selected time range, and thirteen (n=13) due to full-text unavailability. Following this preliminary filtering phase, the remaining studies underwent a multi-stage screening process involving title, abstract, and full-text assessment. Articles were excluded if they did not propose technological solutions for remote rehabilitation or were not aligned with the predefined conceptual macro-areas of the review. Specifically, twelve records (n=12) were excluded during title screening, four (n=4) during abstract screening, and thirty-eight (n=38) after full-text reading. Overall, fifty-four studies (n=54) were included in the final review.

3. Results

All included studies proposed technological solutions for telerehabilitation in the form of applications, frameworks, or prototype systems. Table 1 organizes them according to six main categories: clinical domain, which refers to the pathology or surgical intervention motivating the rehabilitation process; XR type, which identifies the use of VR, AR, or NIVR technologies to support rehabilitation exercises and improve patient engagement; IoMT, which includes wearable devices and connected sensors used to collect physiological and biomechanical data for patient monitoring and functional assessment; AI task, which describes the role of AI within the HDT framework, primarily in markerless tracking and movement analysis through the automated detection of human body joints; HDT implementation level, which indicates how closely the proposed solution approximates a full HDT-based rehabilitation system, based on the operational definition formulated in Section 1; and the study maturity level, which indicates the maturity of the proposed solution based on how it was tested and validated. This classification enabled a structured comparison of the technological approaches adopted across studies and facilitated the identification of recurring design patterns in telerehabilitation systems.

To provide an overview of the distribution of the identified categories across the reviewed literature, Fig. 2 summarizes the main findings. Fig. 2(a) presents the prevalence of clinical domains, XR technologies, and IoMT technologies, Fig. 2(b) illustrates the distribution and co-occurrence of the AI tasks identified in the selected studies, while Fig. 2(c) shows the classification of the studies according to HDT implementation level and study maturity level.

Moreover, to understand how AI, XR, and IoMT co-occur within individual studies, a cross-tabulation analysis has been performed, and results have been reported in Table 2.

Table 2 shows that single-technology studies dominate, with XR only the most frequent and AI + XR the most common combination.

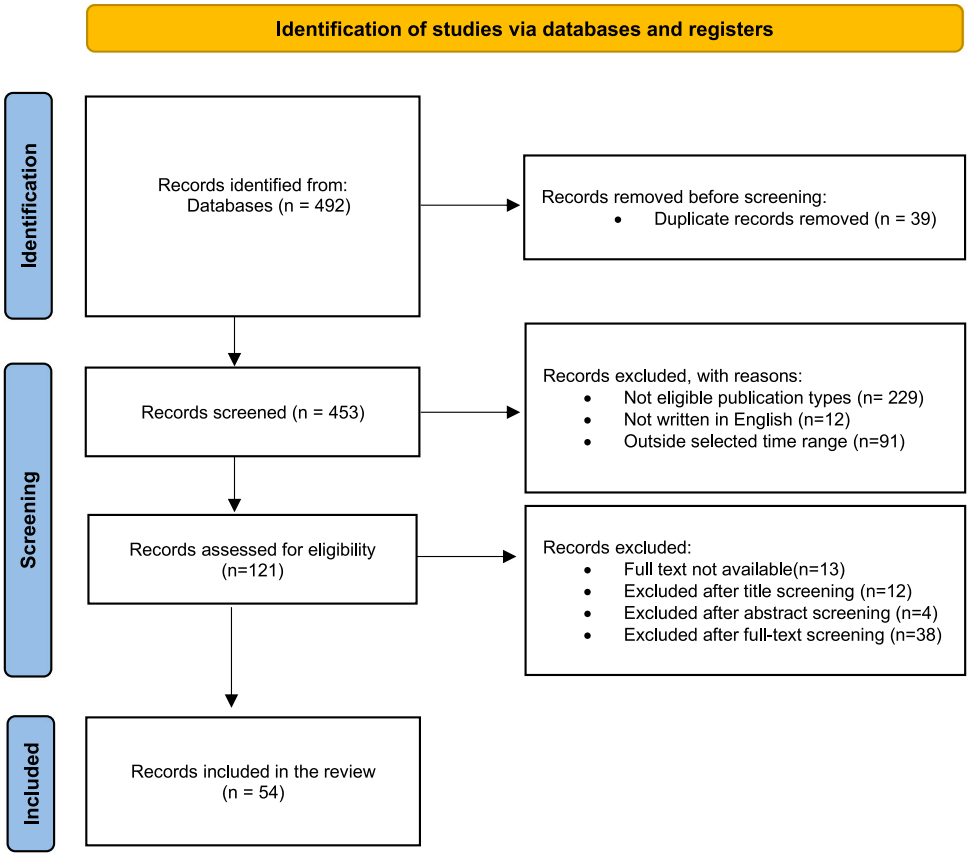


Fig. 1. Flow diagram of the study selection process conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses guidelines.

Full integration of all three technologies remains rare, suggesting this is still an early-stage direction for HDT-based telerehabilitation.

To provide a more comprehensive analysis and interpretation of the findings, this section is organized as follows. Section 3.1 analyzes the differences among rehabilitation frameworks adopted across different clinical domains. Section 3.2 examines the role and challenges associated with the integration of IoMT technologies in rehabilitation systems. Section 3.3 discusses the functions and limitations of XR technologies within rehabilitation frameworks. Section 3.4 focuses on the role and challenges of integrating AI technologies into rehabilitation systems. Section 3.6 analyzes the level of HDT implementation and maturity of the selected studies.

3.1. Clinical application domains

The included studies can be grouped into three main clinical domains: neurological and neuromuscular disorders, orthopedic and musculoskeletal conditions, and generic application domains.

3.1.1. Neurological and neuromuscular disorders

Among the selected articles, twenty studies (n=20) focused on neurological disorders and brain injuries. Stroke was the most frequently investigated condition, addressed in eleven (n=11) studies [2,3,5,27,32,34,38,50,60,66,75], while one (n=1) study specifically examined Parkinson's disease [29]. Five (n=5) additional contributions proposed rehabilitation solutions applicable to both stroke and Parkinson's disease populations [30,42,48,54,55]. The remaining studies addressed Duchenne and Becker muscular dystrophy [39], oromotor disorders and cerebral palsy [49], and generic neuromuscular disorders [33].

Rehabilitation protocols were generally based on intensive and repetitive movement exercises aimed at improving functional independence, mobility, and quality of life [49]. One of the most frequently monitored parameters was Range of Motion (ROM), which refers to the degree of joint flexion–extension [2], internal-external rotation [38], and abduction-adduction achieved during movements [3]. ROM is particularly suitable for telerehabilitation as it can be objectively quantified, enabling continuous assessment of patient progress. For example, Barak Ventura et al. [75] reported that achieving 40–60 degrees of wrist extension in post-stroke patients is essential for performing most activities of daily living.

Several studies also evaluated qualitative aspects of movement, such as fluidity, symmetry, and postural stability. These characteristics were typically assessed through task-specific biomechanical parameters. For instance, Amprimo et al. [29] proposed exergames for Parkinson's disease rehabilitation in which patient performance was evaluated through metrics including movement speed, execution time, inter-limb symmetry, balance, and postural stability.

3.1.2. Orthopedic and musculoskeletal conditions

Twenty-two (n=22) studies addressed orthopedic and musculoskeletal rehabilitation following surgery, traumatic injuries, or chronic degenerative conditions affecting the locomotor system. Thirteen (n=13) studies focused on post-surgical rehabilitation, including orthopedic surgery and arthroplasty [47,65,68,73], spinal and abdominal surgery [52,53], amputations [36,64], and general post-surgical rehabilitation [4,26,40,51,70]. The remaining studies investigated non-surgical musculoskeletal conditions, including postural dysfunctions and chronic

Table 1
Classification of the included articles by clinical domain, type of XR technology, integration of IoMT devices, AI task, HDT implementation level, and study maturity level implemented in the proposed telerehabilitation solution.

Ref	Year	Clinical domain	XR type	IoMT	AI task	HDT implementation level	Maturity level
[26]	2021	Orthopedic and Musculoskeletal Conditions	N/A	Yes	EPR	P	M4
[3]	2021	Neurological and Neuromuscular Disorders	NIVR	No	N/A	E	M3
[27]	2021	Neurological and Neuromuscular Disorders	AR	No	N/A	G	M2
[4]	2021	Orthopedic and Musculoskeletal Conditions	N/A	Yes	N/A	P	M5
[28]	2021	Orthopedic and Musculoskeletal Conditions	VR	No	MCP/MTAQA/EPR	P	M3
[29]	2022	Neurological and Neuromuscular Disorders	VR	No	MTAQA	P	M4
[30]	2022	Neurological and Neuromuscular Disorders	N/A	No	MTAQA	E	M2
[31]	2022	Orthopedic and Musculoskeletal Conditions	NIVR	No	N/A	E	M4
[32]	2022	Neurological and Neuromuscular Disorders	VR	No	N/A	E	M4
[33]	2022	Neurological and Neuromuscular Disorders	VR	No	N/A	P	M2
[34]	2022	Neurological and Neuromuscular Disorders	VR	No	MCP	P	M3
[35]	2022	Generic Application Domains	N/A	No	HPE	E	M2
[36]	2023	Orthopedic and Musculoskeletal Conditions	VR	No	HPE	E	M2
[37]	2023	Generic Application Domains	N/A	Yes	MCP	E	M2
[38]	2023	Neurological and Neuromuscular Disorders	VR	No	MTAQA	G	M4
[39]	2023	Neurological and Neuromuscular Disorders	VR	No	N/A	E	M5
[40]	2023	Orthopedic and Musculoskeletal Conditions	NIVR	No	HPE	E	M2
[41]	2023	Generic Application Domains	N/A	No	MTAQA	E	M2
[42]	2023	Neurological and Neuromuscular Disorders	VR	No	N/A	G	M4
[43]	2023	Orthopedic and Musculoskeletal Conditions	VR	No	N/A	E	M5
[44]	2024	Generic Application Domains	VR	Yes	GEN AI	G	M1
[45]	2024	Orthopedic and Musculoskeletal Conditions	VR	Yes	N/A	E	M3
[46]	2024	Orthopedic and Musculoskeletal Conditions	N/A	Yes	MCP	P	M2
[47]	2024	Orthopedic and Musculoskeletal Conditions	AR	No	N/A	P	M5
[48]	2024	Neurological and Neuromuscular Disorders	VR	No	N/A	E	M1
[49]	2024	Neurological and Neuromuscular Disorders	NIVR	No	N/A	P	M2
[50]	2024	Neurological and Neuromuscular Disorders	VR	No	MTAQA	G	M2
[51]	2024	Orthopedic and Musculoskeletal Conditions	N/A	No	MTAQA	E	M2
[52]	2024	Orthopedic and Musculoskeletal Conditions	N/A	No	MCP	P	M4
[53]	2024	Orthopedic and Musculoskeletal Conditions	N/A	No	MCP	E	M2
[54]	2024	Neurological and Neuromuscular Disorders	N/A	No	HPE	E	M3
[55]	2024	Neurological and Neuromuscular Disorders	N/A	No	MCP	E	M3
[56]	2024	Generic Application Domains	N/A	No	HPE	E	M3
[57]	2024	Generic Application Domains	N/A	No	HPE	P	M3
[58]	2024	Generic Application Domains	N/A	No	EPR	E	M2
[59]	2024	Generic Application Domains	VR	Yes	EPR	P	M1
[60]	2025	Neurological and Neuromuscular Disorders	N/A	Yes	N/A	G	M4
[61]	2025	Orthopedic and Musculoskeletal Conditions	VR	Yes	N/A	E	M2
[5]	2025	Neurological and Neuromuscular Disorders	VR	No	MTAQA	P	M1
[62]	2025	Orthopedic and Musculoskeletal Conditions	VR	No	N/A	E	M4
[63]	2025	Orthopedic and Musculoskeletal Conditions	AR	No	N/A	P	M5
[64]	2025	Orthopedic and Musculoskeletal Conditions	AR	No	HPE/MTAQA	P	M4
[2]	2025	Neurological and Neuromuscular Disorders	N/A	Yes	N/A	P	M4
[65]	2025	Orthopedic and Musculoskeletal Conditions	VR	No	N/A	E	M4
[66]	2025	Neurological and Neuromuscular Disorders	AR	Yes	N/A	E	M4
[67]	2025	Generic Application Domains	VR	No	N/A	P	M2
[68]	2025	Orthopedic and Musculoskeletal Conditions	N/A	No	MCP	E	M4
[69]	2025	Orthopedic and Musculoskeletal Conditions	NIVR	No	GEN AI	E	M2
[70]	2025	Orthopedic and Musculoskeletal Conditions	NIVR	No	HPE	P	M3
[71]	2025	Generic Application Domains	N/A	No	HPE	E	M3
[72]	2025	Generic Application Domains	N/A	Yes	MTAQA	E	M3
[73]	2025	Orthopedic and Musculoskeletal Conditions	VR	No	N/A	E	M3
[74]	2025	Generic Application Domains	VR	Yes	N/A	P	M2
[75]	2026	Neurological and Neuromuscular Disorders	N/A	No	MCP	P	M2

Abbreviations: AR = Augmented Reality; VR = Virtual Reality; NIVR = non-immersive Virtual Reality; GEN AI = Generative Artificial Intelligence; EPR = Emotion and Pain Recognition; HPE = Human Pose Estimation; MCP = Movement Classification and Prediction; MTAQA = Movement Temporal Analysis and Quality Assessment; N/A = Not Applicable; G = Genuine HDT implementation; P = Partial HDT-like system; E = General enabling technology; M1 = Conceptual/Framework; M2 = Prototype/Technical validation; M3 = Healthy-subject evaluation; M4 = Patient evaluation; M5 = Clinical/real-world deployment.

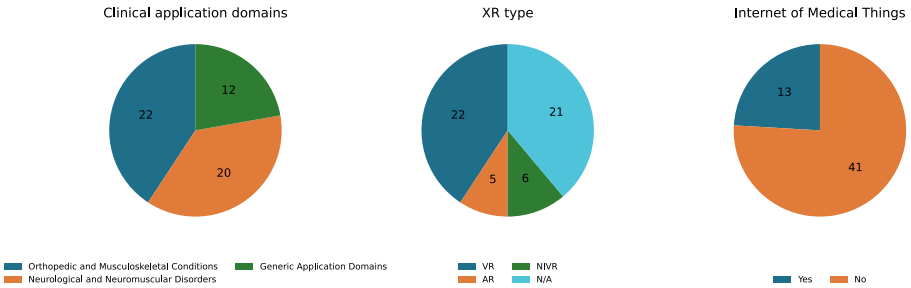
neck or upper-limb pain [28,45,69], osteoarthritis and joint disorders [31,46,62,63], and non-specific low back pain [43,61].

Similarly to neurological rehabilitation, orthopedic rehabilitation protocols mainly focused on quantitative movement assessment, particularly ROM evaluation [62]. Several studies also analyzed movement symmetry through metrics such as the Symmetry Index, which compares motion patterns between the left and right sides of the body [53]. Pain assessment represented another critical aspect, frequently evaluated through patient-reported measures such as the Visual Analogue Scale (VAS), as pain serves as an important safety indicator during rehabilitation exercises [4,31]. In addition, several systems are explicitly aimed at minimizing compensatory movements in order to prevent joint overload and secondary musculoskeletal strain. For this reason, some studies favored neutral, non-gamified VR environments designed to prioritize controlled and biomechanically accurate movement execution over engagement-oriented interaction design [73].

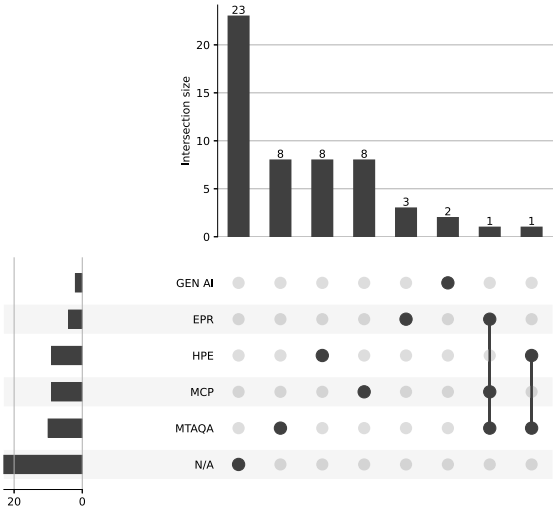
3.1.3. Generic application domains

This group includes twelve (n=12) studies proposing generalized frameworks and algorithmic solutions applicable across multiple rehabilitation domains. Eleven (n=11) studies focused on generic telerehabilitation systems for physical rehabilitation [35,37,41,44,56–59,67,71,74], while one proposed a platform specifically designed for motor and respiratory reactivation exercises [72].

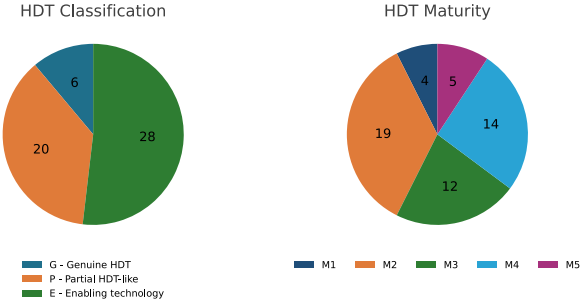
Similar to domain-specific rehabilitation systems, these studies combined quantitative and qualitative movement assessment. In addition to



(a) Distribution of application domains, XR and IoMT technologies across the reviewed studies.



(b) Distribution and co-occurrence of AI tasks across the reviewed studies. Generative AI (GEN AI), Emotion and Pain Recognition (EPR), Human Pose Estimation (HPE), Movement Classification and Prediction (MCP), Movement Temporal Analysis and Quality Assessment (MTAQA), Not Available (N/A).



(c) Distribution of the included studies according to HDT implementation level (genuine HDT implementations (G), partial HDT-like systems (P), and general enabling technologies (E)) and study maturity level (from conceptual framework proposals (M1) to clinical real-world deployment (M5)).

Fig. 2. Graphical overview of the selected studies.

ROM evaluation, several approaches analyzed movement smoothness, stability, and execution consistency through automated biomechanical metrics. For example, Caramia et al. [72] proposed an IMU-based framework using sensors attached to the wrists, ankles, and trunk to assess rehabilitation exercises through multiple indicators. Movement smoothness was quantified using the Log Dimensionless Jerk (LDLJ), where lower values corresponded to smoother gestures, while Dynamic Time Warping (DTW) was employed to evaluate movement stability by comparing acceleration signals across repetitions. In addition, Peak Range of Motion (PKROM) was used to measure the maximum ROM achieved during each exercise repetition.

3.2. Role of Internet of Medical Things

Among the included records, thirteen (n=13) studies integrated IoMT technologies to support remote rehabilitation through the acquisition, transmission, and analysis of physiological and biomechanical

Table 2
Cross-tabulation of the combinations of enabling technologies adopted across the reviewed studies.

Technology combination	N. of studies	%
AI only	14	25.9
XR only	16	29.6
IoMT only	3	5.6
AI + XR	11	20.4
AI + IoMT	4	7.4
XR + IoMT	4	7.4
AI + XR + IoMT	2	3.7
Total	**54**	**100.0**

data [2,4,26,37,44–46,59–61,66,72,74]. Within HDT-based rehabilitation frameworks, IoMT systems are mainly employed to enable continuous patient monitoring, real-time feedback delivery, and remote supervision by clinicians, thus extending rehabilitation activities beyond conventional clinical environments.

Most of the identified solutions follow a common architectural paradigm with three main components: wearable or environmental sensing devices, local edge devices such as smartphones or home hubs, and cloud-based infrastructures for data storage, synchronization, and remote access. Wearable sensors are typically used to acquire parameters related to body movement, muscular activity, posture, or force generation, while local devices act as gateways for preliminary data processing and communication with remote platforms. Cloud infrastructures then support data visualization, therapy management, and bidirectional interaction between patients and healthcare professionals.

Several studies highlight that IoMT technologies support personalized and adaptive rehabilitation through the dynamic adaptation of therapy programs according to patient-specific needs. For example, some systems employ wearable electromyography sensors to acquire muscular activity and provide visual biofeedback through smartphone applications, allowing patients to better understand and modulate muscle activation during rehabilitation exercises [26]. Other approaches integrate distributed wearable sensors, such as inertial measurement units and pressure sensors embedded into bands or insoles, to monitor posture, gait, and movement quality during home-based rehabilitation sessions [60]. In these cases, sensor data are continuously transmitted to remote platforms that allow physiotherapists to supervise exercises and modify rehabilitation programs remotely.

However, as IoMT-based systems often heavily rely on cloud infrastructures for data storage and processing, several challenges still limit their large-scale adoption, including issues related to data privacy and cybersecurity, network latency and bandwidth requirements, interoperability among heterogeneous devices, usability in home environments, and energy consumption constraints associated with wearable sensors.

3.3. Role of XR technologies

Among the included records, thirty-three (n=33) articles propose rehabilitation solutions integrating XR technologies. More specifically, twenty-two (n=22) studies employ immersive VR technologies [5,28,29,32–34,36,38,39,42–45,48,50,59,61,62,65,67,73,74], six (n=6) adopt non-immersive VR solutions [3,31,40,49,69,70], and five (n=5) use AR technologies [27,47,63,64,66].

Across these studies, XR technologies were primarily employed to guide patients through rehabilitation exercises using interactive virtual environments. Most solutions adopted gamified approaches, often implemented as exergames, to increase patient engagement and reduce the repetitive nature of conventional rehabilitation protocols [27,48,62]. For example, Powell et al. [34] proposed OpenButterfly, a VR-based exergame for the HTC Vive headset in which patients perform upper-limb rehabilitation exercises by interacting with a virtual butterfly along predefined trajectories. The system integrates biomechanical analysis and machine learning techniques to estimate quantitative parameters, such as ROM, enabling objective assessment of patient performance during rehabilitation.

In contrast, five (n=5) studies proposed non-gamified rehabilitation experiences. These approaches were mainly motivated by concerns regarding patient safety and movement quality during rehabilitation exercises. In particular, Guldager et al. [73] argued that competitive or fast-paced game mechanics may encourage incorrect posture and unsafe movements, especially in shoulder rehabilitation. Consequently, the authors developed an immersive VR physiotherapy environment in which patients interact with an instructor in a shared virtual space and observe their own movements through a synchronized avatar reflected in a virtual mirror. However, the system was evaluated only through usability questionnaires and qualitative feedback from an experienced physiotherapist, without quantitative assessment of rehabilitative outcomes. Among the remaining non-gamified solutions, only Conroy et al. [65] evaluated therapeutic effectiveness, reporting performance comparable to traditional rehabilitation in terms of ROM and movement speed. Nevertheless, no comparison with gamified rehabilitation systems was conducted, making it difficult to determine whether non-gamified approaches are more effective or safer than exergame-based solutions.

The level of immersion represented another major distinction among XR-based rehabilitation systems. Immersive VR technologies were mainly adopted for their ability to provide high levels of sensory immersion, which can support pain management through cognitive distraction mechanisms that redirect patients' attention from movement-related discomfort toward virtual tasks. Several studies reported that VR-based interventions may reduce perceived pain through attentional distraction and cognitive engagement, potentially decreasing reliance on invasive pharmacological or surgical treatments [48]. In addition, VR can help disrupt maladaptive predictive patterns associated with painful movements by reshaping patients' expectations and redirecting attention away from discomfort, particularly in conditions such as non-specific low back pain and neck pain [43]. VR has also been applied in post-ischemic stroke rehabilitation for pain management and as a distraction strategy during anxiety- or pain-inducing medical procedures, leveraging immersive visual and auditory stimuli to redirect patients' attention from discomfort toward virtual tasks [32].

Conversely, AR and non-immersive VR solutions mainly prioritized safety, usability, and environmental awareness over full sensory immersion. These approaches allow patients to maintain a continuous perception of the surrounding environment, reducing the risk of disorientation and improving suitability for home-based rehabilitation scenarios. For instance, Lim et al. [47] highlighted that immersive VR systems may cause discomfort due to the occlusion of the real environment and may be less suitable for exercises such as balance training. In contrast, AR-based solutions integrate virtual elements into the physical environment while preserving spatial awareness, making them particularly suitable for functional and balance-oriented rehabilitation tasks.

Despite their potential, XR-based rehabilitation systems present several recurring limitations. Immersive technologies may cause cybersickness, visual fatigue, and discomfort, especially in the most fragile people, such as the elderly, or post-stroke and vestibular-impaired patients [47,73]. Moreover, technical issues such as motion-to-photon latency can negatively affect both safety and user experience by disrupting the sensorimotor loop and increasing cybersickness [67]. Finally, immersive XR applications demand significant computational and bandwidth resources, particularly when integrated with AI-based movement analysis [5,36].

3.4. Role of AI

Among the retrieved articles, thirty-one (n=31) studies proposed rehabilitation systems in which AI represented a core operational component. Across these systems, AI technologies fulfilled five main functional roles: human pose estimation; movement temporal analysis and

quality assessment; movement classification and prediction; emotion and pain recognition; and generative data modeling. Although these categories are not mutually exclusive, and several systems integrated multiple AI components within the same processing pipeline, they reflect distinct design objectives and methodological strategies that are separately analyzed in the following subsections.

3.4.1. Human pose estimation

In nine (n=9) studies, AI was employed for Human Pose Estimation (HPE), a computer vision task aimed at the markerless detection and tracking of anatomical keypoints, particularly human body joints. These approaches enable the extraction of kinematic and postural information from image data and constitute a key component for updating the HDT.

Two main design strategies emerged. The first relied on high-accuracy multi-camera systems based on OpenPose [35,36,71], primarily intended for detailed 3D reconstruction and biomechanical analysis. These solutions supported virtual patient representation and movement assessment but required dedicated hardware, camera calibration procedures, and high-bandwidth communication infrastructures, increasing deployment complexity and costs [36]. In addition, their performance was affected by occlusions, body posture, and reconstruction inaccuracies, particularly in home-based scenarios [35].

The second strategy focused on lightweight frameworks optimized for real-time execution on consumer-grade devices. Most studies adopted MediaPipe-based solutions [54,56,64,70], often combined with downstream machine learning modules for gesture recognition, exercise classification, or rehabilitation assessment. Similar objectives were pursued through alternative lightweight architectures such as MoveNet and custom CNN-based models [40,57]. These approaches improved accessibility and facilitated home-based deployment, although challenges related to depth estimation accuracy, robustness to occlusions, and clinical precision remain unresolved [54].

What emerges from the analyzed studies suggests a progressive shift from complex multi-camera solutions toward lightweight and accessible HPE frameworks better suited to home-based telerehabilitation, while highlighting the need for further improvements in robustness and measurement accuracy.

3.4.2. Movement temporal analysis and quality assessment

In ten (n=10) studies, AI was employed for movement temporal analysis and quality assessment, with the aim of evaluating the correctness and quality of rehabilitation exercises over time. Unlike approaches based solely on static kinematic measurements, these systems analyzed complete movement sequences to generate rehabilitation quality scores or automatically assess exercise execution.

A common architectural pattern emerged across the reviewed studies. Movement data acquired through cameras, depth sensors, inertial measurement units, VR controllers, or motion capture systems were represented as temporal sequences of joint positions and biomechanical features, which were subsequently processed by machine learning models. Most approaches relied on recurrent architectures, particularly Long Short-Term Memory (LSTM) networks [5,30,64], while more recent studies explored Temporal Convolutional Networks and Transformer-based models to improve temporal representation learning and reduce computational requirements [41,51].

The reviewed systems adopted both vision-based and wearable sensing approaches. Camera-based solutions enabled markerless monitoring of rehabilitation exercises, whereas wearable sensors such as IMUs and accelerometers provided greater robustness to occlusions and lighting variations [28,72]. However, wearable systems introduced additional challenges related to sensor precision and reliability, particularly when low-cost devices were employed [72].

A major challenge across the analyzed studies concerned the scarcity and limited standardization of rehabilitation datasets, which are often collected from healthy subjects simulating pathological movements, raising concerns about their generalizability to real patient populations [30,51]. In addition, rehabilitation quality labels frequently relied on subjective evaluations, limiting consistency across datasets and studies [5,30,38,51]. Most systems were also validated under controlled laboratory conditions rather than real-world home environments, where variations in lighting, sensor placement, and exercise execution may significantly affect performance [5,29,50,72]. Finally, a persistent trade-off emerged between assessment accuracy and deployment feasibility, as more sophisticated models often required computational resources incompatible with consumer-grade devices commonly used in telerehabilitation [5,29,41,51].

3.4.3. Movement classification and prediction

Nine (n=9) studies employed AI for movement classification and prediction tasks, including the recognition of rehabilitation exercises, the classification of patient health states, and the prediction of future kinematic or clinical outcomes.

Most systems relied on data acquired from wearable sensors, pressure sensors, VR tracking systems, or haptic devices. Classical machine learning algorithms such as K-Nearest Neighbors (KNN) and Support Vector Machines (SVM) were frequently adopted due to their computational efficiency and interpretability [28,37,46]. Other studies explored neural network-based and hybrid approaches capable of combining handcrafted biomechanical features with representations learned directly from sensor data [53,55]. Unsupervised learning techniques were also investigated to identify clinically relevant movement patterns without predefined labels [68].

Beyond classification, several studies focused on predictive modeling tasks, including the estimation of future joint kinematics and rehabilitation outcomes from multimodal data [34,52,75], suggesting a gradual transition from traditional feature-based approaches toward multimodal architectures capable of integrating heterogeneous rehabilitation signals.

However, most studies relied on proprietary datasets involving a limited number of participants, restricting model generalizability. In addition, many approaches were strongly dependent on specific sensing configurations, reducing their transferability across different rehabilitation settings. A recurring challenge also concerned the trade-off between interpretability and predictive performance: while traditional machine learning models were generally more transparent and computationally efficient, more complex architectures often achieved higher accuracy at the cost of reduced explainability, an important consideration in clinical rehabilitation contexts where therapists must understand and trust AI-supported decisions.

3.4.4. Emotion and pain recognition

Four (n=4) works propose rehabilitation systems in which AI is employed to detect patients' emotional state, pain levels, or psychophysiological engagement, dimensions that directly influence therapy adherence and clinical outcomes but remain invisible to conventional kinematic systems.

Three main sensing strategies emerged. The first relied on vision-based approaches, such as the YOLO-based facial expression recognition system proposed by Centeno et al. [58], which used a KNN classifier to estimate pain levels from facial landmarks in real time. The second strategy employed physiological sensing modalities. In particular, Houzangbe et al. [59] combined EEG, electrodermal activity, heart rate, and eye-tracking signals to estimate cognitive engagement during VR-based rehabilitation tasks, while Yassin et al. [26] used surface EMG to monitor muscular effort and stress during remote rehabilitation sessions. Some systems also integrated adaptive mechanisms based on affective information. For example, Houzangbe et al. [59] used psychophysiological signals to dynamically adjust rehabilitation task difficulty according to the patient's engagement level. Finally, the third strategy proposed by Elmakias et al. [28] infers the presence of pain indirectly, by training a Time Series Forest classifier on head and hand

kinematic data labeled Pain or No-Pain by the patient: the model captures pain as a quantifiable loss of movement fluency, with anomalous oscillations on the axes perpendicular to the intended motion, rather than as a directly measured physiological event.

However, the main limitation reported across these studies concerns the difficulty of obtaining reliable ground-truth labels for pain and emotion, as self-reported scales are inherently subjective and clinician-assigned evaluations may vary across raters.

3.4.5. Generative AI

Only two (n=2) studies explicitly proposed Generative AI as a functional component of rehabilitation systems, making it the least represented AI paradigm within the analyzed articles. This is somewhat in contrast with the broader HDT literature, where generative models, and mobile Artificial Intelligence-Generated Content (AIGC) in particular, are often regarded as a core architectural component for enabling timely and efficient physical-to-virtual synchronization [76,77], even outside the rehabilitation domain. Nevertheless, the two identified approaches highlight the potential of generative models to address several structural limitations of AI-driven rehabilitation systems, spanning synthetic data generation, personalized virtual patient construction, adaptive rehabilitation content, and multimodal patient modeling.

Chen et al. [44] proposed an architecture employing generative models to address the scarcity of individual-level and rare-disease data by synthesizing multimodal medical images and disease-specific records to augment existing electronic health record datasets. Beyond data augmentation, the same approach was used to construct high-fidelity, patient-specific HDTs from multimodal inputs. These virtual representations were continuously fine-tuned to reflect the evolving state of individual patients and support personalized rehabilitation within a virtual physical therapy training platform. Huang et al. [69] developed a mobile 3D reconstruction pipeline combining photogrammetric multi-view synthesis and Gaussian splatting to generate patient-specific body representations from smartphone images for remote scoliosis assessment, demonstrating the potential of generative reconstruction techniques for lightweight and personalized patient modeling.

Overall, these studies highlight the potential of generative models to address data scarcity and support patient-specific modeling in HDT-based rehabilitation. However, several challenges remain unresolved. First, the limited clinical validation of models trained on or producing synthetic data raises concerns about the reliability of AI-generated medical information. Synthetic data or generated feedback may fail to accurately represent pathological patterns, potentially affecting clinical decision-making if used without rigorous validation. Second, the deployment of generative AI in real-time HDT applications may impose demanding computational and communication requirements, particularly when low-latency and highly reliable multimodal interaction is required. Although these aspects are not directly addressed by the included studies, they are receiving increasing attention in the broader AIGC-enabled HDT literature [76,77]. Finally, this emerging literature also highlights privacy, security, and data integrity concerns associated with the exchange of sensitive multimodal information between physical and virtual twins, as well as risks related to the generation and propagation of inaccurate or unrepresentative AI-generated content [76,77].

3.5. Role of network connectivity

Network connectivity emerged as a fundamental enabling factor across the reviewed telerehabilitation solutions. Since most systems relied on continuous communication between patient-side and clinician-side components, internet access was essential for remote monitoring, data transmission, and clinical supervision.

Twenty-two studies (n = 22) explicitly addressed connectivity-related aspects, discussing the technical challenges and requirements associated with remote communication infrastructures. A key shared characteristic is the reliance on cloud computing infrastructures to store large volumes of clinical data, deploy artificial intelligence inference without overloading local hardware, and synchronize web-based applications. One of the primary roles of connectivity concerned remote AI inference and computational offloading. Several systems transmitted sensor or motion data to external servers where ML algorithms were executed, reducing the computational burden on local devices. For example, Wang et al. [55] proposed an upper-limb rehabilitation platform in which movement data acquired through wearable sensors were transmitted to a remote server for gesture classification and exercise evaluation. Similarly, Elmakias et al. [28] proposed a system that offloads the analysis of VR-generated motion data to an external server running ML algorithms for anomaly detection and pain assessment. These approaches enabled the use of lightweight consumer devices while supporting computationally intensive AI processing.

A second architectural pattern involved cloud-based storage and synchronization, as several systems employed remote infrastructures to store rehabilitation data, synchronize patient and clinician interfaces, and support continuous monitoring over time. For instance, Zedda et al. [60] adopted a remote server infrastructure for secure storage and management of patient sensor data, while Yassin et al. [26] used cloud synchronization to enable real-time communication between the physiotherapist interface and the patient application during rehabilitation sessions.

Despite these advantages, several recurring network-related limitations emerged. Latency represented one of the most critical challenges, particularly in VR-based rehabilitation systems requiring real-time feedback. Delays in data transmission and remote processing may disrupt interaction fluidity and reduce user immersion during rehabilitation exercises [5].

The case study by Xiang et al. [74] combines a time-sensitive networking (TSN) protocol with edge-based processing close to the physical master and HDT domains. Compared with a traditional Ethernet architecture, this approach reduces latency and jitter in both immersive interaction and periodic data streams, while improving perceived video fluency and tactile-visual synchronization. These findings suggest that combining deterministic communication with edge processing can support tight PT–VT synchronization under the stringent timing requirements of haptic-based rehabilitation.

In the post-stroke VR-based rehabilitation system proposed by Alsheikhy et al. [5], reliability and responsiveness are ensured through an end-to-end latency of 30 ms, a minimum frame rate of 60 fps, and limited Jitter. Delays in virtual reality environments may arise from hardware limitations, network bandwidth constraints, or the computational demands of real-time data processing. To mitigate these issues, the authors implemented a low-latency optimized feedback algorithm, enabling the timely delivery of therapeutic guidance and preserving the quality of user interaction during rehabilitation sessions.

Falkowski et al. [67] identify latency as one of the most critical factors affecting the teleoperation of rehabilitation exoskeletons. Their experimental results demonstrate that the complete communication cycle between the VR-based Digital Twin and the exoskeleton can be maintained within acceptable limits for safe and effective remote control. In particular, real-world communication tests conducted between Poland and Turkey showed an average ping of < 51.29 ms, a standard deviation of < 1.58 ms, and no packet loss observed during the experiments. The maximum end-to-end latency observed during the full communication cycle was approximately 212 ms, remaining below the < 300 ms threshold generally considered acceptable for manual teleoperation. This value represents the end-to-end latency perceived by the user and includes the entire communication chain, from the interaction with the Digital Twin, through the cloud database and the Industrial Personal Computer (IPC), to the servomotor controller and, ultimately, the exoskeleton. The study also highlights that the cloud database used as an intermediary introduces additional delays and represents one of the main bottlenecks of the system, but the

latency contributions of the individual intermediate stages were not reported; therefore, it is not possible to isolate and quantify the specific contribution of data transmission to the overall system latency. To mitigate this issue, the authors suggest the future adoption of the Automation Device Specification (ADS) protocol, which would enable more direct communication with the exoskeleton, as well as the integration of 6G networks to further reduce latency and improve the overall responsiveness of telerehabilitation systems.

Chen et al. [44] in their virtual physical therapy case study implement semantic communication and AIGC to reduce VR video transmission requirements by sending compact semantic representations instead of raw video streams, thereby lowering bandwidth consumption and communication overhead while preserving users' Quality of Experience. Given the amount of data transmitted, bandwidth and reliable, stable, and secure connectivity represent a key constraint for immersive HDT-based healthcare applications. The authors cite a general latency requirement < 1 ms for Artificial Intelligence-Generated Content and $0.5 - 2$ ms for immersive virtual service but do not cite a minimum throughput requirement.

Bandwidth constraints also represented a significant issue, especially in multi-camera rehabilitation systems transmitting high-volume image streams. For example, Silva et al. [36] reported that network bandwidth limitations forced the proposed multi-camera architecture to operate at reduced frame rates in order to avoid transmission bottlenecks.

Another major concern involved cybersecurity and privacy. The continuous transmission of sensitive biomedical data over the internet requires secure communication strategies and compliance with medical data protection standards. Consequently, several studies adopted encryption protocols, Virtual Private Networks (VPNs), and secure distributed architectures to reduce the risk of unauthorized access and improve data protection [26,44,57,60,66].

Quantitatively, security-related considerations were explicitly discussed in several of the included studies, yet only a few studies implemented concrete technical safeguards. None of the reviewed studies reported an experimental evaluation of security performance, such as penetration testing or resilience benchmarking. A parallel pattern emerged for scalability: although invoked as a design objective in sixteen studies, none reported empirical evidence of scalable operation, such as load testing, multi-site deployment, or assessment under concurrent multi-patient use. This asymmetry between the frequency with which security and scalability are acknowledged as necessary and the near-absence of their experimental validation constitutes one of the implementation gaps identified by this review.

3.6. HDT implementation level and study maturity level

In addition to the technological dimensions analyzed above, each study was classified according to the operational definition of HDT introduced in Section 1, distinguishing between genuine HDT implementations, partial HDT-like systems, and general enabling technologies.

The classification was based on three criteria: (C1) longitudinal updating, i.e., whether the virtual representation was continuously or periodically updated with patient data over time rather than generated from a single snapshot; (C2) active use of the virtual representation, i.e., whether patient-derived information was used to generate feedback, adapt the rehabilitation process, or predict the evolution of the patient's state rather than solely for passive monitoring; and (C3) representation completeness, i.e., whether the virtual model captured multiple aspects of the patient rather than a single isolated organ, function, or physiological parameter. Studies satisfying all three criteria were classified as genuine HDT implementations (G), those satisfying two criteria as partial HDT-like systems (P), and those satisfying one or none as general enabling technologies (E). This classification identified six (n=6) genuine HDT implementations, twenty (n=20) partial HDT-like systems, and twenty-eight (n=28) general enabling technologies, as shown in Fig. 2(c).

Each study was also classified according to its level of empirical and clinical maturity using a five-level scale, independently of the number of HDT criteria satisfied. M1 (Conceptual framework) included studies proposing a conceptual model or architecture without empirical validation. M2 (Prototype/technical validation) included implemented systems evaluated primarily in terms of technical feasibility or performance, using synthetic or public datasets, simulated scenarios, or preliminary engineering tests. M3 (Healthy-subject evaluation) included systems evaluated with healthy participants performing rehabilitation-related tasks. M4 (Patient evaluation) included studies involving the target clinical population in case studies, pilot or feasibility studies, or other preliminary clinical evaluations. Finally, M5 (Advanced clinical evaluation) included solutions evaluated through more structured clinical studies, such as randomized controlled trials, multicenter studies, or large-scale longitudinal evaluations. Applying this scale across the 54 included studies yielded four (n=4) studies at M1, nineteen (n=19) at M2, twelve (n=12) at M3, fourteen (n=14) at M4, and five (n=5) at M5, as shown in Fig. 2(c).

Cross-tabulation of study maturity and HDT implementation level revealed a clear separation between HDT completeness and clinical maturity. None of the studies classified as genuine HDT implementations reached M5, with these studies remaining concentrated at earlier stages of development and, at most, preliminary patient evaluation. Conversely, all studies reaching M5 were classified as partial HDT-like systems or general enabling technologies. Thus, the most clinically mature evidence identified in the review concerns systems implementing only selected components of the HDT paradigm rather than complete HDT architectures, indicating that greater HDT completeness has not yet been accompanied by an equivalent level of clinical validation, highlighting the evaluation of complete HDT systems in robust clinical studies as an important direction for future research.

4. Discussion

This systematic review examined remote rehabilitation from a technological perspective, with the aim of identifying recurring architectural patterns, highlighting persistent limitations, and deriving design guidelines for HDT-based telerehabilitation frameworks in response to the research questions outlined in Section 1.

The analysis presented in Section 3 presents a technologically mature but architecturally fragmented field, in which several enabling technologies have been successfully applied to telerehabilitation but have not yet converged into unified HDT frameworks. This fragmentation is further confirmed by the cross-tabulation of HDT implementation level and study maturity level, which shows that the studies conceptually closest to a genuine HDT have not undergone rigorous clinical validation, while the studies validated in randomized or real-world settings implement only partial or enabling components of the HDT paradigm. Building on these findings, this section synthesizes the evidence, identifies the main technological challenges, and derives practical recommendations for future HDT-based telerehabilitation systems.

This section is articulated as follows: Section 4.1 summarizes the findings reported in Section 3 and explicitly answers the three research questions; Section 4.2 adopts a Quality Function Deployment (QFD) perspective to translate clinical and operational requirements into prioritized technological enablers for HDT-based telerehabilitation; lastly, Section 4.3 derives a set of design guidelines and outlines the implications for future research.

4.1. Synthesis of findings and recurring technological challenges

The following paragraphs provide a point-by-point response to the three research questions formulated in Section 1, summarizing the findings and the recurring technological challenges that emerge from it.

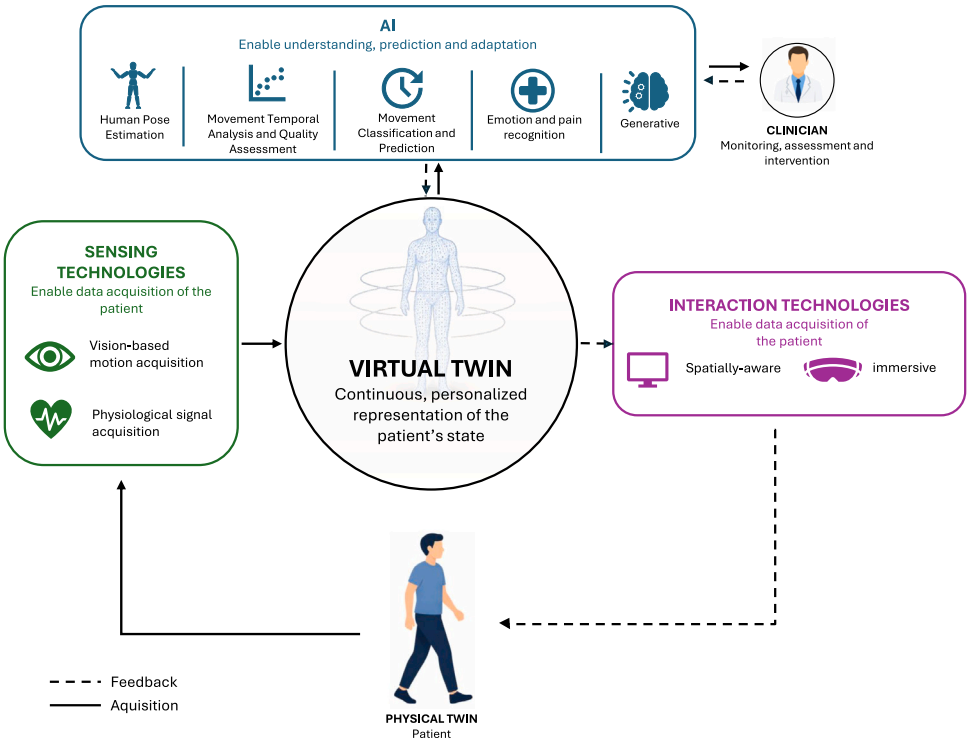


Fig. 3. HDT-based telerehabilitation framework architecture.

RQ1: How is remote rehabilitation currently implemented across different clinical applications? Remote rehabilitation is mainly applied in two primary clinical areas: firstly, neurological and neuromuscular disorders, and secondly, orthopedic and other musculoskeletal conditions. This distribution reflects a deliberate focus on pathologies for which intensive, repetitive, and easily quantifiable motor training is essential for functional recovery. Across both domains, ROM emerges as the most consistently adopted quantitative outcome measure, complemented by qualitative descriptors of movement smoothness, symmetry, and stability, as well as patient-reported indicators such as the Visual Analogue Scale for pain. The convergence on a relatively narrow and shared set of biomechanical and clinical parameters suggests that, despite the diversity of pathologies, the underlying functional targets of rehabilitation are amenable to a unified technological abstraction, which is precisely the conceptual space in which HDT frameworks are designed to operate.

RQ2: What role do digital technologies, particularly XR, AI, and IoMT, play in enabling the development of Human Digital Twins for telerehabilitation?

The analysis of the reviewed studies revealed a common technological workflow through which sensing, AI, XR, and connectivity can contribute to HDT-based telerehabilitation.

Fig. 3 summarizes this workflow and highlights the functions that distinguish a HDT from a conventional intelligent telerehabilitation platform. According to the operational definition introduced in Section 1, these include a patient-specific virtual representation that evolves through continuous or periodic physical-to-virtual updating, supports predictive or adaptive functions, and can return patient-specific feedback to the physical domain. These functions establish a closed PT-VT loop, whereas conventional telerehabilitation systems may implement only individual components of this workflow.

IoMT and vision-based technologies provide the main acquisition layer. Markerless computer vision approaches capture body movements through cameras, while wearable devices collect biomechanical and physiological data [26,33,37,46,53,60,61,72]. When acquired longitudinally, these data can support the updating of the patient-specific virtual representation over time.

AI provides the analytical and predictive layer of this workflow. Across the reviewed studies, AI was mainly employed for human pose estimation [35,36,40,54,56,57,64,70], movement quality assessment [5,30,38,41,50,51,72], movement classification and prediction [34,37,46,52,53,55,68,75], emotion and pain recognition [26,58,59], and, more recently, generative modeling [44,69]. These functions support the interpretation of patient data, objective assessment of rehabilitation exercises, and, in more advanced implementations, prediction and personalization of the rehabilitation process.

XR provides an interaction layer through which patient-specific information can be translated into exercise guidance, corrective feedback, and adaptive rehabilitation experiences [3,5,27–29,32,34,38–40,42–45,47–50,61–66,69,70]. Immersive solutions were frequently used to enhance engagement through gamified rehabilitation, whereas AR and non-immersive approaches can offer advantages when accessibility, safety, or awareness of the physical environment are relevant [73].

Connectivity links these components and enables data exchange between the physical and virtual domains. Several systems relied on cloud infrastructures for data storage, synchronization between patient and clinician applications, remote monitoring, and computational offloading [26,28,44,55,57,60,66]. For more interactive HDT applications, communication performance becomes particularly relevant. Xiang et al. [74], for example, showed how low-latency communication and edge processing can support tighter physical–virtual synchronization in applications involving immersive and haptic interaction.

HDTs in telerehabilitation are enabled not by a single technology but by the convergence of sensing, AI, XR, and connectivity solutions organized as a closed, bidirectional loop that collectively supports continuous patient representation, predictive and adaptive feedback, and remote clinical supervision. However, this level of integration remains limited in the current literature. As shown by the cross-tabulation in Table 2, only two studies jointly integrated AI, XR, and IoMT, while nearly two-thirds relied on a single enabling technology. This discrepancy highlights the gap between the integrated HDT paradigm and its current implementation in telerehabilitation systems.

RQ3: What are the main technological challenges limiting the effectiveness and scalability of remote rehabilitation? The main technological

challenges limiting the effectiveness and scalability of remote rehabilitation cluster into four interrelated families: connectivity and infrastructure constraints, data and modeling limitations, intrinsic trade-offs imposed by the rehabilitation context, and barriers related to clinical interpretability and integration.

A first cluster of limitations concerns connectivity and infrastructure. Latency, bandwidth, and cybersecurity of biomedical data transmission are repeatedly identified as critical bottlenecks, particularly in solutions that combine real-time XR feedback with cloud-based AI inference [5,36,60,66]. The reliance on cloud infrastructures, while necessary to manage large clinical datasets and computationally intensive models, exposes telerehabilitation systems to network instability, regulatory compliance burdens, and privacy risks that are not yet fully resolved by the encryption strategies and decentralized architectures reported in the literature.

A second cluster of challenges relates to data and modeling. Across both pose estimation and movement quality assessment studies, the scarcity, heterogeneity, and limited representativeness of rehabilitation datasets represent a structural limitation. Widely used benchmarks such as UI-PRMD and KIMORE are typically based on healthy subjects simulating pathological movements, raising legitimate concerns regarding their generalizability to real patient populations [30,51]. The definition of ground truth labels, particularly for movement quality and for affective dimensions such as pain and engagement, remains subjective and inconsistent across evaluators [38,51,58,59].

Moreover, classifiers and predictors trained on a specific sensor configuration rarely transfer to alternative hardware, undermining clinical scalability and contributing to a persistent gap between offline laboratory validation and real-world home deployment.

A third cluster of challenges is intrinsic to the trade-offs imposed by the rehabilitation context itself. Models capable of high accuracy often exceed the computational budget of consumer-grade devices and home network connections, while lightweight alternatives sacrifice positional accuracy and depth resolution that may be clinically relevant [40,41,54,57]. Similarly, immersive VR maximizes engagement and pain modulation but reduces environmental awareness and may be unsuitable for balance-oriented exercises, whereas AR and non-immersive VR preserve safety at the cost of reduced sensory immersion [47,48,73]. Gamification enhances adherence but may incentivize compensatory or unsafe movement strategies, motivating the adoption of neutral, non-gamified environments in specific orthopedic settings [73].

A final, transversal challenge concerns clinical interpretability and integration. Several studies emphasize that, regardless of model accuracy, clinical adoption requires that therapists understand and trust the system's outputs [46,52,55]. The compromise between explainable but less flexible algorithms and high-performing but opaque deep models has not been systematically addressed in the rehabilitation literature, and the lack of standardized evaluation protocols across studies further complicates cross-comparison and clinical translation.

4.2. Quality Function Deployment for HDT-based telerehabilitation

The findings discussed in the previous sections identify the main technologies currently adopted in HDT-oriented telerehabilitation systems, as well as their strengths and limitations. However, it remains unclear which technological capabilities should be prioritized when designing integrated HDT frameworks. To address this issue, a Quality Function Deployment (QFD) analysis was performed [78,79] to systematically translate the clinical and operational requirements emerging from the literature into technological enablers with the goal of prioritizing the features that should be considered in the development of future HDT-based telerehabilitation systems.

The QFD was developed through a structured focus group involving all the authors of this study, whose backgrounds are in biomedical, production, management, and computer science engineering, with specific expertise in human-centered technology development. No external clinicians, therapists, patients, or independent technical experts were involved.

Requirements and technical features were initially identified independently by each author from recurring clinical needs, technological limitations, and design components emerging from the reviewed studies. The individual lists were then consolidated through group discussion, retaining items identified by at least two authors. Each requirement was assigned an importance weight on a five-point scale (1 = marginal, 5 = critical), following standard QFD practice [78]. Each author independently scored the requirements according to their recurrence and relevance across the reviewed literature. Individual scores were then averaged and rounded to the nearest integer. When scores for the same requirement differed by more than two points, the supporting evidence was jointly re-examined, and a final score was established by consensus.

Relationships between requirements and technical features were independently evaluated using the standard House of Quality scale (weak = 1, medium = 3, strong = 9) [78]. Disagreement was flagged when individual assessments differed by more than one relationship level (e.g., weak versus strong). In these cases, the corresponding evidence was re-examined, and the final relationship level was established by consensus. The correlations among technical features represented in the roof of the House of Quality (Fig. 4) were assessed using the same independent evaluation and consensus procedure. The resulting technical priorities were calculated by combining requirement importance weights and relationship scores according to the same procedure.

Fig. 4 reports the obtained QFD matrix, summarizing the main requirements and key architectural capabilities identified for the development of HDT-based telerehabilitation frameworks.

For the QFD analysis, eleven requirements were identified.

Several requirements were associated with the long-term adoption and effective use of telerehabilitation systems in unsupervised home environments. High patient engagement requires sustaining motivation and adherence throughout long-term rehabilitation programs, mitigating the repetitive nature of therapeutic exercises. High usability demands that the system can be operated independently by patients with minimal cognitive effort, while low setup complexity requires reducing the time and technical effort needed to prepare the system before each session.

A second group of requirements was related to the effectiveness and safety of the rehabilitation process. High movement tracking accuracy requires reliable measurement of kinematic parameters against validated reference systems, addressing the limited benchmarking frequently reported in the literature. Continuous rehabilitation supervision requires the ability to monitor patient progression, adherence, and exercise execution remotely, reducing the dependence on scheduled clinical visits. Closely related to this aspect, high patient safety demands the detection of unsafe compensatory movements, excessive mechanical loads, or pain-related behaviors that could compromise rehabilitation outcomes.

The reviewed studies also highlighted several challenges affecting the large-scale deployment of telerehabilitation solutions. High hardware affordability requires the adoption of cost-effective technologies suitable for consumer-grade environments, overcoming the reliance on laboratory-grade equipment observed in many studies. Robustness to environmental variability requires reliable operation under heterogeneous home conditions, while high scalability refers to the ability to maintain performance across different patient populations, rehabilitation protocols, and deployment contexts.

Finally, the growing reliance on AI-driven decision support and remote data management highlighted the importance of transparency and trustworthiness. High explainability requires that clinicians can understand the rationale behind system-generated assessments and recommendations, while high data security demands the protection of sensitive biomedical information during transmission and storage, ensuring compliance with regulatory and ethical requirements.

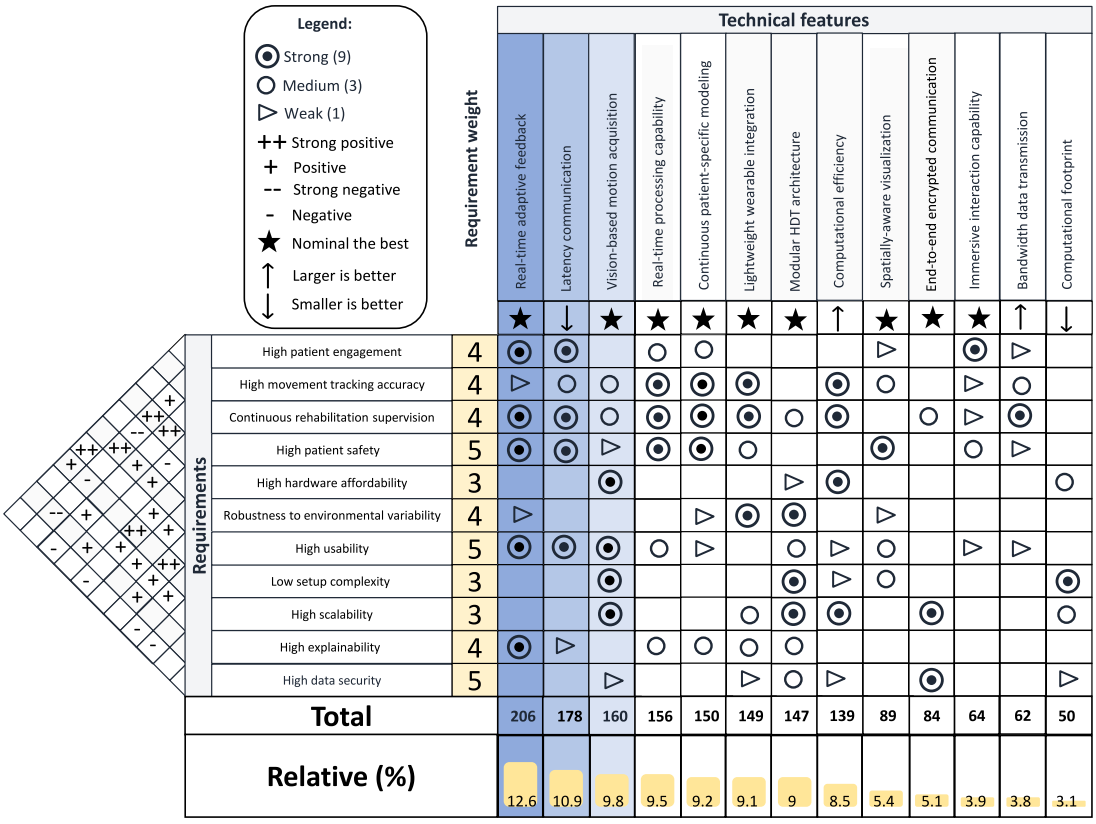


Fig. 4. Quality Function Deployment (QFD) matrix illustrating the relationships between the main requirements of HDT-based telerehabilitation systems and the corresponding architectural and technical features identified throughout the reviewed literature.

For the QFD analysis, thirteen technical features were identified.

Some of the identified features are related to patient monitoring and data acquisition. Vision-based motion acquisition refers to the ability to reconstruct the patient's pose from camera streams through markerless tracking approaches, a solution widely adopted to monitor rehabilitation exercises without requiring dedicated wearable equipment. Lightweight wearable integration refers to the continuous acquisition of biomechanical and physiological data through wearable sensors, reflecting the growing use of inertial and biosignal devices in telerehabilitation applications.

A second set of features concerns the processing and utilization of patient data. Continuous patient-specific modeling is the ability to maintain an updated digital representation of the patient's condition and rehabilitation progress, enabling personalized therapy adaptation over time. Real-time processing capability refers to the ability to acquire, analyze, and respond to patient data fast enough to support in-session feedback and monitoring. Closely related to this aspect, high computational efficiency and low computational footprint describe the capability to perform these operations while minimizing processing, memory, and storage requirements, thereby facilitating deployment on consumer-grade and edge devices.

The reviewed literature also highlighted several features aimed at improving patient interaction and engagement. Real-time adaptive feedback is the ability to dynamically tailor feedback according to the patient's performance and condition during rehabilitation sessions. Spatially-aware visualization refers to the presentation of clinically relevant information while maintaining awareness of the physical environment and body position. Immersive interaction capability enables rehabilitation activities to be delivered through interactive three-dimensional environments, an approach frequently adopted to increase engagement and adherence.

Finally, several features relate to the integration and operation of distributed rehabilitation systems. Modular HDT architecture refers to the ability to organize system functionalities into independently updatable components, facilitating extensibility and long-term maintenance. Low-latency communication and high-bandwidth data transmission support the timely exchange of patient data and feedback between local and remote components, while end-to-end encrypted communication ensures the secure transmission of sensitive biomedical information and compliance with data protection requirements.

The cumulative importance scores shown at the bottom of Fig. 4 summarize the outcome of the QFD analysis by quantifying the overall relevance of each technical feature with respect to the identified requirements. As such, they provide a basis for prioritizing the technological capabilities that should receive the greatest attention in future HDT-based telerehabilitation frameworks.

The importance scores reveal that the highest-priority technical features are those directly involved in the continuous observation, interpretation, and adaptation of the rehabilitation process. In particular, real-time adaptive feedback, vision-based motion acquisition, continuous patient-specific modeling, real-time processing capability, and low-latency communication achieved the highest scores. This result is consistent with the findings of the review, which showed that the primary value of HDT-based telerehabilitation lies in its ability to continuously monitor the patient, assess rehabilitation performance, and dynamically support exercise execution outside clinical environments. Among these features, real-time adaptive feedback emerged as the most influential. The reviewed studies repeatedly highlighted the importance of providing patients with immediate guidance and corrective actions, both to improve exercise quality and to compensate for the absence of direct therapist supervision. The high ranking of vision-based motion acquisition and real-time processing capability reflects the growing shift toward markerless and home-based rehabilitation solutions. The literature consistently showed that accurate movement assessment depends on the ability to acquire and analyze patient movements continuously and with minimal operational burden. Likewise,

low-latency communication emerged as a critical enabler because delays directly affect feedback effectiveness, remote supervision, and the overall responsiveness of the rehabilitation system.

Features such as lightweight wearable integration, modular HDT architecture, computational efficiency, and spatially-aware visualization occupied an intermediate position. These technologies do not directly determine rehabilitation effectiveness but play an important supporting role by improving scalability, interoperability, deployment feasibility, and user experience. Their ranking suggests that successful HDT systems require not only accurate monitoring and assessment capabilities but also architectures capable of operating reliably in heterogeneous real-world conditions.

Conversely, immersive interaction capability, high-bandwidth communication, low computational footprint, and end-to-end encrypted communication received comparatively lower scores. This result reflects their more indirect contribution to the clinical objectives considered in the QFD analysis. For example, immersive XR environments can improve engagement and motivation, but the reviewed studies also demonstrated that effective rehabilitation can be delivered through AR and non-immersive solutions. Similarly, high-bandwidth communication is not always essential when local processing and transmission of summarized data are possible. End-to-end encrypted communication received a lower score as it contributes primarily to trustworthiness and regulatory compliance rather than directly affecting rehabilitation outcomes, despite remaining indispensable for any healthcare deployment.

Finally, a one-at-a-time (OAT) sensitivity test was performed on the QFD weight structure to assess the robustness of the technical feature prioritization [80]. Each of the 11 requirement weights was varied individually by ±20% and ±30%, while the remaining weights were held fixed, yielding 44 perturbation scenarios. For each scenario, technical feature scores were recalculated, and the resulting ranking was compared to the baseline ranking using Spearman's rank correlation coefficient. Across all scenarios, the correlation coefficient ranged from 0.92 to 1.00, with a mean value of 0.99. The requirement "High patient safety" produced the largest rank shifts when perturbed, while "High explainability" produced none. The top-ranked technical features, including real-time adaptive feedback and latency communication, kept their position in nearly every scenario. These results confirm that the QFD-derived prioritization is robust to moderate changes in individual requirement weights.

The roof of the House of Quality, shown in Fig. 4, highlights the relationships between the identified requirements, revealing both synergies and trade-offs that characterize the design of HDT-based telerehabilitation systems.

Requirements related to affordability, usability, setup simplicity, patient engagement, and scalability were found to be mutually reinforcing, suggesting that accessible and easy-to-use systems are more likely to achieve widespread adoption in home-based rehabilitation settings. Similarly, movement tracking accuracy, robustness to environmental variability, and patient safety exhibited strong positive relationships, reflecting the dependence of safe rehabilitation on reliable monitoring under realistic operating conditions. Another group of positive correlations linked continuous rehabilitation supervision, explainability, data security, and patient safety, indicating that trust in AI-supported rehabilitation systems depends not only on technical performance but also on transparency, reliability, and protection of sensitive information.

At the same time, the analysis revealed several recurring trade-offs. The most important concerns the relationship between hardware affordability and movement tracking accuracy, reflecting the tension between low-cost sensing technologies and clinical-grade measurement precision repeatedly reported in the reviewed literature. Additional conflicts emerged between data security and system accessibility, as stronger security mechanisms may increase implementation complexity and reduce usability. Another trade-off was identified between continuous rehabilitation supervision and data security, since the continuous acquisition and transmission of biomedical data inherently increases privacy and cybersecurity risks.

This pattern is consistent with the implementation gap identified in Section 3.5: the trade-offs between data security and accessibility, and between continuous supervision and data security, likely discourage the routine implementation and experimental validation of security mechanisms in home-based settings, where minimizing cost and setup complexity is often prioritized over resource-intensive validation efforts.

These findings suggest that the design of HDT-based telerehabilitation systems should not aim to maximize individual requirements independently. Rather, effective solutions must balance competing objectives while leveraging the positive interactions that exist between usability, reliability, safety, and trust.

4.3. Design guidelines and implications for future research

The analysis conducted in the previous sections indicates that the effectiveness of HDT-based telerehabilitation depends not on individual technologies, but on their integration into coherent and patient-centered systems. Based on the evidence collected from the reviewed studies and the prioritization obtained through the QFD analysis, the following design guidelines are proposed to support the development of telerehabilitation frameworks and to identify the most relevant directions for future research.

Guideline 1 - Design the HDT as a closed-loop system providing real-time adaptive feedback. The QFD analysis identifies real-time adaptive feedback as the most important technical feature of an HDT-based telerehabilitation framework. The value of sensing and patient modeling is realized only when the information extracted from the patient is translated into actionable feedback that can guide rehabilitation exercises. Future systems should therefore implement a closed-loop architecture in which patient data are continuously acquired, processed, and used to adapt exercise difficulty, feedback modalities, and rehabilitation goals during the session. Such an approach can improve patient engagement, support motor learning, and partially compensate for the absence of in-person clinical supervision.

Guideline 2 - Prioritize low-latency communication and real-time processing across the entire HDT pipeline. A HDT can only support continuous rehabilitation supervision if data acquisition, processing, and feedback generation occur with minimal delay. The QFD highlights low-latency communication and real-time processing capability among the most important technical enablers. Future frameworks should therefore minimize communication bottlenecks and computational delays through edge computing, efficient data processing pipelines, and hybrid edge-cloud architectures. Maintaining real-time responsiveness is essential to ensure safe exercise execution and effective adaptive feedback.

Guideline 3 - Build the core of the digital twin around vision-based perception. The QFD analysis shows that the main value of a HDT-based telerehabilitation system comes from its ability to continuously represent the patient's condition and use this information to support personalized rehabilitation. Vision-based motion acquisition represents the most suitable baseline solution for home-based rehabilitation because it enables markerless movement tracking with limited setup complexity and hardware requirements. When camera-based monitoring alone is insufficient, wearable sensors can be integrated as complementary data sources to improve robustness and provide additional physiological or biomechanical information.

Guideline 4 - Adopt modular and extensible architectures. The analyzed systems frequently consisted of multiple components dedicated to sensing, data processing, patient modeling, user interaction, and remote supervision. As technologies and clinical requirements continue to evolve, future HDT frameworks should be designed as modular systems in which individual components can be independently updated, replaced, or extended. Modularity facilitates interoperability, simplifies

maintenance, supports the integration of emerging technologies, and reduces the risk of technological obsolescence.

Guideline 5 - Prioritize practical interaction technologies. The QFD indicates that interaction technologies should be selected according to their contribution to usability, safety, and accessibility rather than their level of immersion alone. Future systems should prioritize interaction modalities that preserve environmental awareness and can be easily deployed in home environments. Spatially-aware visualization, AR, and non-immersive VR environments are often more compatible with long-term home rehabilitation than fully immersive solutions. Immersive XR technologies should be reserved for clinical scenarios in which their benefits clearly outweigh the additional costs and deployment complexity.

Guideline 6 - Implement security and scalability as fundamental design requirements. The QFD analysis highlighted several trade-offs that cannot be ignored in the design of HDT-based telerehabilitation systems. In particular, higher measurement accuracy is often associated with increased hardware costs, while continuous monitoring and remote supervision may introduce additional privacy and cybersecurity challenges. Future research should therefore focus on achieving an appropriate balance between clinical performance, affordability, scalability, and data protection. Security and privacy should be treated as fundamental design requirements rather than as secondary implementation concerns, ensuring that future HDTs remain both clinically effective and trustworthy. Beyond the priorities identified through the QFD analysis, the review itself shows that although security and scalability are widely recognized as essential, they are rarely implemented through specific technical mechanisms and are rarely empirically validated.

5. Conclusions

This systematic review investigated the role of digital technologies in enabling Human Digital Twins (HDTs) for telerehabilitation, with the aim of identifying the technological foundations of current solutions, analyzing recurring architectural patterns, and deriving design guidelines for future developments. Following the PRISMA methodology, fifty-four studies published between 2021 and 2026 were analyzed and classified according to clinical domain, XR technology, IoMT integration, AI task, HDT implementation level, and study maturity level.

The results show that telerehabilitation is increasingly supported by the convergence of AI, XR, and IoMT technologies. Markerless motion capture, wearable sensing, AI-driven movement analysis, and XR-based rehabilitation environments emerged as the most adopted technological components. However, despite the maturity of these technologies, most solutions remain focused on specific rehabilitation functions rather than implementing fully integrated HDT frameworks capable of continuously representing and adapting to the patient's condition.

To translate these findings into practical recommendations, a QFD analysis was conducted to prioritize the technological enablers of HDT-based telerehabilitation systems, and a set of design guidelines has been proposed, emphasizing continuous adaptation, multimodal sensing, modular architectures, deployability, and the balance between accuracy, scalability, and security.

Several limitations of this study should be acknowledged. First, the literature search was restricted to studies published between 2021 and 2026, potentially excluding earlier contributions relevant to digital rehabilitation and patient digital modeling. Second, the concept of HDT in rehabilitation is still evolving, and no widely accepted definition or reference architecture currently exists. Consequently, many of the reviewed studies describe only partial implementations of the HDT paradigm, requiring several conclusions to be inferred from technologically related telerehabilitation systems. Finally, although the QFD analysis provides a structured approach for prioritizing technological features, the assignment of requirement weights and relationship scores inevitably involves a degree of expert judgment. Therefore, despite the robustness observed in the sensitivity analysis, the resulting priorities should be interpreted as an exploratory, evidence-informed ranking rather than an objective hierarchy of technical features.

Future research should focus on the development and clinical validation of integrated HDT ecosystems that combine multimodal sensing, AI-driven patient modeling, adaptive rehabilitation strategies, and remote supervision. Addressing these challenges will be essential for transforming HDTs into a clinically deployable paradigm for personalized and scalable rehabilitation.

CRediT authorship contribution statement

E. Pelosin: Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **C. Innocente:** Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **G. Marullo:** Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation. **L. Ulrich:** Writing – review & editing, Validation, Supervision, Methodology, Investigation, Formal analysis, Conceptualization. **S. Moos:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Funding acquisition. **E. Vezzetti:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Funding acquisition.

Ethics statement

Ethical approval was not required for this study because it is a systematic review based solely on previously published literature and did not involve the collection of data from human participants, animals, or identifiable personal information.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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