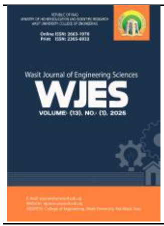

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Review Article

Engineering Perspectives on Rehabilitation Robotics: An Integrative Review of Control Strategies, Optimization Methods, and IoT-Enabled Platforms

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ABSTRACT

Rehabilitation robotics has evolved into an interdisciplinary field that integrates mechanical design, control theory, optimization methods, and information technologies to improve motor rehabilitation outcomes. This review examines rehabilitation robotics from an engineering perspective based on 70 peer-reviewed studies published between 2014 and 2024, selected from an initial pool of approximately 120 articles. Four main domains are analyzed: control strategies, bio-inspired and metaheuristic optimization methods, cloud/IoT-enabled rehabilitation platforms, and emerging human-robot interaction approaches, including voice-based control. While prior reviews have often addressed these topics separately, this work presents an integrated taxonomy and highlights cross-domain synergies that support the development of advanced rehabilitation systems. The analysis identifies two major research gaps: the integration of multimodal biosignals with real-time adaptive control, and the development of affordable modular systems for resource-limited environments. The findings provide an engineering-oriented synthesis for the design of intelligent, accessible, and sustainable rehabilitation robots.

Keywords: Rehabilitation Robotics, Control Strategies, Optimization Algorithms, Cloud-Based Technologies, Patient-Centric Design, Multimodal Bio-Signals, Sustainability, AI Integration, Voice-Control.

1. Introduction

Stroke, war injuries, or accidents are regarded as one of the most significant causes of mortality, ranking third after cancer and heart disease [1]. A stroke, as specified by the World Health Organization (WHO), is a brain malfunction lasting for more than 24 hours. According to reports, approximately 30% of those who have had a stroke suffer from lasting disabilities, while about 20% necessitate extensive rehabilitation plans. In the aftermath of a stroke, the patient goes through three distinct stages in the course of recovery. They include the acute stage, which lasts up to one week; the sub-acute stage, which lasts approximately six months, and lastly the chronic stage [2]. A stroke predominantly leads to functional disability of the arm, wrist and hand [3]. Rehabilitation can treat or reduce the consequences of a stroke [4]. Rehabilitation requires that the patient work with a professional therapist who will assist them in performing repetitive motions of the affected limb [2]. Nevertheless, considerations that impact both the therapist and the patients include the therapist's availability, rehabilitation implement costs, and therapy session duration [5]. Moreover, rehabilitation programs require individualized interactions between therapists and patients. However, interactive rehabilitation necessitates a significant amount of time and effort from the patient as well as the therapist [2]. Based on these facts, the researchers have devised robots used in rehabilitation therapy as assistive tools. Rehabilitation robots can perform repeated motions on a patient's extremity and provide intensive, precise, quantitative, and risk-free rehabilitation [6, 7]. This paper offers a review of the recent literature on rehabilitation robots. The review is organized into three interrelated sections: (1) rehabilitation robot control strategies, (2) optimizing rehabilitation robots by using optimization algorithms, and (3) rehabilitation robots with a cloud storage function. By framing this review within an engineering application perspective, the work directly addresses the multidisciplinary engineering challenges and solutions in rehabilitation robotics.

The structure of this review is organized as follows: Section 2 presents the review methodology. Section 3 discusses control strategies for rehabilitation robots. Section 4 and 5 examine optimization algorithms and cloud/IoT integration, respectively. Section 6 provides a comparative analysis of control approaches. Sections 7 to 10 cover optimization techniques, cloud-based systems, patient-centric design, and multimodal biosignals. Sections 11 to 14 address the economic, sustainability, quantitative, and ethical dimensions of rehabilitation robotics. Section 15 outlines a future research roadmap. Section 16 highlights voice-controlled systems as a new HRI trend. Finally, Section 17 concludes the review with key insights and directions.

1.1. Motivation and Contribution

The last ten years of rehabilitation robotics technology development has produced better assistive devices but research studies fail to connect essential parts of their work including control methods and optimization techniques and cloud/IoT systems and human-robot interaction methods. Previous review papers often investigate one technical area at a time because they lack a comprehensive framework while they pay insufficient attention to both cross-domain connections and engineering implementation difficulties. The current system presents obstacles to researchers and practitioners because it divides information into different sections, which prevents them from understanding how various disciplines can work together to develop effective rehabilitation solutions that address patient requirements in a scalable manner. This research study presents a multiscale engineering approach to connect four research fields through an academic study framework which enables complete analysis of the research fields. The work makes its contribution through four main components which include: (1) a study of 70 peer-reviewed articles which were published between 2014 and 2024, (2) a detailed taxonomy which describes how control systems, optimization methods, IoT architecture, and interaction techniques connect with each other, (3) a study which shows existing research patterns and their missing elements and future research possibilities, and (4) an engineering framework which presents practical design methods for creating and deploying future rehabilitation robots. This review is considered the initial study that provides an integrated categorization that merges these four research domains with an engineering analysis of view and practical guide, serving as a new framework for research and application in the connection among diverse fields of rehabilitation robotics.

2. Review Methodology

The review used a systematic and thematic framework to examine high-quality research on rehabilitation robots. A comprehensive search was conducted across academic databases, including IEEE Xplore, Scopus, ScienceDirect, and SpringerLink, to identify peer-reviewed journal articles and high-quality conference papers published between 2014 and 2024. The selection process used keywords including rehabilitation robotics, robotic control strategies, optimization algorithms, IoT in rehabilitation, and adaptive therapy systems. The initial review process began with approximately 120 research papers. Studies were included based on their relevance to the following core domains:

- Control strategies for rehabilitation robots.
- Bio-inspired and metaheuristic optimization algorithms.
- Cloud and IoT integration in robotic rehabilitation.
- Emerging interaction paradigms, with a particular emphasis on voice-controlled interfaces, as a forward-looking trend.

Duplicates, non-English papers, and studies lacking sufficient technical detail were excluded. Following this filtering process, the final dataset comprised 70 peer-reviewed articles. In addition to thematic classification, the selected papers were analyzed for innovation, experimental validation, and citation relevance to ensure depth and diversity. The goal of this methodology was to capture not only the breadth of existing research but also to identify research trends, gaps, and future opportunities. The comparative figures presented in this review are based on quantitative synthesis of the studies included in the final reviewed dataset.

2.1. Taxonomy of Rehabilitation Robotics Research

The literature from this study has been organized into four main research areas which include control strategies, optimization algorithms, cloud/IoT integration, and Human-Robot Interaction (HRI). The HRI domain includes different interface types which range from ergonomic controls to biosignal-based systems and new voice-command technologies that are explained in Section 16. Table 1 presents the proposed taxonomy that summarizes these domains.

Table 1. Taxonomy Table of Rehabilitation Robotics Research.

Main Domain	Focus Area	Techniques	Applications
Control Strategies	Classical and intelligent control	PID, fuzzy logic, sliding mode control, neural networks	Joint trajectory tracking, motion accuracy
	Adaptive and Hybrid Controllers	Fuzzy-PID, RBFNN, ADRC, INNAC, FAP	Patient-specific assistance, disturbance rejection
Optimization Algorithms	Metaheuristic Techniques	Genetic Algorithm, Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Whale Optimization Algorithm (WOA), Grey Wolf Optimizer (GWO)	Controller tuning, inverse kinematics, path planning
	Multi-objective and hybrid optimization	NSGA-II, MAPID, Hybrid GA-ACO, BFSGA	Trade-off analysis, energy efficiency, dynamic adaptation
Cloud & IoT Integration	Remote monitoring and data management	AWS IoT, MQTT, Edge AI, ThingSpeak	Home-based rehab, therapist supervision, real-time feedback
	Decision support and scalability	Big data processing, cloud storage, ML-enabled platforms	Progress tracking, scalable therapy programs
Human-Robot Interaction	Patient-centric design	Ergonomics, adjustability, feedback mechanisms	Long-term comfort, intuitive use
	Emerging modalities	Voice commands, EMG/EEG interfaces	Hands-free interaction, signal-driven control

3. Rehabilitation Robots Control Strategies

Since the robot performs repetitive movements, it needs a reliable controller to maintain the level of performance in the presence of disturbances and reduce the effect of disturbances and uncertainty. Automated feedback control is crucial in modern medicine. Research on feedback techniques for controlling rehabilitation robots began in the late 1950s. It remains an active study subject, with many researchers implementing automatic control systems to track the desired repeated trajectory and establish a stable system free of errors. Consequently, the challenge is to develop control systems that would provide an efficient and optimal performance, despite the patient's varied physical characteristics and responses to exercises [8, 9]. The primary goal of rehabilitation robotic devices control systems aims to achieve two objectives which involve accurate execution of rehabilitation treatment protocols and safeguarding patient safety. The controller needs to operate dynamic human body models which include all environmental factors that impact human physical performance to achieve its intended goals [10, 11]. Reinkensmeyer et al. in [12] established important basic principles which serve as essential foundations for rehabilitation robotics research through their work on upper-limb therapy devices which include the MIME system. Their early robot-assistant training with Electromyographic (EMG) feedback and adaptive "assist-as-needed" strategies have influenced over many of the control strategies discussed in the later studies. These contributions laid the groundwork for personalized and responsive robotic interventions that remain central to modern rehabilitation protocols. Contemporary research into adaptive nonlinear controls for rehabilitation robot systems, along with related literature in brief:

(Elbagoury et al., 2014) [13] proposed a therapy to control rehabilitation robots for stroke patients using neural networks based on the Levenberg-Marquardt method. Their Results show that it loosely interprets EMG data in real time to control rehabilitation robots better.

(Jiang et al., 2015) [14] proposed a new Fuzzy Neural Network (FNN) for improving control in the arms of rehabilitation robots. Their results indicate that the FNN controller worked well in controlling the position of the rehabilitation robotic arm. It gave a very fast response, had less overshoot, and very minimal vibration.

(Khoshdel et al., 2015) [15] proposed an innovative interval type-2 fuzzy logic approach for impedance variation of rehabilitation robotics for the lower limb. Their simulation findings demonstrate that the voltage-based variable impedance control that has been proposed is more effective than voltage-based impedance control in therapeutic exercises.

(Ajayi, 2016) [16] proposed the use of Central Pattern Generators (CPGs) and feedback control techniques to analyze, simulate, and control joints that are associated with the human lower extremities in order to implement control strategies using a lower limb exoskeleton practically. His results show a satisfactory performance of the proposed strategy.

(Rezage and Tokhi, 2016) [17] proposed fuzzy PID control of lower limb exoskeleton for elder people. Their results show a satisfactory performance of the proposed strategy.

(Chen et al., 2017) [18] proposed a wearable exoskeleton suit be developed in order to assist people who are paralyzed in recovering the capacity to walk, stand up, and sit down (STS). Their results indicate that CUHK-EXO helped a paralyzed patient significantly in accomplishing STS and walking. The joint angles of the exoskeleton aligned with the designed reference trajectories; the torque generated by the exoskeleton actuators was sufficient to support the patient’s STS and gait movements.

(Liu et al., 2018) [19] proposed Adaptive Sliding Mode Control (ASMC), an approach specially designed for the wearable lower extremity exoskeleton. Their results indicate that the ASMC significantly reduces jitter and closely follows a trajectory with precise details, in contrast with a PID controller and traditional sliding mode control methods.

(Wang et al., 2018) [20] proposed a fuzzy PID control technique for rehabilitation robots intended for lower limb training, allowing both passive and active training modes. Their results show that the fuzzy PID controller performs better than the ordinary PID control.

(Shi et al., 2019) [21] proposed a new fuzzy-adaptive impedance control strategy using information from sEMG. Their Results demonstrate that the robots can update the fundamental assistive forces and impedances by the magnitude of the user's volitional activity; the successful implementation was produced in impedance control strategies, as an assist-as-needed methodology.

(Masengo et al., 2020) [22] proposed a Proportional-Integral-Derivative (PID) controller for lower limb rehabilitation robots in order to adjust and reduce discrepancies. Their results show that the actual trajectory signal was very well aligned with the reference trajectory signal with minimal error, thus a potential for rehabilitation to occur; this was realized through the use of the PID controller.

In this regard, (Chen et al., 2021) [23] proposed three control approaches for the control of a 3-prismatic-revolute-spherical ankle rehabilitation robot: adaptive fuzzy PID, GA-based PID, and classic PID. Their result shows the proposed adaptive fuzzy PID controller tuned by the Genetic Algorithm, exhibited superior signal tracking and faster response times compared to conventional PID control in suppressing overshoot for various input signals.

Meanwhile, (Li et al., 2021) [24] have established a control strategy for an upper limb rehabilitation robot developed from the modified Active Disturbance Rejection Control (ADRC) algorithm, with modifications to allow the desired rehabilitative motion of the elbow and wrist joints in the upper limbs. Their results prove that the method proposed improves control accuracy for the rehabilitation robot with an increased tracking capability and robustness.

(Shao et al., 2021) [25] proposed a novel method called Improved Neural Network Adaptive Control (INNAC) for patients who have suffered a stroke that can control the bending angles of each finger on a hand rehabilitation robot actuated by Flexible Pneumatic Muscles (FPMs). Their results show that this approach is superior to Single Neuron Neural Network Adaptive Control (SNNAC) in terms of control effect. It possesses good stability and anti-interference ability; therefore, even with the presence of external interferences, it quickly resumes its normal tracking state.

(Zhao, 2021) [26] proposed an impedance controller reliant on the integration of Electromyographic signal data and force feedback data for an upper limb rehabilitation robot. Their results illustrate that impedance control acts as a buffer to support the patient's movement, which ensures that the patient-robot system is physically compatible with the external world.

(Miao et al., 2021) [27] proposed a sliding mode control mechanism where the control gain is modified using an Adaptive Radial Basis Function Neural Network (ARBFNN) for a lower limb rehabilitation robot to avoid jitter. Their results reveal convergence of the strongest guarantee by the control strategy embedded within the robot. This robot understands the intention of human body motion and is also capable of performing the two training activities of drawing straight lines and curves with different subjects.

(Zhang et al., 2022) [28] proposed a Radial Basis Function Neural Network Adaptive Sliding Mode Controller (RBFNNASMC) for tracking and controlling patients' walking intentions through lower limb exoskeletons, as well as performing modification of RBF network weights by way of an adaptive law. Their results show the RBFNNASMC controller offers better gait tracing capabilities than PID controllers.

(Zaway et al., 2023) [29] proposed Fuzzy Fractional Order Proportional Integral Derivative (FOPID-FLC) controller for a 2-DOF lower limb exoskeleton depends on an improved method of controlling that mixes the rewards of fuzzy reasoning and fractional calculus. Their findings demonstrate that the FOPID-FLC controller outperforms the standard FOPID controller across various performance metrics, including IAE, ISE, IAU, IATE, ITSE, and MSE.

(Alsubaie and Alotaibi, 2023) [30] proposed a model-based feedback linearization control technique for control the rehabilitation robot, which employs deep neural networks and real-time observations to learn any changes in system dynamics during training periods, thereby determining uncertainties beyond training data. Their results demonstrate that the proposed control method was found to be practical and applicable in real-life situations that are marked with unforeseen movement patterns and widespread unpredictability.

(Hu et al., 2023) [31] proposed a Fuzzy Adaptive Passive (FAP) control technique for an End-effector Bilateral Upper Limb Rehabilitation Robot (EBULRR), focusing on impulsive measures and task performance, in order to enhance the patient's self-control safely during therapy sessions. Their results show that the proposed FAP control strategy not only improved subject initiative during training but also enhanced motor learning ability, ensuring safety while providing adaptive assistance based on task performance and impulse evaluation.

(Ren, Liu and Wang, 2023) [32] proposed three different training modes for the upper limb rehabilitation robot: PID control, bilateral control and active control, which correspond with various stages of the rehabilitation process. Their results demonstrate a significant linear regression linkage between anticipated reference values and genuine elbow joint angles, with an R-squared value of 94.41% and an average error of four degrees.

(Tian et al., 2023) [33] proposed a Force/Position-based Velocity Control (FPVC) approach for active training-based Hybrid End-effector Lower limb Rehabilitation Robot (HE-LRR). Their results demonstrate that the efficiency of the end effector in movement control is relatively high when a reference trajectory, desired velocity, and control parameters are provided, and these parameters can control the active participation of participants.

(Jin et al., 2023) [34] proposed a fuzzy logic controller to help in guiding the movement of the robot based on human gait patterns and requirements. Their results show that the gait rehabilitation robot can replicate more natural walking dynamics, making the rehabilitation experience smoother and more effective.

(Tkue, 2024) [35] proposed a solution through Fuzzy Sliding Mode Control (FSMC) for a 2-DoF lower limb exoskeleton rehabilitation robot, combining sliding mode control and fuzzy logic to address complexities in lower limb rehabilitation. Their results show superior performance in handling the nonlinear dynamics of lower limb rehabilitation compared to a traditional sliding mode controller.

(Jenhani and Gritli, 2024) [36] proposed development of a robust affine state-feedback controller for stabilizing a knee rehabilitation exoskeleton robot, crucial for individuals with locomotor disorders. Their results demonstrate that the designed Linear Matrix Inequality (LMI)-based controller successfully achieves excellent stabilization of the knee exoskeleton system.

From a comparative perspective, the reviewed control strategies reveal important trade-offs between robustness, adaptability, and implementation complexity. Classical and model-based controllers generally offer interpretability and ease of implementation, but their performance may degrade in the presence of strong nonlinearities and patient-specific uncertainties. In contrast, intelligent and adaptive approaches, such as fuzzy and learning-based controllers, provide greater flexibility and robustness under variable rehabilitation conditions, although they often require more careful tuning, higher computational effort, or more extensive validation. These differences suggest that controller selection should be guided by the balance between accuracy, adaptability, and real-time feasibility.

4. Optimizing Rehabilitation Robots by Using Optimization Algorithms

Optimization can be regarded as a procedure that aids in determining the best feasible solution to any given situation to realize the desired features of the cost function and therefore attain an overall optimal solution [37, 38]. The optimization algorithms employ multiple agents (solutions) to traverse the search space in order to resolve an optimization problem [39, 40]. Here, a brief review of recent developments in related optimization algorithms for rehabilitation robot systems is summarized:

(Jamwal et al., 2014) [41] proposed Nondominated Sorting Genetic Algorithm II (NSGA II) for optimization of a parallel ankle rehabilitation robot. Their findings show that the algorithm provided a non-dominated set of solutions providing better objective values while satisfying the design constraints.

(Jamwal and Hussain, 2015) [42] proposed a Fuzzy-based Sorting Genetic Algorithm (FSGA) to improve physical designs of parallel robots that treat ankle ailments. Their results reflect that the FSGA shows a higher ability to discriminate in finding optimal solutions and converging them to desirable levels, hence solving drawbacks observed in heretofore evolutionary algorithms.

(Jamwal and Hussain, 2016) [43] proposed a fuzzy-based multi-objective evolutionary approach, Biased Fuzzy Sorting Genetic Algorithm (BFSGA), to optimize the design of a cable-actuated parallel ankle rehabilitation robot. Their results show BFSGA has managed to put 118 solutions on the first Pareto Front among 500, which demonstrates its capacity to make wide-ranging alternatives available for decision-making purposes.

(Y. Hassan and S. Ghintab, 2016) [44] proposed the optimization of force-position controllers for a wearable lower limb rehabilitation robot through the Ant Colony Optimization (ACO) algorithm. Their results show that ACO-tuned controllers have substantially better position trajectories as compared to manual tuning, where an average enhancement is seen in the elliptic trajectory.

(Sabah et al., 2021) [45] proposed an Optimal Sliding Mode Controller (OSMC) depending on Whale Optimization Algorithm (WOA) for a lower limb rehabilitation robot. Their results show the efficiency of the proposed OSMC, which is fast in response, performs with very little overshoot, and steady-state error is minimal.

(Nguyen et al., 2021) [46] proposed the self-adaptive control parameters in Differential Evolution with search space improvement (Pro-ISADE) as a solution to the inverse kinematics problems of human upper limbs in rehabilitation robotics through an optimization method that utilizes differential evolution with self-adaptive control parameters and enhances the search space. Their results indicate a potential application of the Pro-ISADE algorithm in addressing the inverse kinematics of upper limb rehabilitation robot arms.

(Azar and Nazar, 2021) [47] proposed a new and efficient method to design a 3-DOF lower limbs rehabilitation robot, which aids in the movement of hip and knee joints by optimizing the angle and angular velocity of the joints using Genetic Algorithm (GA) for accomplishing the trajectory as defined using artificial neural networks later on. Their results demonstrate that the proposed method is capable of learning the physiotherapist's actions at a particular stage and for every individual patient, and to imitate the same independently.

(Mirrashid et al., 2022) [48] proposed an Ant Colony Optimization (ACO) algorithm to adjust the PID controller parameters of the upper limb rehabilitation robot, improving its control. Their outcomes show the superiority of employing the ACO-PID controller in tracking, stability, and finite-time convergence relative to other PID control strategies.

(Sabah et al., 2022) [49] proposed an Adaptive Proportional-Integral-Derivative controller (APID) to verify the APID succeeds in controlling the 2-DoF lower limb rehabilitation robot system efficiently. Their results show that the APID controller controlling the lower limb rehabilitation robot leads to sub-optimal results for both linear and non-linear trajectories.

(Li et al., 2022) [50] proposed the upper limb rehabilitation robot structure to be optimized through the utilization of a multi-objective Genetic Algorithm (GA) in order to improve human comfort during interaction. Their results show that the general comfort achieved after optimization was quantified at a level of comfort which registered 0.2507, thus demonstrating a great deal of progress made on human comfort during interaction.

(Sabah et al., 2022) [51] designed a lower limb rehabilitation robotic system that uses the Modified Adaptive PID (MAPID) controller with modifications derived from the Grey Wolf Optimization technique. Based on the obtained results, the rehabilitation robot showed better performance when using MAPID compared to APID, without any overshoot and very small steady-state error.

(Hassan et al., 2022) [52] proposed an Optimal Model-Based Adaptive Controller (OMBAC) to govern a two-link rehabilitation robot, which was intended for the therapy of the upper limb using a grasshopper optimization algorithm. The results show that the suggested OMBAC is very effective, with a fast-settling time, low steady-state error value, and has less overshoot.

(Cen et al., 2022) [53] proposed an adaptive multi-time variable weight enhanced trapezoidal velocity algorithm that was combined with a trajectory smoothing enhancement algorithm to optimize the suitability of trajectories in rehabilitation training. They also proposed an improved Genetic Algorithm, showing a significant reduction in optimization time and a superior solution for Rehabilitation Robots. This means that with this algorithm, it is possible to optimize trajectory model parameters according to the constraints of training to ensure that the rehabilitation training provided is high-quality and comfortable for patients.

(Guo et al., 2023) [54], proposed a Multi strategy enhanced Whale Optimization Algorithm, called MWOA, applied for trajectory planning in an upper-extremity exoskeleton rehabilitation device and focused on isokinetic rehabilitation interventions. This study proves that MWOA has superiority in convergence precision and stability for handling complex constraints, hence effectiveness for trajectory optimization.

(Liu et al., 2023) [55] developed a framework of optimum design and optimization, considering a multi-functional rehabilitation robot, named EEGO, which could structurally adapt to realize four different functions: bedside training, sit-to-stand training, sit-to-walk training, and ground walking training. From the findings, it was observed that such a device indeed provides some positive power-assisting effect on patients and thus meets the goal of reducing lower-extremity stress to enable gait activities.

(Li et al., 2023) [56] recommended a GA to optimize trajectory tracking control mechanisms of an upper limb rehabilitation robot. Their result shows that the use of a GA remarkably enhances the effectiveness of trajectory-tracking control systems in upper limb rehabilitation robotics.

(Li et al., 2023) [57] developed a torque control method for a rehabilitation exoskeleton using a PSO-optimized RBF neural network. Their approach shows superior tracking accuracy and faster convergence compared to traditional PID control. The PSO-RBFNN system achieved near-zero trajectory error and significantly reduced steady-state errors at both hip and knee joints.

(Xia et al., 2023) [58] suggested improving rehabilitation robots' trajectory planning by applying the Crow Search Algorithm (CSA) and its improved version, known as the Multi Crow Search Algorithm (MCSA). Their obtained results demonstrate that the new MCSA outperforms the original CSA because it results in minimum impact and energy consumption, hence being more advantageous when it comes to optimizing joint trajectories in a rehabilitation robotics framework.

(Li et al., 2024) [59] proposed a new decision support system was for the training of upper limb rehabilitation robots by optimizing the training algorithm using a random forest approach in hybrid reasoning, specifically Rule-Based Reasoning (RBR) and Case-Based Reasoning (CBR), to instantly alter training parameters for patients. Their results show that combining machine learning algorithms with expert knowledge results in better rehabilitation training plan development which marks a major improvement for dynamic rehabilitation decision-making.

Studies showed that optimization-based methods used for rehabilitation work have both potential effectiveness and operational practicality challenges. The methods of review are fundamentally different in their convergence behavior, computational expense and practical applicability. The bio-inspired and metaheuristic algorithms offer an interesting tool for tuning parameters in complex systems with nonlinear dynamics that would effectively enhance controller performance, without the need for an accurate mathematical model. The three main limitations of the methods are their computational intensity, their dependence on certain parameter configurations, and their irregularity seen across various research contexts. In practice, the significance of the attempted methods is apparent when it comes to incorporating them into control setups, devised with an offline or semi online parameter optimization mechanism.

5. Rehabilitation Robots with Cloud Storage Functions

Cloud Computing (CC) is a technology that is growing at a rapid rate, offering storage, networking, and computing services that can be accessible and utilized via the internet. Cloud services are a unique property of CC, as they are pay-per-use and elastic, resulting in a reduced cost and time commitment for users [60, 61]. Cloud robotics refers to the use of network-connected robots that leverage the advantages of parallel computation and data exchange. These robots connect to the internet and utilize the vast resources of big data to perform rapid collective learning and collaboration. CC offers solutions that enhance the functionalities of networked robotics while addressing constraints. Cloud robotics integrates two complementary cloud systems, namely a decentralized cloud enabling M2M interactions among robots and an infrastructure cloud enabling M2C communication [62]. A brief overview of some of the recent research work carried out related to cloud robotics in rehabilitation robotic systems is as follows:

(Jiang et al., 2017) [63] proposed an assessment system for upper limb rehabilitation based on IoT, including a computing cloud and a classification algorithm. Their results show that with feature analysis of mean value, standard deviation, entropy, and energy of motion signals performed on the cloud, the system allows for a proper assessment of rehabilitation progress.

(Yang et al., 2018) [64] proposed the integration of IoT technology with machine learning algorithms and a robotic hand for rehabilitation purposes. The cloud component becomes imperative because these algorithms require heavy computational power and storage capacity, which can be effectively offloaded to cloud servers for processing. Therefore, the integration of cloud technologies points to a significant increase in the scalability, performance, and functionalities of the stroke rehabilitation system by enabling access to on-demand computation resources and complex data processing.

(Bouteraa et al., 2020) [65] introduced some cloud-based methods to introduce the sophisticated robot to help support the patient in various wrist movements to take proper care and therapy of the patient. Results show promising improvements in patient care and therapy efficiency, especially in remote settings where therapists can control the robots remotely.

(Bouteraa and Abdallah, 2020) [66] suggested the application of cloud technology within an IoT-enabled robotic system designed for wrist rehabilitation. Their results demonstrate that integration between systems improves the operational efficiency and dependable performance of the robot which supports wrist rehabilitation therapy.

(Pavón-Pulido et al., 2020) [67] proposed integration of Cloud Computing (CC) approaches with IoT architectures for intelligent control of a rehabilitation exoskeleton robot aims to enhance the system's performance. Their results demonstrate that the system achieves effective data sharing and processing through cloud technology. The robot system operates successfully when the therapist works at a distance from the robot system.

(Shaaf et al., 2021) [68] suggested an online multisensory system for home-based monitoring in arm rehabilitation; this enables health practitioners to monitor the recovery process in stroke patients and give necessary feedback. The proposed system's processing part is designed through the web-based IoT platform called ThingSpeak. This involves the package of Arduino Mega Controller (AMC) and ESP Wi-Fi shield. Their results show that the ThingSpeak tool’s contribution to visualization in the monitoring process facilitates better and easier interpretation and analysis of the patient's progress during arm rehabilitation exercises.

For processing and analyzing the data of an upper limb rehabilitation robot-based home, (Jamwal et al., 2023) proposed the cloud-based methods in [69]. The authors argued that, with the help of cloud technology, remote therapists can access the processed data regarding the monitoring of rehabilitation progress in stroke patients at home. Therefore, on time, one can intervene and make necessary changes in the strategy of rehabilitation.

The reviewed studies show that there is no single best method which works for all situations. The IoT and cloud-based rehabilitation platforms deliver significant benefits which enable remote monitoring and provide data access and maintain uninterrupted medical treatment in home rehabilitation environments. The system faces operational challenges because of its latency issues, data security requirements, need for interoperability, and system infrastructure. The systems enhance scalability and connectivity according to their clinical performance, which depends on both their communication system and their ability to sense and control and provide user-friendly interface functions.

6. Comparative Analysis of Control Strategies

The effectiveness and accuracy of robotic therapy depend on the control strategies which rehabilitation robotics implement. The system provides therapeutic session stability through its combination of basic PID controllers and its advanced adaptive control methods. The common usage of PID controllers which operate simply breaks down because they fail to handle the complex nature of human-robot interactions. The advanced control methods which include adaptive sliding mode control and fuzzy logic-based controllers achieve superior performance results in both trajectory tracking and disturbance rejection tasks.

The research demonstrated by (Liu et al., 2018) [19] found that ASMC effectively reduced jitter which occurs in conventional PID controllers making it a better choice for rehabilitation work that requires dynamic and real-time operation. The research conducted by (Wang et al., 2018) [20] found that fuzzy PID controllers delivered superior performance for both passive and active training while maintaining system stability with minimal overshoot. Table 2 summarizes the strengths, limitations, and applications of various control strategies, while Figure 1 compares their performance across key metrics such as trajectory accuracy, stability, and computational load.

Table 2. Comparison of Control Strategies.

Control Strategy	Strengths	Limitations	Applications
PID Controller	Simple, easy to implement	Struggles with non-linearity and adaptability	Basic trajectory tracking
Fuzzy Logic Controller	Handles uncertainty, adaptable to dynamic changes	Requires computational resources	Upper and lower limb rehabilitation
Adaptive Sliding Mode Controller (ASMC)	High stability, jitter reduction	Complexity in design	Real-time trajectory tracking
Neural Network-Based	Learns and adapts to patient behavior	Requires training data, computationally intensive	Complex motion control and customization
Hybrid (e.g., Fuzzy-PID)	Combines the strengths of multiple strategies	Implementation complexity	Multimodal rehabilitation

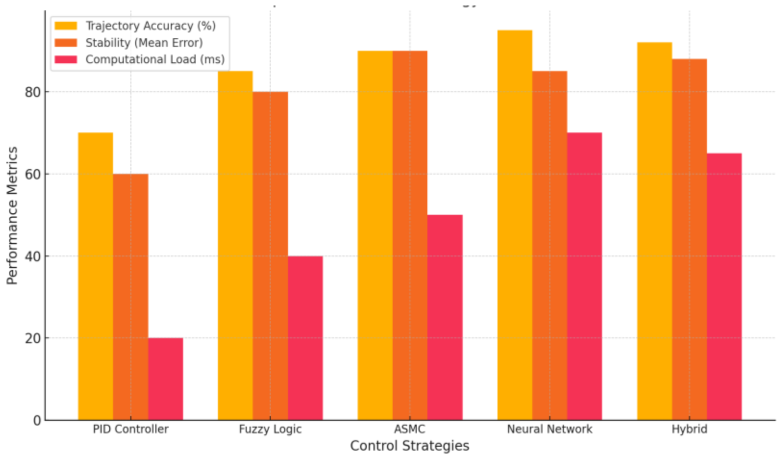

Figure 1. Comparison of Control Strategy Performance.
(Bar Chart Comparing Trajectory Accuracy, Stability, and Computational Load).

7. Optimization Techniques in Rehabilitation Robotics

Optimization techniques improve functionality and efficiency in rehabilitation robots. Using algorithms like Genetic Algorithms (GAs), Ant Colony Optimization (ACO), and Whale Optimization Algorithm (WOA), researchers have been pressuring the optimization of trajectory planning, setting the parameters, and improving interaction quality. This means that Jamwal et al. in [41] claimed using GAs resulted in constraint relaxation for design improvement and enhanced performance, and Sabah et al. in [45] had put forward evidence that WOA functioned well through reduction of steady state errors. Their application areas, essential features, and uses of these optimization techniques are laid down in Table 3, comparing the performance of these optimizations in terms of convergence speed, accuracy, and adaptivity in Figure 2.

Table 3. Optimization Techniques in Rehabilitation Robotics.

Optimization Algorithm	Key Features	Applications	Advantages
Genetic Algorithm (GA)	Solves complex design problems	Trajectory planning for upper/lower limbs	High adaptability and robustness
Ant Colony Optimization (ACO)	Pathfinding and parameter optimization	Force-position controllers	Efficient trajectory tracking
Whale Optimization Algorithm (WOA)	Mimics social hunting behavior	Sliding mode control for lower limbs	Quick convergence, reduced errors
Particle Swarm Optimization (PSO)	Simulates social behaviors in optimization	Controller tuning	Fast convergence, high accuracy
Hybrid Algorithms	Combines multiple optimization methods	Multimodal rehabilitation	Balances computational load and efficiency

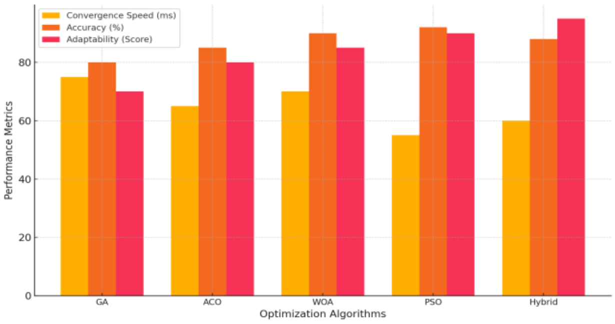

Figure 2. Optimization Algorithm Performance Comparison.
(Bar Chart Comparing Convergence Speed, Accuracy, and Adaptability).

8. Cloud-Based Robotics and IoT Integration

Cloud computing and Internet of Things technologies have developed rehabilitation robotics into systems which provide remote therapy treatment and enable continuous patient monitoring and allow for uninterrupted data sharing. The study conducted by Jiang and his colleagues in 2017 [63] presented an IoT system which processed motion data through cloud computing to evaluate patients. The researchers Shaaf and his colleagues in 2021 [68] developed home monitoring systems which used cloud technology for arm rehabilitation. Table 4 presents the technological components which include their attributes and benefits while Figure 3 shows the advantages which these systems provide.

Table 4. Optimization Techniques in Rehabilitation Robotics.

Technology	Key Features	Applications	Advantages
IoT Integration	Real-time data transmission	Patient progress monitoring	Immediate feedback, remote accessibility
Cloud Computing	Data storage and advanced processing	Motion data analysis	Scalability, reduced device requirements
IoT-Cloud Hybrid Systems	Combines IoT connectivity with cloud storage	Remote therapy and assessment	Enhanced collaboration and data sharing
Home-Based IoT Systems	Localized IoT-enabled therapy systems	Arm and limb rehabilitation	Cost-effective and patient-friendly

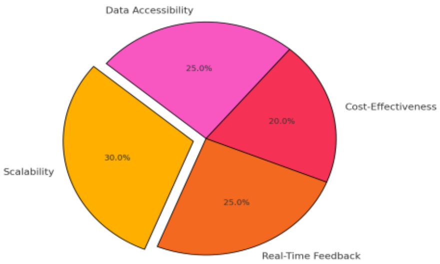

Figure 3. Benefits of Cloud-Based and IoT-Enabled Systems in Rehabilitation Robotics**.**

9. Patient-Centric Design and Usability

Patient-centric design requires three essential elements which include user-friendly interfaces and ergonomic features and cultural adaptability. The system provides adjustable components together with intuitive controls which meet the requirements of different patient groups. (Chen et al. 2017) [18] demonstrated that design elements play a critical role in wearable exoskeleton suits which researchers use to improve mobility. Table 5 outlines key design elements, their impacts, and examples, while Figure 4 compares design priorities.

Table 5. Design Elements and Impacts.

Design Element	Key Features	Impact on Usability	Examples
Ergonomic Design	Adjustable components, lightweight materials	Enhanced comfort and extended usage	Wearable exoskeletons
User-Friendly Interfaces	Intuitive controls, multilingual support	Increased accessibility and patient satisfaction	Tablet-based control systems
Cultural Adaptability	Design tailored to regional and cultural needs	Wider acceptance and usage in diverse regions	Locally tailored rehabilitation systems
Feedback Mechanisms	Real-time user and therapist feedback	Continuous design improvement and customization	Integrated progress trackers

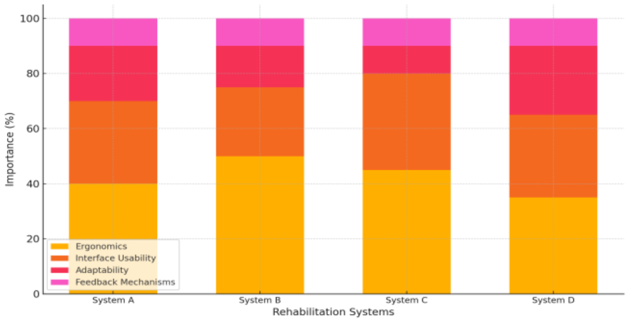

Figure 4. Patient-Centric Design Priorities in Rehabilitation Robotics.

10. Integration of Multimodal Bio-Signals

The integration of multi-modal bio-signals which include EMG together with EEG and motion capture technology has enhanced both the accuracy and the flexibility of rehabilitation robots. The work of Shi et al. 2019 [21] showed how surface EMG signals functioned in real-time impedance control for a robot which provided personalized therapy. The research conducted by (Zhao 2021) [26] established force feedback together with EMG signals to enhance therapy compatibility and treatment effectiveness. Table 6 displays essential bio-signals which include their characteristics and usage while Figure 5 shows the treatment results from single signal systems compared to multimodal signal systems.

Table 6. Integration of Multimodal Bio-Signals.

Bio-Signal Type	Key Features	Applications	Advantages

Electromyography (EMG)	Measures muscle activity	Adaptive robotic control	Real-time adjustments, improved precision
Electroencephalography (EEG)	Captures brain activity	Neurorehabilitation and cognitive training	Monitors patient focus and intent
Motion Capture Systems	Tracks physical movements	Trajectory optimization	Enhanced feedback, dynamic tracking
Multimodal Integration	Combines signals from various sources	Comprehensive therapy systems	Tailored rehabilitation, holistic feedback

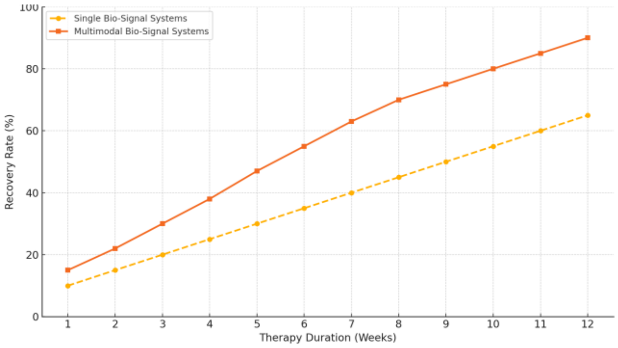

Figure 5. Impact of Bio-Signal Integration on Therapy Effectiveness.

11. Economic and Social Implications

Rehabilitation robots reduce access costs and geographical barriers for equitable access to treatments. Advances in cloud software and IoT make it possible to lower running costs by providing increased autonomy to man. Great potential for cost savings by implementing this new technology is demonstrated by (Jiang et al., 2017) [63]. This publication will evaluate economic and social results in Table 7, while a line-dual axis graph in Figure 6 will illustrate the dynamics between costs and benefits over time.

Table 7. Economic and Social Implications.

Aspect	Economic Implications	Social Implications	Examples
Cost Reduction	Minimizes long-term therapy expenses	Increases accessibility to underserved areas	Remote IoT-based rehabilitation
Scalability	Adapts to growing healthcare demands	Equitable access across diverse populations	Cloud-enabled therapy solutions
Initial Cost Barrier	High upfront costs	Limits adoption in low-resource settings	Affordable modular robotic systems
Quality of Life	Enhances patient independence	Reduces caregiver burden	Home-based rehabilitation systems

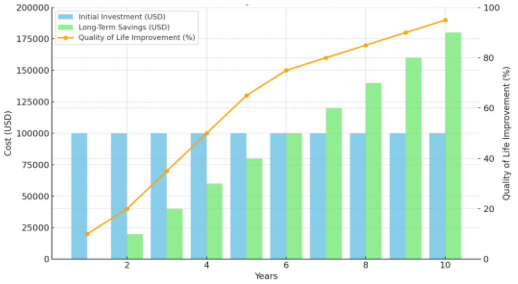

Figure 6. Cost and Benefit Analysis of Rehabilitation Robotics.

12. Sustainability in Rehabilitation Robotics

Some of the primary design considerations in rehabilitation robotics are grounded on sustainability. The design for modules, that is recyclable material, and renewable energy fall in line with the global sustainability assumptions. For example, modular systems can prolong life through the easy option of upgrades and repairs to diminish electronic waste. Table 8 gives sustainability aspects and their benefits; Figure 7 shows how these aspects lead to cost reduction, extended life span, and lessened environmental impact.

Table 8. Sustainability Aspects and Benefits.

Sustainability Aspect	Key Features	Benefits	Examples
Energy Efficiency	Reduced power consumption	Lowers operational costs	Solar-powered robotics
Modular Design	Replaceable and upgradable components	Extends lifespan, reduces waste	Modular exoskeletons
Recyclable Materials	Use of eco-friendly and recyclable materials	Minimizes environmental impact	Bio-degradable robot casings
Renewable Energy Use	Powered by solar or wind energy	Reduces reliance on non-renewable resources	Off-grid rehabilitation robots

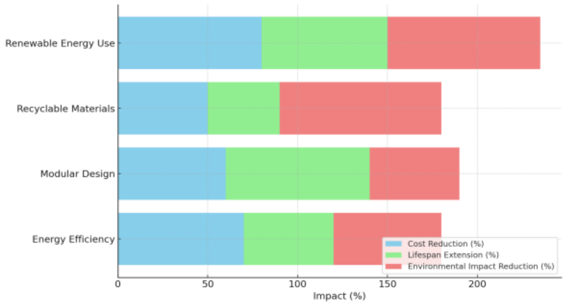

Figure 7. Sustainability Benefits in Rehabilitation Robotics.

13. Quantitative Metrics for Evaluation

Standard measures in a rehab robotics review are quantitative, one measuring means for comparisons across systems. The therapy efficiency and system sustainability of the treatment can be measured through three specific metrics which include recovery rate, energy utilization, and patient satisfaction. The research conducted by Shi et al. [21] used recovery rate as its primary method to evaluate patients progress throughout their treatment. All the key evaluation criteria have been listed in Table 9, while relative evaluations of these measures are illustrated in Figure 8.

Table 9. Quantitative Evaluation Metrics.

Metric	Description	Measurement Method	Application
Recovery Rate	Improvement in patient mobility or function	Pre- and post-therapy assessments	Therapy outcome evaluation
Therapy Adherence	Percentage of prescribed therapy completed	Attendance and completion records	Patient engagement monitoring
Energy Efficiency	Power consumption during operation	Power meters and energy audits	System sustainability assessment
System Durability	Wear and tear over time	Maintenance and repair logs	Long-term cost evaluation
Patient Satisfaction	Feedback from patients	Surveys and interviews	User-centric design validation

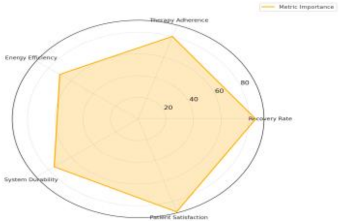

Figure 8. Quantitative Evaluation Metrics for Rehabilitation Robotics.

14. Ethical and Legal Considerations

The ethical and legal problems which rehabilitation robots encounter stem from three main issues which include data protection and responsibility for damages and patients' rights to make choices. The solution requires interdisciplinary teamwork together with explicit operational rules which will create fair and secure robotic treatment solutions. Table 10 highlights key ethical concerns and solutions, while Figure 9 presents their distribution.

Table 10. Ethical and Legal Concerns.

Aspect	Key Concerns	Proposed Solutions	Impact on Adoption
Data Privacy	Protection of sensitive patient information	Encryption, GDPR compliance	Increases trust in technology
Patient Autonomy	Ensuring patients retain control	Shared decision-making models	Enhances patient satisfaction
Liability and Accountability	Responsibility for system failures	Clear legal frameworks	Reduces legal disputes
Balance in Care	Over-reliance on robots	Combining human and robotic therapy	Maintains holistic care

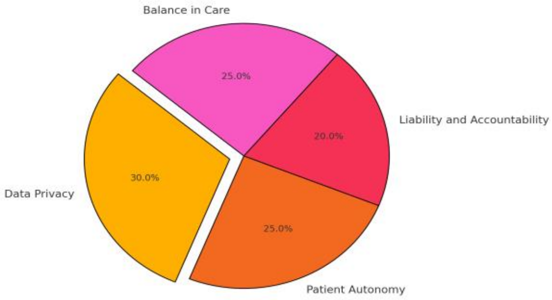

Figure 9. Ethical and Legal Challenges in Rehabilitation Robotics.

15. Proposed Future Research Roadmap

Research should study different areas, which include advanced AI integration, multimodal therapy, low-cost modular designs, and ethical frameworks. The project requires two main elements which include sustainable practices together with better Human-Robot Interaction (HRI) capabilities. Table 11 summarizes future research areas and their expected benefits, while Figure 10 visualizes their prioritization.

Table 11. Future Research Areas.

Research Area	Key Objectives	Expected Benefits
Advanced AI Integration	Real-time adaptive therapy	Personalized and efficient care
Multimodal Therapy Systems	Integrating physical, cognitive, and sensory inputs	Comprehensive rehabilitation
Low-Cost Modular Designs	Affordable and scalable solutions	Increased accessibility
Sustainability and Green Robotics	Energy efficiency and recyclable materials	Environmental responsibility
Ethical and Legal Frameworks	Clear guidelines for robotic use	Builds trust and accountability
Smart Healthcare Ecosystems	Integration with IoT and cloud platforms	Enhanced data-driven decision-making
Human-Robot Interaction (HRI)	Emotionally adaptive robots	Improved patient engagement and satisfaction

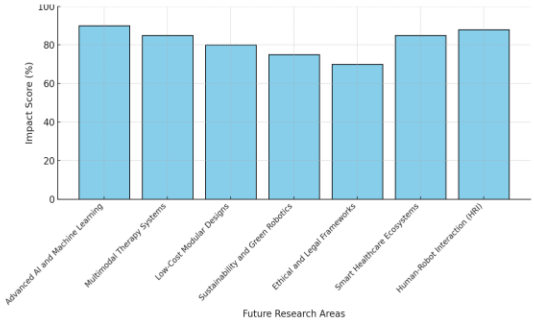

Figure 10. Prioritized Areas for Future Research in Rehabilitation Robotics.

16. Voice-Controlled Rehabilitation Robots

Voice-controlled rehabilitation robots make a new promising interaction in general HRI. The system enables patients to control robotic systems through voice commands which provide a natural and accessible method that does not require physical contact with the system. The system works as an important tool which helps people who have upper-limb disabilities and patients who require in-home rehabilitation. The ASR engine of an automatic speech recognition system goes through the uttered commands such as “start”, “stop”, and “move forward” and then transforms them into action for the robot. The mode requires minimal physical and mental effort which enables patients to achieve greater independence while participating in their treatment. Voice-operated systems will gain better reliability through the development of intelligent systems which will use fuzzy logic and context-aware processing to manage uncertainty that comes from different speech patterns and background noise. The HRI research field still studies voice interfaces for rehabilitation robotics which have gained rising popularity. The latest advancements in recognition technology together with voice commands have demonstrated their practical application for lower-limb exoskeletons according to research that shows their actual working capabilities [70]. The systems achieve intent-aware control through biosignal input (EMG or EEG) and AI-based intention authentication which enables robots to understand their current frame intentions and respond to them. The system needs to address three main challenges which include understanding different ways people speak, developing methods to recognize speech in noisy settings, and handling multilingual speech and speech from people with disabilities. Voice control systems represent an emerging HRI paradigm which leads toward the creation of intelligent systems that support rehabilitation in an inclusive way. Emerging interaction paradigms especially voice-based control systems demonstrate ability to enhance accessibility and create hands-free operation solutions for rehabilitation robotics. Their main strengths include intuitive use and support for patients with limited manual interaction capability. The system effectiveness gets reduced through speech variability environmental noise and language dependence and the system has not been tested in actual situations. The approaches present potential yet they require extensive testing through both research studies and clinical trials before they can achieve general use.

17. Conclusion

Rehabilitation robots serve as a field which connects multiple disciplines that use mechanical design and control engineering and cognitive computing and information technology. The review combined 70 studies which were conducted between 2014 and 2024 to establish four major categories which included control strategies and optimization algorithms and integration of cloud/IoT and human-robot interaction. The research shows that adaptive and intelligent control methods and hybrid optimization methods and IoT-based remote rehabilitation systems have made important advancements according to the results of the research study which contained certain common issues that included insufficient multimodal biosignal usage and the requirement for affordable modular systems and the restricted development of culturally adaptable interfaces. The current research results provide an engineering framework to assess these outcomes which will assist in developing future rehabilitation robotics systems that focus on intelligent design and scalable solutions for enhanced patient experience. The engineering perspective established through this research will become essential for future endeavors which will advance both research and practical use of robotics technology in this domain.

17.1 Implications for Engineering Practice

The insights of this review could better serve as a foundation for the rational design and future application of rehabilitation robots. Results recommend that control engineers would preferably formulate adaptive model-based control strategies allowing real-time biosignal integration. In optimization engineering, it suggests the modifications required in hybrid metaheuristic approaches that complement the desired objectives, such as energy efficiency, trajectory precision, and user comfort. The introduction of IoT and cloud promises scalability architecture toward data analytics, thus benefiting in the commencement of remote monitoring, prognostics and health assessment, as well as conducting large-scale clinical trials. Lastly, the consideration of accessibility through user interaction paradigms like voice commands and intent recognition in the design procedure could extend high adaptability for patients suffering from severe mobility impairment. These technological orientations could accelerate the translation of research outcomes into real-time rehabilitative solutions.

Declaration of Competing Interest

The authors declare that there are no conflicts of interest regarding the publication of this manuscript.

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Author Contributions

Noor Sabah Mohammed Ali conceived the study and carried out the entire work, including literature search and selection, data extraction and synthesis, taxonomy development, analysis and interpretation of findings, and writing the original draft of the manuscript. Muna Hadi Saleh and Nizar Hadi Abbas provided overall supervision, scientific guidance, and critical review, including validation of the technical content and editing of the manuscript. All authors discussed the results and approved the final version of the paper.

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