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Assessing the relevance of biosignal-controlled robotic rehabilitation technologies: a systematic review

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Abstract

Technology is transforming rehabilitative medicine by enhancing accessibility and personalisation. Robot-assisted rehabilitation uses robotic systems for recovery from physical and neurological impairments, enabling intensive, repetitive training with real-time feedback. These systems aim to restore motor function and mobility and to increase independence in daily life, needs that are growing in light of population ageing. Rather than revisiting control algorithms or mechanical design, this review aims to investigate the combined use of bio-signals and robotic rehabilitation systems, and to discuss their potential in rehabilitation settings outside disease-specific clinical frameworks. We reviewed studies published from 2020 through early 2025 to capture recent advances in this rapidly evolving field. Our objective was to assess the relevance of these technologies to rehabilitation outcomes, such as improvements in motor function or other clinical metrics. We considered robot-assisted systems driven by biosignals such as electromyography (EMG), electroencephalography, or electrocardiography and included only studies reporting measurable rehabilitative outcomes. Following PRISMA guidelines, we searched Scopus, PubMed, and WoS databases. Of 207 records screened, 15 met the inclusion criteria. Overall, the included studies suggest that contemporary biosignal-controlled robotic rehabilitation, particularly EMG-driven approaches, may support more intensive, personalised, and engaging therapy than conventional care alone, although the current evidence remains preliminary. Preliminary findings indicate that, by closing the loop among patient, device, and therapist, these systems may reduce muscle activity and support improvements in motor performance; however, the evidence base remains heterogeneous and generally underpowered. To support future clinical adoption, the field needs adequately sized, head-to-head trials with standardised outcome measures, longer follow-up, and transparent reporting of adherence, adverse events, user experience, and implementation barriers, including training and cost. These steps will be important to further assess efficacy and evaluate usability in real-world settings.

Acronyms

AFO - Adaptive frequency oscillator
CCI - Co-contraction index
CNN - Convolutional neural network
DL - Deep learning

DoF	- Degrees of freedom
ECG	- Electrocardiography
EEG	- Electroencephalography
EMG	- Electromyography
FES	- Functional electrical stimulation
FR	- Frequency ratio
F/T	- Force/torque
GMM	- Gaussian mixture model
HRV	- Heart rate variability
IoT	- Internet of things
LSTM	- Long short-term memory
MAC	- Model accuracy classification
MAE	- Mean absolute error
MAV	- Mean absolute value
ML	- Machine learning
MNF	- Mean frequency
MNP	- Mean power
MRAC	- Model reference adaptive control
NN	- Neural network
OSCS	- Optimised stimulation control system
PAMs	- Pneumatic artificial muscles
R-LLGMN	- Recurrent probabilistic neural network
RFF	- Random Fourier features
RLS NN	- Recursive least squares neural network
RL	- Reinforcement learning
RMS	- Root mean square
RMSE	- Root mean square error
RoM	- Range of motion
sEMG	- Surface electromyography
SSI	- Simple square integral
SVM	- Support vector machine
ULCDRR	- Upper-limb cable-driven rehabilitation robot
VR	- Virtual reality
XR	- Extended reality

1. Introduction

By increasing treatment accessibility, customisation, and efficacy, technology-assisted solutions are changing rehabilitation medicine. Often equalling or surpassing conventional approaches in specific outcomes, robotics, virtual reality (VR), wearable sensors, telerehabilitation, and smart assistive technologies are now used to improve motor and cognitive rehabilitation [1, 2]. Robot-assisted rehabilitation, in particular, employs advanced robotic systems to support individuals in recovering from physical or neurological impairments resulting from injuries, illnesses, or other conditions. This method represents a technological advancement in the field of rehabilitation. By enabling high-dose, repetitive training with objective measurement and real-time feedback, these systems are designed to support improvements in motor performance, mobility, and, when translated into daily function, independence in activities of daily living [3, 4].

Several studies report that robotic interventions can increase the amount of active participation or voluntary effort during training compared with conventional therapy alone [5–7]. The integration of traditional rehabilitation with robotic therapy enhances functional recovery, reducing recovery time by increasing treatment intensity [8] and personalising rehabilitation programs [9]. Beyond clinical outcomes, in recent years, robotic rehabilitation has been discussed in relation to demographic challenges, including population ageing and the growing prevalence of neurological disability [10, 11]. Many platforms incorporate social and gamified elements, supporting patient engagement and 'productivity' [12, 13]. These interactive systems guide, enhance, stimulate, and facilitate the neuroplastic processes associated with motor learning [14]. In the context of post-stroke recovery, the use of robotic devices allows for faster and more effective rehabilitation, compared to conventional training [15]. Despite the benefits of automation, the therapist remains central. He should play a key role in administering robotic therapy, including tasks such as adjusting the robot's parameters, preventing the use of compensatory strategies that could harm the patient, and finding the right balance between challenging tasks that promote rehabilitation and those that might discourage patients [16–18]. The implementation of robot-assisted therapy platforms that require minimal supervision can increase the intensity of the therapy by allowing one therapist to supervise multiple patients simultaneously, thereby reducing the therapist's workload [4] and supporting remote training through telerehabilitation [19]. In this context, IoT technologies allow for smooth and as-needed communication between therapists, patients, and robotic systems, optimising the therapy process and expanding access to care [20]. IoT technologies mark an important step forward in robotic rehabilitation, with real-time data on patient performance and vital signs that could be collected to monitor and adjust therapy protocols continuously [21]. This data-driven approach not only improves the accuracy of robotic interventions but also supports more flexible and accessible remote rehabilitation.

Within this evolving landscape, robotic rehabilitation devices are commonly classified into two categories: end-effector systems and exoskeletons, based on how they support and interact with users' limbs [14]. Here's an overview:

- End-Effector Devices: these systems interact with the user at a single distal contact point (e.g. hand or foot), guiding the limb through a defined workspace [22]. Compared with exoskeletons, they generally offer a simpler mechanical structure and faster setup, and can be adjusted to accommodate different body sizes and impairment levels [23];
- Exoskeletons are external robotic devices that are mounted on the body, providing motor support and assistance to people with disabilities [17]. They can offer precise control of multiple DoF for complex limb movements. These systems can be sub-classified into fixed exoskeletons, which operate within a predefined space, and wearable exoskeletons, in which the mechanical structure moves in coordination with the user [24]. Wearable exoskeletons support user mobility and, when properly designed, can improve comfort and efficiency and be adapted to patient-specific needs.

In addition to the mechanical classification, robotic rehabilitation devices can also be distinguished based on the way they interact with the patient. Robotic devices can be classified into:

- Assistive/compensatory: these devices enhance the ability to perform an action or enable actions that would otherwise be impossible [25];
- Interactive/rehabilitative: when the goal is to promote and accelerate the recovery of impaired function, for example, by enhancing neuroplasticity mechanisms, both in the acute and chronic phases. These technologies are further classified based on the predominant context of their application: diagnostic (e.g. quantitative electroencephalography), therapeutic (e.g. transcranial direct current stimulation), or combined diagnostic-therapeutic (e.g. VR) [17, 26].

A further distinction concerns the macro-function or body district that the robotic device aims to assist/compensate, or rehabilitate. Systems are mainly distinguished by the upper and lower limbs:

- Upper limb rehabilitation is essential for helping individuals regain the ability to perform tasks like reaching and manipulating objects [27]. It primarily targets coordinated control across the shoulder (commonly modelled with 3 DoF), elbow flexion-extension (1 DoF), forearm pronation-supination (1 DoF), and wrist motion (typically 2 DoF), which together enable coordinate movements. This coordination is particularly important for those with motor impairments, as it directly impacts their ability to perform everyday activities.

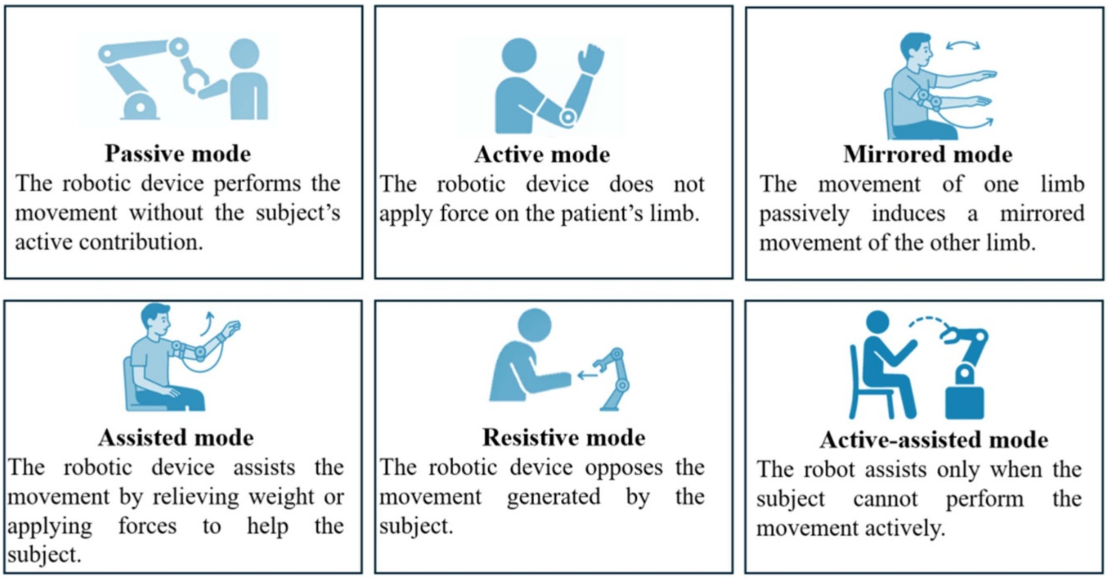

Figure 1. Classification of robotic rehabilitation systems by type of assistance provided.

- Lower limb rehabilitation aims to improve hip, knee, and ankle/foot function to restore locomotion and postural stability [28, 29]; Given their role in propulsion, balance control, and body support, lower-limb gains translate into improved gait and functional mobility, supporting greater independence. This area of rehabilitation is particularly relevant in various clinical contexts, including orthopaedic trauma, degenerative diseases, and neurological conditions.

A key advantage of robotic rehabilitation is the ability to actively involve the subject in therapy: the robot can help active patient-initiated movement rather than passively moving a limb. Concerning the assistance modes provided by the device [30, 31], those can be mainly classified as :

- Passive mode, active mode, assisted mode, active-assisted mode, mirrored mode, resistive mode,

as shown in figure 1.

To actively assist patients, modern rehabilitation robots often integrate biosignal inputs, i.e. measurable physiological signals from the user, to detect the user's movement intent and adjust assistance accordingly.

With biosignal, we refer to measurable bioelectrical physiological signals generated by the human body (e.g. neural, muscular, or cardiovascular activity) that can be acquired and processed to infer the user's state or intention and to control assistive or rehabilitative devices [32, 33].

Biosignals commonly employed in robotic rehabilitative systems (see figure 2) include:

- **EMG** provides direct information on muscle activation patterns, enabling the assessment of residual motor function and voluntary effort during rehabilitation [34, 35]. EMG signals are widely used for intention detection, human–robot interaction, and adaptive control strategies in assistive and rehabilitative robotic devices [34, 36–38].
- **EEG** measures changes in electrical potentials over the scalp with millisecond resolution using electrodes on the skin surface [39, 40]. EEG is particularly important in rehabilitation scenarios involving impaired voluntary movement, as it allows the detection of motor intention and mental workload, supporting brain-computer interface-based control and neuroplasticity-oriented therapies [41–45].
- **ECG** captures cardiac electrical activity and can be used to derive indices such as heart rate and HRV, which are commonly employed as indirect markers of autonomic modulation [46]. During rehabilitation sessions, ECG and HRV monitoring can support the assessment of the patient's physiological load and has been investigated in relation to fatigue and stress-related responses [47, 48]. Continuous ECG monitoring allows safety and enables the adaptation of robotic training intensity according to cardiovascular responses [49–51].

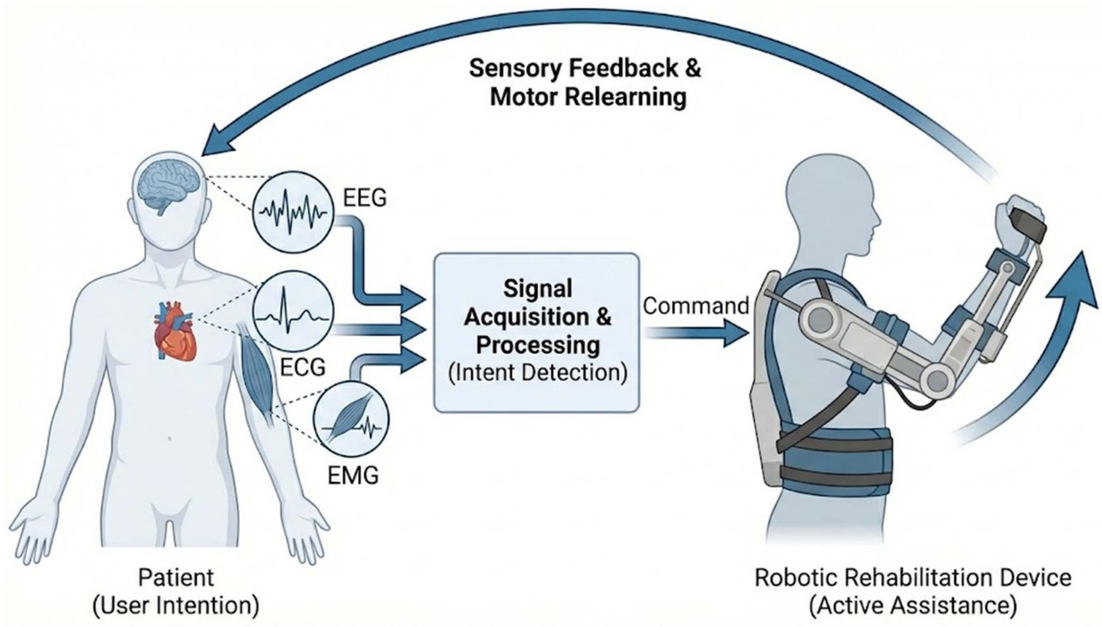

Figure 2. Robotic rehabilitation device controlled by biosignals.

In addition to biomechanical signals, physiological signals are increasingly considered in the design and control of robotic rehabilitation devices. Biosignals can provide insight into the user's physiological and cognitive state and can contribute to the estimation of movement attempt or intent. This enables adaptive assistance strategies in real time, supporting protocol personalisation and continuous monitoring of user responses. This strategy supports an interactive closed-loop therapy where the patient's own signals are used to bridge the gap between intention and execution, promoting motor relearning through active participation. Among biosignals, EMG provides information about the status of the peripheral nerves and muscles [52]. The electrical behaviour of muscle tissue during contraction provides information on the innervation status and biochemical condition of the examined muscle [53]. Given the strong relationship between muscle electrical activity and the force generated, sEMG is widely used as a non-invasive method to estimate the generated force and joint torque. It is also central in developing control algorithms [54, 55] for robotic applications based on user intent, such as robotic arms [56–58], exoskeletons [59, 60], and prosthetic devices [61]. The patients' muscle activation is one main expression of the rehabilitation efficacy [62]. Even in cases where patients cannot generate sufficient joint torques, sEMG can detect user intent and thus control exoskeletons, making it a valuable source for promoting mobility and recovery outcomes [63].

However, biologically controlled rehabilitation robotics remains heterogeneous and rapidly evolving, with substantial variation in sensing modalities, control architectures, and the level of clinical validation. Prototypes and pilot studies have been reported across multiple patient populations and clinical conditions. In detail, most prior reviews indicate that robot-assisted rehabilitation can be effective [10, 17, 61, 64, 65], but they often zoom in on a single disorder or a narrow class of technology [30, 66–69].

Given the available research, a systematic review evaluating the rehabilitative effects of biosignal-driven robotic solutions is still lacking.

Existing reviews, surveys, and editorials predominantly focus on exoskeleton control strategies [70–74] or on biosignal-based approaches [75–86], none of these works directly address the specific focus of this study. This highlights the novelty and originality of the present review. Rather than focusing on control algorithms or mechanical design features, this review synthesises evidence on rehabilitation outcomes achieved using biosignal-controlled robotic systems. Indeed, our focus is on robot-assisted systems driven by biosignals such as EEG, EMG, or ECG, as depicted in figure 2, rather than on technological feasibility, including control strategies or mechanical design. Accordingly, only studies reporting the use of biosignals and rehabilitative benefits, for example, improvements in motor function, e.g. muscle activation, Range of Motion (RoM), active torque, or other clinical outcomes, were included, with particular emphasis on studies employing experimental designs to confirm their advantages.

To capture recent advances in this rapidly evolving field, we reviewed studies published between January 2020 and early 2025.

Ultimately, the novelty of this review lies in its emphasis on the integration of biosignals into robotic control and on rehabilitative effectiveness within robotic solutions.

2. Methods

2.1. Goal and search strategy

The literature screening was conducted using the following inclusion criteria:

- Focus on studies assessing the relevance of technologies supported by robotic devices used in rehabilitation and controlled through biosignals.
- Select studies reporting improvements in rehabilitation-relevant outcomes resulting from the proposed solution, including clinical and functional measures.

We included studies investigating robot-assisted systems for movement actuation (e.g. exoskeletons, end-effector robots) in which the robot was controlled or modulated by biosignals. VR or other experiential interaction systems were considered only when they were integrated into a robotic rehabilitation setup (e.g. providing task scenarios or augmented feedback), but standalone VR-based interventions without a robotic component were not included.

This review was conceived as a perspective on biosignal integration within robotic rehabilitation systems, focusing on emerging biosignal-controlled robotic paradigms rather than on disease-specific clinical protocols. Therefore, we did not aim to comprehensively cover the extensive literature on well-established conditions such as stroke or Parkinson's disease. This decision was motivated not only because these disease-specific systematic reviews are already available [67, 87, 88], but also because disease-specific characteristics, compensatory mechanisms, and clinical protocols could act as confounding factors when the primary aim is to isolate and analyse the role of biosignals in robotic control. Such a choice could have introduced confounding factors and unnecessarily expanded the review, thereby reducing the specificity of our study aim. Instead, our eligibility criteria were defined in terms of the presence of a biosignal-controlled robotic intervention and the reporting of rehabilitation-relevant outcomes, irrespective of the underlying diagnosis. As a consequence, we did not systematically search for or pool disease-specific evidence for these highly investigated conditions, which we explicitly acknowledge as a limitation of the present review.

2.2. Information sources and database querying

To conduct this literature review, the PRISMA method (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) [89, 90] was followed, serving as a useful guide for systematic reviewers to enhance the reporting phase. The search query entered into three databases, Scopus, PubMed, and Web of Science, was a logical string containing the following keywords and their synonyms, which were searched in the title, abstract, or keywords of indexed records: 'robotic' or 'robot-assisted' in conjunction with the term 'rehabilitation', and biosignals such as ECG, EMG, and EEG. Documents that were not scientific articles published in specialised journals and records not in English were excluded. Here the query used in Pubmed: Search: (('robotic' OR 'robot-assisted') AND 'rehabilitation' AND ('EMG' OR 'ECG' OR 'EEG') NOT ('ERG' OR 'Electroretinography' OR 'Electroretinogram' OR 'EGG' OR 'Electroglottography') NOT ('Parkinson' OR 'Alzheimer' OR 'neurocognitive diseases' OR 'neurocognitive disease' OR 'stroke' OR 'tetraplegia' OR 'quadriplegia' OR 'cancer' OR 'multiple sclerosis' OR 'spinal cord' OR 'cerebral palsy' OR 'autism' OR 'acquired brain injury' OR 'neurological' OR 'neuromuscular' OR 'neurodegenerative' OR 'hemiplegia' OR 'consciousness' OR 'cognitive' OR 'randomised' OR 'trial' OR 'paediatrics' OR 'paediatric' OR 'neonatal' OR 'imagery' OR 'image' OR 'images' OR 'imaging' OR 'elderly' OR ''elderly person' OR 'elderly people')) AND ('2020'[Date—Publication]: '2025'[Date—Publication]) AND (English[Language]).

2.3. Time frame selection

Studies published between January 2020 and January 2025 were prioritised to ensure that the review reflected the most recent phase of development in robotic rehabilitation and biosignal interpretation. This choice was motivated mainly by the rapid evolution of the field. The main objective of the temporal restriction was to examine evidence that is more representative of current technological and methodological approaches.

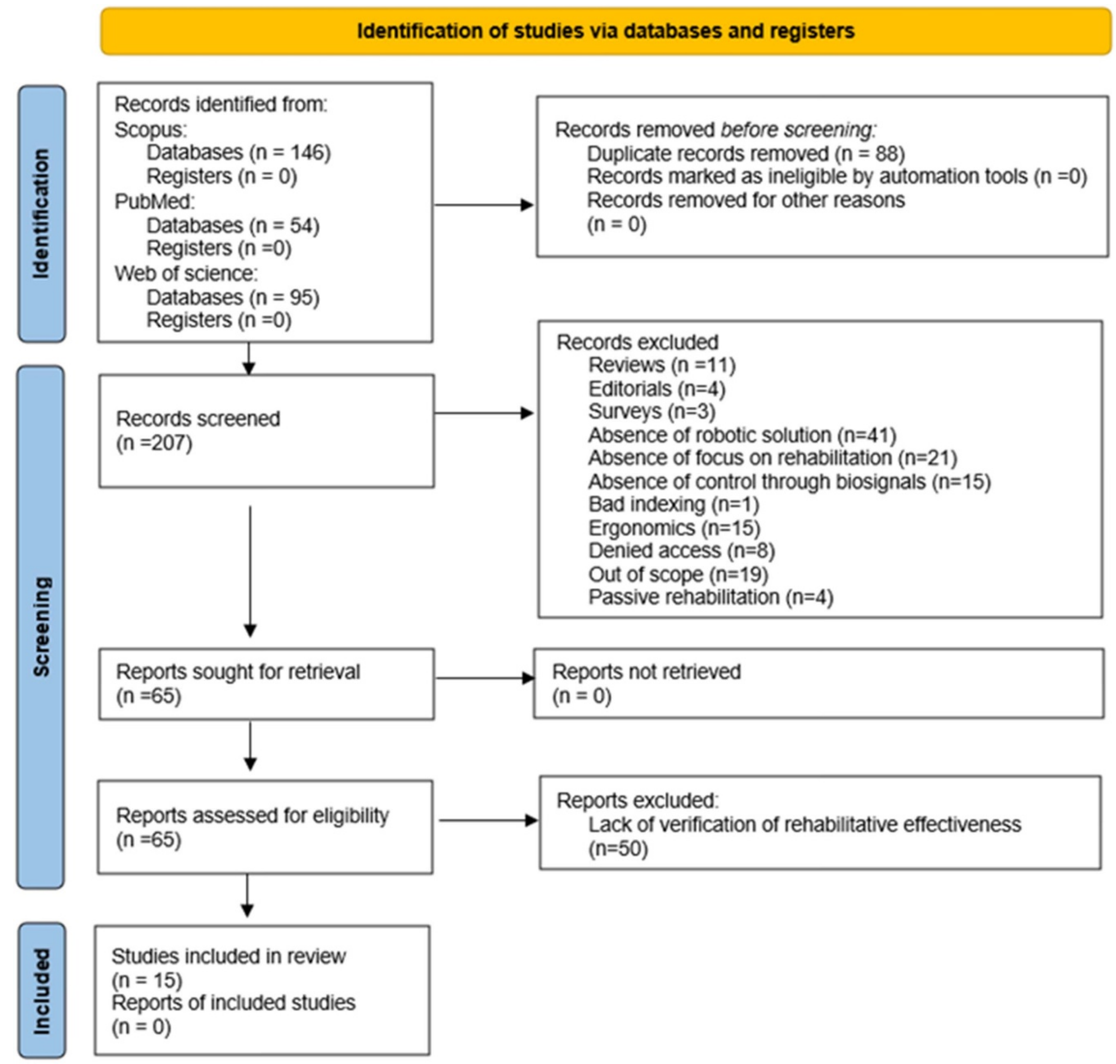

Figure 3. Workflow for screening of the articles following PRISMA guidelines.

2.4. Data extraction and study classification

First, basic bibliographic information was extracted for each record to be screened (i.e. authors, title, publication year, DOI, and abstract). To reduce the risk of bias, three independent reviewers then assessed the records against the predefined inclusion/exclusion criteria. Eligible studies subsequently underwent full-text review and data clustering. Inter-rater agreement was assessed using Fleiss' kappa, yielding a value of 0.784, which indicates substantial agreement.

2.5. Screening flow

The following diagram in figure 3 shows the topics related to the included and excluded articles. The search of the PubMed database returned 54 articles, the search in Scopus returned 146, and the search in Web of Science returned 95, for a total of 295 records. After removing duplicates ($n = 88$), 207 records remained. Next, titles and abstracts were screened, resulting in the exclusion of 140 records. In particular, records were excluded if they were reviews ($n = 11$), editorials ($n = 4$), or surveys ($n = 3$); did not focus on rehabilitation ($n = 21$) and robotic solutions ($n = 41$); did not include biosignal-based control ($n = 15$); were incorrectly indexed (e.g. classified as original articles but actually reviews), $n = 1$; focused primarily on ergonomics ($n = 15$); had restricted or denied access ($n = 8$); addressed passive rehabilitation only ($n = 4$); or fell outside the scope ($n = 19$). Thus, 65 full-text articles were assessed for eligibility. Of these, 50 were excluded after full-text review due to the absence of (i) an experimental rehabilitation protocol, (ii) rehabilitative outcomes, or (iii) evidence of performance improvement attributable to the proposed solution, criteria that were essential for inclusion in this study. Consequently, 15 articles were included in this systematic review. In each selected study, relevant information was extracted to compare methods, populations, and results. In particular, the following data

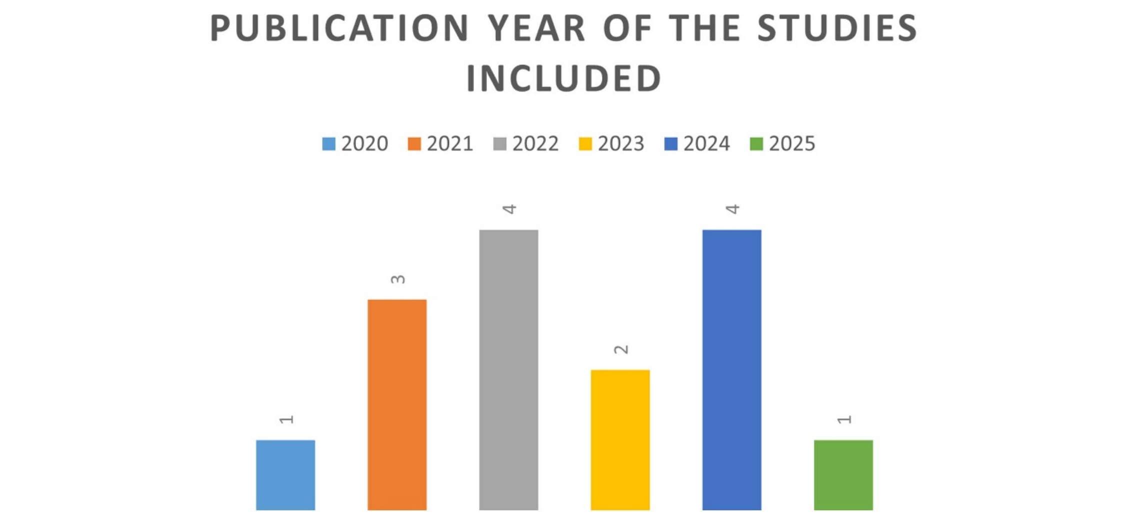

Figure 4. Number of studies included in the review per year of publication (2020–2025).

were collected: the included studies were grouped and discussed according to the following variables: target joint, robotic device type and core technology used in the solution, the role of biosignals, the signal acquisition hardware, the extracted features, and the rehabilitative application of the proposed solution.

3. Results

3.1. Descriptive characteristics of the included studies

A total of 15 articles were included in the results of the systematic review. As shown in figure 4, there is an increase in the publication of studies on the topic in 2022 and 2024.

Of the 15 included papers, 11 addressed upper-limb rehabilitation and 4 addressed lower-limb rehabilitation. The analysis was performed separately for the two groups; within each group, studies were discussed in the following order: (i) description of the rehabilitative robotic solutions and integration of biosignals (e.g. EMG) within the control architecture and/or feedback loop, and (ii) experimental Protocol, study population and outcomes.

3.2. Upper limb rehabilitation

Table 1 summarises the included articles on upper limb rehabilitation, including the joint, the kind of robotic device, the main technology used, the role of the biosignal, the acquisition device, the features extracted and the rehabilitative relevance.

Whether through exoskeletons, soft/wearable exosuits (as actuated gloves), or hybrid systems that incorporate FES, or IoT-based devices, robotic solutions are central in improving motor function and in supporting recovery. The common points across these studies are:

- Use of robotic assistance: robotic systems are integrated into the rehabilitation program to support motor function and recovery, improving real-time feedback;
- Real-time Feedback: sensors allow for adaptive responses that improve the effectiveness of rehabilitation, customising exercises or assistance based on individual needs. This aspect is also improved thanks to the use of IoT-based solutions.
- Subject-specific customisation: these systems are designed to offer personalised rehabilitation protocols according to the subject's condition. Using techniques such as pain detection, compensatory movements, and tracking motion, the technology can adapt the rehabilitation process to the individual's progress and limitations.

3.2.1. Rehabilitative robotic solutions and the integration of biosignals

Toro-Ossaba *et al* [91] presented a soft exoskeleton for the elbow, controlled by myoelectric signals using a MRAC approach. This system was able to reduce the muscular effort (joint torque RMS) required by the subject during flexion-extension movements. EMG was acquired with two channels from the biceps and triceps at 1024 Hz, providing a continuous estimation of the torque generated by the user. The raw EMG was filtered using a 4th-order Chebyshev band-pass filter with cutoff frequencies 10–500 Hz to attenuate DC offset and noise. The filtered signal was then segmented using a sliding-window approach with window length WL = 200 samples and increment WInc = 100 samples. For each window, the RMS was computed to obtain the RMS envelope. To further smooth the envelope and improve stability, a 1st-order Butterworth low-pass filter with a cutoff frequency of 1 Hz was applied. Finally, the resulting envelope was normalised by the maximum RMS value obtained during the calibration procedure. An adaptive Kalman filter was employed (as part of an adaptive state estimator) to estimate the exoskeleton state (joint angle and angular velocity) from the exoskeleton input-output measurements. In active mode, the estimated joint torque obtained from the processed biceps/triceps EMG (with an offset correction) was used as the reference-model input, enabling the exoskeleton to modulate assistance in real time according to the user's estimated torque need.

In another case, a rigid wrist exoskeleton was used to provide repetitive upper limb training [92]. The intended motion is estimated from EMG patterns and used to control both a wrist assist robot and FES. EMG acquired at 1000 Hz was A/D-converted and preprocessed with a 2nd-order Butterworth band-pass filter, full-wave rectification, and 2nd-order low-pass smoothing. The resulting signals were baseline-corrected using rest EMG, normalised by each channel's maximum value, and further normalised so that the sum across channels equals one, yielding a muscle activation pattern vector. A R-LLGMN, incorporating a Markov model and Gaussian mixture modelling, estimated in real time the most likely intended movement. Based on the inferred intention, the system delivered robotic assistance and applied FES to induce the corresponding wrist motion;the existence of the system drive is determined by a threshold value. In a subsequent extended study, the same hybrid robot-FES system was used to investigate motor learning and retention effects associated with EMG-based hybrid instruction [93]. While the core technological architecture and EMG processing pipeline remain unchanged, the focus shifted to the quantitative evaluation of learning outcomes, including movement accuracy, smoothness, stability, and retention.

In addition to rigid exoskeletons, soft wearable robots and end-effector devices have been developed for hand rehabilitation. Sierotowicz *et al* [94] presented a rehabilitation platform that integrates an actuated soft glove controlled by an intention-detection system based on ML applied to muscular activity. The actuated soft glove (Myo-glove) is designed to assist hand closure. The glove was lightweight and compliant. Movement intention was detected through forearm EMG using ML techniques, specifically Ridge Regression and RFF. The EMG sampled at 2 kHz was pre-processed to extract an activation envelope, using a 35–350 Hz band-pass filter, full-wave rectification, and a 4 Hz low-pass filter; this envelope served as input to ML models to continuously estimate the intended grasp force. The estimated force was then integrated in a closed-loop control architecture to generate proportional assist-as-needed actuation, leading to reduced muscular activation, particularly at medium-to-high force targets. Khan *et al* [95] developed a soft robotic sleeve based on PAMs to assist flexion and extension of the elbow in baseball pitchers. The system integrates a pump that supplies air to the actuators and EMG sensors to enable an EMG-triggered active, providing pneumatic support only when the triceps or biceps exceed the activation threshold. The EMG signals, acquired from the biceps and triceps at 1 kHz, were processed through full-wave rectification and second-order Butterworth band-pass filtering (20–450 Hz) and normalised to maximal baseline activation. Processed EMG was used both to trigger assistance and to evaluate rehabilitation outcomes. This approach provided and enhanced rehabilitation. EMG was also used to evaluate the reduction of muscle activation and the CCI. Osborn *et al* [96] report on a high-tech, osseointegrated anthropomorphic prosthetic arm that was used extensively in a home setting by an amputee. The device included 26 articulated joints and 17 actuators, providing an integrated human-machine interface model for restoring upper limb function and offering therapeutic benefits. The EMG control was advanced, relying on a linear discriminant analysis pattern recognition classifier applied to 16 wireless EMG channels (Myo Bands) to enable simultaneous control of the fingers, wrist, and elbow. EMG signals recorded at 1 KHz were processed using sliding windows (200 ms, 20 ms step), and standard time-domain features (e.g. mean absolute value, waveform length, zero crossings, slope sign changes) were extracted to classify movement intentions.

In the prosthetic domain, Yang and Liu [97] showed a myoelectric prostheses proposing a convolution neural network-based approach capable of decoding multi-DoF wrist movements directly from raw EMG signals sampled at 1926 Hz, without manual feature extraction. A large dataset of sEMG signals with 3D wrist kinematic labels was collected, and an end-to-end CNN was trained to map EMG patterns to complex wrist movements across multiple axes in real time. The CNN operated directly on segmented raw EMG signals, recorded from the forearm, without manual feature extraction, and provided

Table 1. Table of studies included for upper limb rehabilitation. Abbreviations: MAV (mean absolute value), MAC (model accuracy classification), MAE (mean absolute error), SVM (support vector machine), GMM (Gaussian mixture model), CNN (convolutional neural network), MRAC (model reference adaptive control), RFF (random fourier features), RLS NN (recursive least squares neural network), DoF (degrees of freedom), NN (neural network), pneumatic artificial muscles (PAMs), co-contraction index (CCI), ULCDRR (upper-limb cable-driven rehabilitation robot), R-LLGMN (a recurrent probabilistic neural network), ML (machine learning), FES (functional electrical stimulation).

References	Joint	Device type	Main technology	Role of EMG	Acquisition device	Features	Rehabilitative Relevance
[91]	Elbow	Soft elbow exoskeleton	MRAC + RLS + Kalman filter	Joint torque estimation from EMG signals.	Harada sEMG + joint sensors	MAE angle/speed, RMS torque (est. + required)	Elbow motor rehabilitation with assisted passive and active movements for functional recovery.
[92]	Wrist	Assistive wrist robot	Probabilistic NN	Motor intention detection for robot+FES.	AMP04 EMG + FES stimulators	Normalised muscle activation vector p(t)	Rehabilitation of patients with upper limb paralysis to improve motor function and facilitate movement relearning.
[93]	Wrist	Assistive wrist robot	R-LLGMN + minimum jerk model	Motor intention decoding + passive learning with FES.	AMP04 EMG + FES stimulators	Normalised EMG amplitudes + coordination vector	Wrist rehabilitation for impaired control to promote motor learning and recovery.
[94]	Fingers	MyoGlove (soft glove)	ML (Ridge Regression & RFF)	Estimates grip force for assisted motion.	Delsys EMG + flex sensors	EMG envelope values used as ML input	Task-oriented hand grasp training for motor-impaired users, enhancing agency and intuitive control for motor recovery.
[95]	Elbow	Soft robotic-based elbow rehabilitation device	PAMs	sEMG used to detect movement intention, monitor muscle activation.	PowerLab system (ADInstruments)	Average EMG amplitude, Peak EMG amplitude and CCI	Portable soft robotic sleeve providing passive and active-assisted elbow rehabilitation for baseball pitchers by supporting flexion-extension while reducing biceps/triceps load.
[96]	Elbow, wrist, fingers	Modular Prosthetic arm	Pattern recognition (EMG)	Residual EMG used to control fingers simultaneously.	Embedded EMG electrodes	MAV + spatial/temporal activation	Functional rehabilitation for upper-limb amputees using advanced prostheses to improve daily activities and personalised skill acquisition.
[97]	Wrist	Robotic arm/hand	CNN	Multi-DOF wrist decoding for intuitive control.	EMG armbands	Raw signals only (no features)	Control of prosthetic and supernumerary robotic limbs for assistive tasks, with preliminary amputee tests indicating motor rehabilitation and functional restoration potential.

(Continued.)

Table 1. (Continued.)

[98]	Arm	ULCDRR	GMM	Decode 3D voluntary forces for synchronisation.	8-channel EMG sensors	3D force from 8 channels; RMSEx, RMSJ, IF	Robot-assisted motor rehabilitation with precise, compliant human–robot interaction under muscle fatigue.
[99]	Wrist	Wrist rehab. robot	Dual fuzzy logic + Kinect	Contraction detection for pain/adaptation estimation.	EMG + Kinect camera	EMG: RMS,SSI, v-order, LOG	Remote wrist rehab. with gesture-based therapist control and fuzzy-logic pain monitoring for safe home therapy.
[100]	Wrist	Wrist IoT Rehab. Robot	Fuzzy logic controller	Estimates fatigue; real-time model adaptation for personalised therapy.	EMG sensors	Mean freq., power, freq. ratio, power spectrum ratio.	Remote-monitored wrist rehabilitation for fractured patients to improve motor function.
[101]	Elbow-forearm	Elbow exo. + FES system	Dual fuzzy logic	Muscle contraction and pain estimation for adaptive control.	Myoware EMG, AgCl electrodes	EMG: LOG, SSI, V-ORDER, RMS	Upper-limb motor rehab. and pain management for forearm fractures and elbow flexion/extension impairment.

real-time predictions (6–8 ms latency) of wrist motion across multiple axes. The versatility of the model was demonstrated through successful control of various devices (robotic arms, prosthetic hands, and even a supernumerary robotic limb) during functional tasks (e.g. pouring liquids, screwing bolts, inserting objects, building block structures). Furthermore, transfer learning techniques were used to adapt the system to amputee users. Still within the field of upper-limb rehabilitation, Zheng *et al* [98] introduced an admittance control system for an upper-limb cable-driven rehabilitation robot, in which the user's 3D voluntary forces were estimated in real time from EMG signals using a GMM. The EMG pipeline was explicitly feature-based rather than raw: signals were acquired at 1 kHz, notch-filtered at 50 Hz, band-pass filtered (20–450 Hz), full-wave rectified, and low-pass filtered (4th-order Butterworth, 4 Hz) to obtain amplitude envelopes. The envelopes were normalised to maximum voluntary isometric contraction, and RMS features were extracted using a 300 ms moving window. Dimensionality reduction was then performed via Principal Component Analysis (retaining 99% cumulative variance) to form the EMG predictor vector. In parallel, end-effector forces measured by a six-axis sensor were median-filtered (5 ms) and min-max normalised to build the force feature vector. The GMM was trained to model the joint probability distribution between processed multichannel EMG features and measured end-effector forces, enabling real-time estimation of force magnitude and direction via Gaussian Mixture Regression. The estimated forces were then employed as inputs to an admittance controller, allowing compliant human–robot interaction based on the user's exerted effort. Incremental learning was employed to compensate for muscle fatigue: the GMM was periodically recalibrated during therapy (updating its statistical parameters) to account for changes in the EMG-force relationship over time.

Another example of a hybrid approach enabling the detection of perceived pain through EMG was presented by Bouteraa *et al* in 2021 [99]. The authors tested their telerehabilitation system, which integrated an IoT-controlled wrist robot with pain detection capabilities, in a real clinical setting under the remote supervision of a physiotherapist. From the extracted EMG signal, the following parameters were used as inputs to a fuzzy logic system to estimate muscle contraction:

- EMG RMS: measures the strength of muscle contraction.
- EMG SSI : estimates muscle energy.
- EMG vorder: estimates exerted muscle force.
- EMG Logdetect: estimates exerted muscle force.

Information on signal-processing steps is not reported in the cited work. A second fuzzy logic module, operating in cascade, estimated pain levels by combining data on muscle contraction, resistive force, and RoM (from motion encoders). If high pain levels were detected but the patient had already achieved sufficient RoM, the system could continue the exercise with reduced intensity. In remote tests, patient pain thresholds were not exceeded thanks to automatic regulation via fuzzy logic. Physiotherapists were able to monitor a 'virtual' pain level in real time through a human-machine interface. This proactive strategy aimed to enhance therapy tolerability by preventing pain peaks that often disrupt or reduce engagement in traditional rehabilitation sessions.

In the context of muscle fatigue monitoring, a further approach was described in the 2022 work by Bouteraa *et al* [100]. In the study, EMG signals were acquired from the forearm during wrist exercises, and through feature extraction (e.g. mean amplitude, spectral entropy) and classification, the patient's muscle fatigue level was estimated. This estimation was then used to update the dynamic model of the wrist and redistribute torque between the patient and robot. When fatigue increased, the controller reduced the load on the patient (increasing robotic assistance), ensuring exercises remained effective yet sustainable. This enabled real-time personalisation of exercise intensity based on the patient's physical state, helping to prevent injury. In the 2022 study [100], an IoT-enabled wrist rehabilitation robot with a dynamic mathematical model was presented to characterise both passive (inertia, damping, stiffness) and active torque components. A cascaded fuzzy logic controller used the output of the fuzzy classifier to compute and update the patient's joint model based on the estimated level of fatigue. It was estimated using four key EMG-based parameters, providing a more detailed analysis compared to the 2021 pain-only model:

- MNF: indicates variations in the average frequency of EMG signal.
- MNP: evaluates muscle power.

- FR: analyses the ratio of high to low-frequency bands, proposed to distinguish between contraction and relaxation.
- Power spectrum ratio: reflects changes in the concentration of spectral power distribution around the dominant peak.

These parameters were processed by the fuzzy classifier, which automatically adjusted robotic assistance to yield a fatigue level. Other information on EMG signal processing is not provided. This fatigue estimate is then incorporated into the wrist torque computation (including fatigue-related torque compensation) and used to adapt robot behaviour and assistance during the rehabilitation session. In a subsequent study in 2024, Abdallah and Bouteraa [101] introduced an OSCS within an upper-limb rehabilitation exoskeleton, integrating a fuzzy logic-based pain detection module to dynamically adjust FES intensity. In this approach, fuzzy algorithms monitored patient biosignals, including EMG, to estimate pain levels and adjust both the exoskeleton control parameters and FES levels in real time. Fuzzy rules defined by experts were used to estimate muscle contraction. The resulting output was then used as input to a second fuzzy system that assessed pain based on resistive torque, muscle contraction, and RoM. Pain monitoring was essential in this context, since the exoskeleton modulated stimulation in response to physiological signals, increasing the intensity of wrist exercise. Three stimulation modes, pain relief, massage, and relaxation, were implemented, with real-time feedback on RoM and angular velocity, ensuring accurate exercise execution. The main controller adjusted the robot and stimulation parameters based on real-time input, enabling the therapy to continue autonomously, under physiotherapist supervision. sEMG signals were acquired at 100 kHz from the extensor digitorum longus and flexor digitorum longus muscles using AgCl electrodes placed according to SENIAM guidelines and recorded through a MyoWare sensor. The raw EMG signals were amplified and processed through a Butterworth band-pass filter (10–2000 Hz) and a 50 Hz notch filter before feature extraction.

The system used four EMG features (RMS, SSI, V-order, and log-detect) as inputs to the fuzzy controller to estimate pain and adapt therapy accordingly. In addition, current sensors captured changes in muscle tension, while motion encoders quantified the achieved RoM.

3.2.2. Experimental protocol, study population and outcomes

Across the literature, rehabilitation designs vary substantially in duration, session frequency, participant type, and study aim. This heterogeneity reflects both technology maturity (prototype validation in healthy volunteers vs evaluation in patients) and study design (feasibility vs clinical trials). Most studies are pilot investigations or feasibility trials involving a small number of subjects, often composed of healthy volunteers, and mainly focus on demonstrating the system's operational principles rather than assessing its large-scale clinical effectiveness. Outcomes range from traditional clinical, functional metrics (for example joint RoM and stiffness) to quantitative indicators of motor performance or interaction (muscle activation, pain level, etc), and patient-reported feedback. Overall, the results suggest positive preliminary trends: functional improvements in the patients involved, greater efficiency in assisted movements, and good acceptance of the technologies. However, the magnitude of these improvements varies and is often assessed only in preliminary analysis.

In the context of wrist rehabilitation, Toro-Ossaba *et al* [91] proposed a myoelectric MRAC approach for elbow flexion-extension, tested in passive mode where the exoskeleton moved the user's arm along a predefined trajectory, and active-assisted mode, where the user attempted the movement while the exoskeleton assisted with the required torque to follow the reference. Ten healthy participants (6 male, 4 female; 18–30 years) performed repeated tasks to build EMG/kinematic datasets for training a muscle torque estimation model. The controller's performance was then evaluated over multiple sessions (passive vs active, with and without recalibration). In active-assisted mode, the torque required by the user was reduced by 34%–40% RMS, indicating substantial assistance. In terms of precision, the average tracking error was approximately 4.5° in passive mode and around 10° in active-assisted mode. While this increase was expected due to user-induced variability in active mode, a 10° error remained within functionally acceptable limits for elbow motion.

Extending this perspective to wrist rehabilitation, Takenaka *et al* in 2023 [92] introduced a hybrid rehabilitation system that combines robotic assistance with FES. In their study, six healthy participants were divided into two groups: three received training with the hybrid robot+FES system, and three formed a control group that trained with only visual feedback. The training involved wrist pointing tasks. Both groups showed similar improvements in task performance, indicating that the hybrid approach was at least as effective as conventional visual-feedback-based training. Notably, differences emerged during the retention test performed seven days later: the hybrid group retained their motor improvements to a greater extent than the control group. This suggested that combining external sensory-motor feedback (via robotics) with internal muscle activation (via FES) promoted more durable motor learning. Hence, the hybrid system not only facilitated movement execution during training but might also have induced stronger motor adaptations, with possible rehabilitation effects similar to those observed during motor learning in healthy subjects.

A 2024 follow-up study by the same authors [93] presented an EMG-controlled hybrid system that integrated a wrist orthosis and FES, all driven by the EMG signals of the users. This system was evaluated in a cohort of twelve healthy male subjects who trained using a serious-game interface designed for wrist pointing tasks. Participants were divided into two groups: one trained with the EMG-robot-FES hybrid system, and the other used visual feedback only. All participants performed the same point-to-target wrist movement over a training schedule that included baseline tests, 20 sessions, and follow-up evaluations (pre-, mid-, post-training, and retention one week later). The hybrid group received real-time multimodal feedback triggered by EMG signals, while the control group relied solely on visual guidance. Both groups improved in accuracy, stability, and smoothness; however, the hybrid group demonstrated better retention and maintained performance gains after one week. These findings demonstrate the potential of EMG-driven hybrid systems in achieving long-term motor rehabilitation outcomes.

In a related direction, the EMG-driven ML approach by Sierotowicz *et al* [94] introduced an exoglove that was evaluated on six healthy participants during a single experimental session. Each subject performed grip tasks under three different assistance conditions: no assistance, control via Ridge Regression, and control via RFF, with variable grip forces (5 N, 10 N, 15 N). The results revealed that both ML-based control strategies reduced muscle activity, particularly in the abductor pollicis brevis and flexor digitorum, by up to 50% at higher force levels (>10 N). The controllers demonstrated good predictive accuracy ($R^2 \approx 0.8$ for Ridge Regression; ≈ 0.73 for RFF) and rapid response times (with a 200–300 ms delay), suggesting potential use in patients with motor deficits. A long-term application of myoelectric control systems was illustrated by Osborn *et al* [96], who described an amputee using an advanced myoelectric prosthesis at home as part of daily activities over several months. This continuous use acted as a form of functional therapy, promoting motor adaptation. Across the observation period, the EMG amplitude required to achieve the same control performance decreased by up to 34.7%, without sacrificing performance. This is consistent with a progressive optimisation of motor command, potentially driven by task-specific motor learning.

In [95], five healthy male baseball pitchers (ages 20–24) tested a soft robotic sleeve under two operating modes: steady passive mode and Active Surge Flex Mode. In steady passive mode, elbow flexion/extension was continuously assisted by PAMs with no voluntary activation required. In Active Surge Flex Mode, PAM assistance was triggered only when EMG exceeded predefined thresholds (0.45 mV for biceps, 0.25 mV for triceps). Each participant performed 10 pitching actions without the device (baseline), followed by 10 in steady passive mode and 10 in Active Surge Flex Mode. Both modes reduced muscle activation during elbow flexion/extension. Specifically, in steady passive mode, biceps activation decreased by 60% and triceps activation by 40%. In Active Surge Flex Mode, where assistance was triggered by EMG thresholds, further reductions were observed: biceps activity decreased by 50% and triceps activity by 30%. The CCI also decreased from 0.31 to 0.12, reflecting a substantial reduction in unnecessary co-activation of antagonistic muscles and suggesting more efficient movement. So, the results suggest that the soft robotic sleeve improved movement efficiency, reduced muscular strain, and may support rehabilitation, alleviating fatigue during repetitive pitching motions.

In [97], the authors collected sEMG data from 14 healthy subjects to train and evaluate a CNN-based framework. The model was then tested online for teleoperation of a robotic arm during representative daily tasks (e.g. pouring, turning a key/screw-like action, and object insertion), showing that EMG-driven DL can be used for real-time command generation in multi-step manipulation tasks. In a separate demonstration, an upper-limb amputee controlled a virtual prosthesis during motor rehabilitation training. The participant was able to control each DoF with notable precision, suggesting potential rehabilitative benefits, although combined movements were reported as difficult, possibly due to the extended post-amputation period. In addition to this approach, Zheng *et al* [98] proposed an Upper limb EMG-based cable-driven robotic system that was tested in a protocol where participants performed tracking movements using the robot's end-effector under active-assisted control. Here, the robot's assistance was modulated based on the estimated voluntary force from EMG. The system was tested on eight healthy individuals, including the induction of muscle fatigue, to evaluate controller adaptability. The proposed calibrated model GMM reduced EMG activity, especially in muscles such as the biceps brachii, triceps (long and lateral heads), and medial/posterior deltoid, compared to the initial model, demonstrating superior adaptation under fatigue and reducing its impact.

While the previous work has focused on healthy populations, recent studies have shifted toward clinical subjects and extended therapy durations, providing a more comprehensive assessment of rehabilitative outcomes. Bouteraa *et al* in 2021 [99] tested a smart telerehabilitation system in a real clinical setting with six subjects recovering from wrist fractures (within one week of cast removal). The 10-d protocol focuses on wrist abduction/adduction and was based on a remotely operated IoT robotic system. The physiotherapist guided the movements, which were reproduced by the robot in real time, tilting the hand of the patient in one direction and maintaining the position for 5 s. This is repeated for three sets of 12 repetitions. The workflow can be described in three different phases:

1. Setup and configuration: The subject remained passive during configuration of the session on the human machine interface of the therapist, including the setting of the safety threshold for pain on the therapist interface. The desired wrist motion was derived from Kinect-based gesture recognition, while the performed joint position/RoM was measured via encoder feedback.
2. Therapeutic exercises with pain monitoring: EMG features, motor current (as resistance proxy), and performed RoM are fused through a cascaded fuzzy logic system to estimate pain. The pain estimated was displayed to the therapist and given into the control loop for safe robot actions.
3. Progress assessment and therapy adjustment: to generate rehabilitation reports including session data (iterations, desired/obtained RoM) are stored and used to generate rehabilitation reports, including the Rehabilitation Progress Factor. A 2-DoF robot and a dynamic model were used for personalised assistance.

Rehabilitation performance showed a recovery of the wrist RoM of up to 73% of the physiological RoM in the best-performing subject, confirming the effectiveness and adaptability of the system, especially when combined with telemonitoring for remote adjustment.

In a 2022 follow-up study by the same authors [100], the emphasis was on adapting therapy under muscle fatigue conditions. The protocol involved three subjects with a recent wrist fracture. The rehabilitation program was performed for ten days. The exercise was repeated three times, resulting in a total of 12 sets. The structure of the rehabilitation protocol was based on three phases:

1. Initial evaluation: Passive assessments were used to characterise joint biomechanics (e.g. passive stiffness and inertia). The robot was fully active while the patient remained passive.
2. Assisted therapy with adaptive resistance: Participants then performed the target movements with robotic support, while real-time monitoring based on EMG adjusted resistance levels automatically.
3. Active training for full recovery: In the final stage, patients executed the movements largely independently, with only minimal robotic assistance.

Improvements were observed in abduction/adduction movements. In the patient showing the best rehabilitation outcomes, active muscle torque rose up to 2.09 Nm. Passive wrist stiffness decreased across patients: for Patient 1, it decreased from 0.26 Nm to 0.21 Nm, while the lowest value of 0.09 Nm was recorded for Patient 3. These findings are consistent with a rehabilitative effect of the proposed approach and suggest a potential increase in therapy efficiency. The integration with telerehabilitation further improved the treatment, enabling remote monitoring and allowing real-time adjustments of rehabilitation parameters. Although the small sample size and the absence of a control group, this study introduced a personalised rehabilitation protocol, which suggested a move from technical feasibility to clinical validation.

Continuing the line of personalised robotic rehabilitation, Bouteraa *et al* in 2024 [101] introduced an OSCS, incorporating both pain monitoring and real-time EMG-driven adjustment, enhancing efficiency and adaptability in rehabilitation. As in earlier studies, the physiotherapist began the therapy through a LabVIEW-based interface, entering subject-specific data (for example, pain threshold, stimulation intensity). The system offered:

- Manual mode: Therapist sets stimulation before motor activity (one of: pain relief/massage);
- Automatic mode: A fuzzy classifier autonomously adjusted stimulation and robotic assistance based on EMG, torque sensors, and RoM encoders. From this information, pain is estimated;
- Relaxation phase: the system automatically switches to a relaxation stimulation mode after each session for recovery.

After two weeks of therapy on a subject with a forearm fracture, the elbow's RoM increased from 60° to 110° (+83%). Improvements were reported in elbow flexion/extension performance (the platform also supports forearm pronation/supination exercises). Passive joint torque decreased by approximately 30%, facilitating joint movement and dynamic therapy adjustment based on pain, facilitated by telemedicine. These results underscore the ability of the system to prevent overload, enhance motor function, and facilitate remote rehabilitation, ideal for patients post-stroke. Although still at the pilot-study stage, these developments highlighted the potential of these systems for more personalised, adaptive, and remotely manageable rehabilitation, although evidence remains at a pilot stage.

3.3. Lower limb rehabilitation

The four studies integrate robotic systems into rehabilitation solutions, emphasising the increasing role of technology in supporting the recovery of movements for patients. The devices analysed adopt advanced control strategies, including ML, predictive models, adaptive control algorithms, and biofeedback based on EMG signals to improve motor recovery. In fact, among the studies included, one of the main approaches identified is the use of EMG for the control of exoskeletons and the personalisation of rehabilitation therapy. A crucial advantage of EMG-based methods is that, regardless of the subject's inability to generate sufficient joint torques, it is still possible to detect the user's movement intention and consequently control the exoskeleton. The reviewed studies examine how biosignal-driven robotic systems contribute to maximising subject engagement and improving rehabilitation efficacy through adaptive control, emphasising how robotic devices can reduce therapist engagement and improve the efficacy of the treatment. Nevertheless, some differences regard the use of the technologies employed. Table 2 summarises the results from the literature analysis concerning lower limb rehabilitation, following the same approach used for the upper limb. The sensors integrated into the proposed solutions include EMG electrodes for detecting muscle signals, force sensors to measure mechanical interactions between the user and the device, and inertial measurement units to track movement. EMG signals are processed to extract features such as muscle activation intent and minimum activation thresholds. The analysed studies describe different rehabilitation approaches designed for specific goals, with differences in experimental protocols and outcomes.

3.3.1. Rehabilitative robotic solutions and the integration of biosignals

Chen *et al* [102] introduced a control method based on a two-layer admittance algorithm that uses the EMG signal of the user to adjust the gait trajectory of the lower extremity exoskeleton, promoting a more active participation in rehabilitation.

This method assigns different impedance levels to the two layers: the outer layer, characterised by lower impedance, acts as an adaptive layer for gait trajectory, while the inner, stiffer layer provides fine-tuning adjustments. Through this strategy, participants were able to operate the exoskeleton to alter walking pace and step timing, adjusting stride length and duration, modifying trajectory amplitude and cycle period. This resulted in changes in walking speed (ranging roughly from 0.110 $m\,s^{-1}$ to 0.120 $m\,s^{-1}$). sEMG signals were acquired from the quadriceps femoris and hamstring muscles using a wearable and multi-channel Myo thigh-band. The signals were pre-processed, including filtering using a particle filter, normalised to each participant's maximum voluntary EMG, and converted into muscle activation levels. An EMG-based intention signal was then computed, combining antagonist muscle activation and further processed across successive strides to isolate the active component used in the admittance control law. By using this EMG-based intention input instead of traditional interaction-force sensing, the system enabled users to adapt gait patterns even when they could not produce sufficient joint torque. The rehabilitation setup included a treadmill, a body-weight support module, a lower-limb exoskeleton with four DoF in the sagittal plane, EMG sensors, and a VR screen providing continuous feedback. The display was placed in front of the user and supplied step-by-step guidance in real time, helping the subject to reproduce defined gait patterns. Additionally, the activation levels of the quadriceps femoris and hamstring muscles were visualised above the instruction panel.

Similarly, studies such as that of Han *et al* [103]. proposed a control model based on adaptive oscillators and admittance control to synchronise the knee exoskeleton's movement with the subject. EMG signals were collected during a learning mode phase, in which the subject performed knee flexion and extension movements while the exoskeleton provided no assistive force, thereby creating a predictive model of the movement. In this phase, surface EMG signals from the quadriceps femoris and biceps femoris muscles were acquired at 1000 Hz, processed using RMS extraction, which has a good correlation with the strength of muscle contraction and more sensitive to muscle fatigue. Butterworth low-pass filtering, normalisation, and associated with the phase of the knee motion estimated via an AFO. A locally weighted regression algorithm was then used to learn a phase-dependent EMG envelope. Once

Table 2. Lower limb rehabilitation solutions. Root mean square error (RMSE), reinforcement learning (RL), force/torque (F/T), -long short-term memory (LSTM), degrees of freedom (DoF), series elastic actuator (SEA), extended reality (XR), adaptive frequency oscillator (AFO).

Reference	Joint	Device type	Main technology	Role of EMG	Acquisition device	Features	Rehabilitative Relevance
[102]	Hip and Knee	Exoskeleton	EMG-based admittance control	Real-time motion intention recognition for assistance	Myo thigh-band EMG	Stride count, mean muscle activity, RMSE	Lower limb rehabilitation for patients with motor impairments.
[103]	Knee	Knee exo-skeleton	Admittance control + AFO	EMG used to model torque in training phase	EMG sensors, torque sensors, Nano-AHRS	EMG RMS, joint angles, torque, AFO phase/freq	Assistive technology designed to support and enhance lower limb gait rehabilitation, aimed at individuals with motor impairments or age-related mobility limitations.
[104]	Knee	1-DoF exo-skeleton	Model Predictive Control + Fuzzy Logic	Real-time joint torque estimation for adaptive support	Surface EMG, encoders, SEA actuator	EMG envelopes, torque estimation via antagonist model	Assist-as-needed control for a knee exoskeleton, intended to support lower-limb rehabilitation in populations with partial motor capacity
[105]	Ankle and foot	XR headset system	XR sim + remote reha. feedback	Controls virtual limb using residual EMG	Intan RHD2216, Azure Kinect, Arduino, RPi	Binary EMG detection, 3D joint coords, EMG fluctuation	Lower limb amputee rehabilitation, facilitating remote interaction between patients and experts, and improving motivation and muscle memory during rehabilitation training.

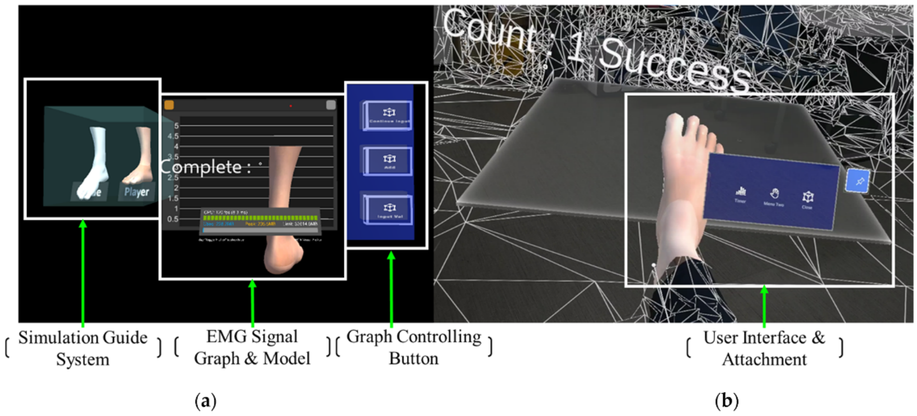

Figure 5. Composition and actual operation of XR system. Reproduced from [105]. CC BY 4.0

the learning phase was complete, the reconstructed EMG envelope was used to scale the assistive torque within an admittance control framework, while the user's movement intention was implicitly captured through the motion phase estimated by the adaptive oscillator, thereby optimising swing-phase assistance of the limb.

Caulcrick *et al* [104] proposed a model predictive control system combined with fuzzy logic to dynamically adapt the assistance provided by a knee exoskeleton based on the user's muscle activity (specifically, the vastus medialis). sEMG signals acquired from the vastus medialis and biceps femoris muscles at 2048 Hz were processed to estimate the human joint torque using a linear agonist-antagonist human torque estimation model. The EMG signal was band-pass filtered (10–100 Hz), followed by rectification and low-pass filtering (2 Hz) to extract the EMG envelope. The estimated human torque was then employed to account for user effort during trajectory optimisation and by the fuzzy logic algorithm, together with reference joint velocity, to infer the appropriate assistance mode. The system was capable of adjusting the assistance level in three modes, responding in real time to variations in the subject's muscle activity, thereby preventing excessive support and encouraging active participation in movement. In fact, the fuzzy logic algorithm detected whether the user is cooperating with the assistance or resisting the motion, and accordingly adjusted the support level.

Visual feedback and augmented reality emerge as complementary tools to enhance rehabilitation effectiveness. Shim *et al* [105] presented an XR rehabilitation system, as shown in figure 5, that integrated EMG signals for patients with lower-limb amputations, combining VR, using two HoloLens 2 headsets, with EMG-mediated control of a virtual robotic prosthesis, thus increasing patient engagement and promoting motor activation. Furthermore, the therapist could supervise and adjust prosthetic parameters in real time via HoloLens 2. The patient wore the headsets and, while performing residual muscle movements, the software classified the EMG signal to move a virtual prosthetic limb in a game-like exercise. The aim was to support residual-muscle training and potentially enhance muscle movement memory within an XR environment. Surface EMG signals were acquired from residual muscles at the amputation site at a sampling frequency of 1 kHz and pre-processed through a 60 Hz notch filter to remove power-line interference, followed by high-pass filtering at 75 Hz and low-pass filtering at 5 Hz to extract a smoothed activation signal. The EMG signal variance was used to discriminate between static and dynamic muscle activation. In addition, a bidirectional LSTM network was evaluated for EMG-based motion detection. The EMG signals:

- Detect residual muscle activation in the amputated area;
- Enable control of the virtual prosthesis based on signal intensity;
- Support the measurement of the patient's improvement in terms of strength and motor control.

Meanwhile, joint movement monitoring:

- Tracked the position of limbs in real time;
- Recorded the range and quality of the movement to evaluate recovery progression.

3.3.2. Experimental protocol, study population and outcomes

In the study by Chen *et al* [102], six healthy subjects (mean age: 24 years, range: 22–30 years) took part in the tests. After the setup and calibration phase, the training was conducted on a treadmill using a lower-limb supportive exoskeleton. Six gait adaptation schemes were evaluated, including an increase/decrease in step length, step duration, and walking speed. Between each adaptation phase (five strides with a fixed trajectory), a normal walking phase was included to restore baseline conditions. Each subject completed three training blocks. Each block consisted of 13 walking trials, with a total duration of approximately 10 min per block. A 5-min rest period was provided between blocks. During the gait adaptation phase, muscle activation was significantly higher compared to walking with a fixed trajectory ($\boldsymbol{p < 0.05}$).

In the study by Han *et al* [103], two male subjects participated in tests while wearing a knee exoskeleton. The participants performed knee flexion and extension movements, first in unassisted mode and then in assisted mode. The exoskeleton was attached to the leg using a soft strap, and the movement was controlled at an oscillation frequency of 1 Hz. Before data collection, the subject practised to become familiar with the motion. The average EMG of the quadriceps femoris and biceps femoris muscles decreased by 57% and 58% in subject 1, and by 58% and 55% in subject 2, respectively. The experimental results showed a reduction in EMG activity during assisted mode compared to unassisted mode. This approach enables detection of the user's movement intention and generates personalised assistive torque, improving the naturalness of movement, while responding dynamically to variations in muscle activity. In the solution by Caulcrick *et al* [104], three healthy subjects were involved to evaluate the system's behaviour in various assistance modes. The knee exoskeleton was used in a seated position to perform flexion-extension movements. Two EMG sensors were placed on the vastus medialis and biceps femoris to estimate muscle torque. Subjects performed sinusoidal knee movements at 0.25 Hz for six cycles, each lasting 4 seconds. Five involvement conditions were tested:

1. Relaxed (robot-dominant, relaxed subject);
2. Extension assistance (subject actively participates in extension);
3. Extension resistance (subject actively resists extension);
4. Flexion assistance (subject actively participates in flexion);
5. Flexion resistance (subject actively resists flexion),

which mapped onto three controller assistance modes (passive, active-assist, safety). Data showed that in the active and assistive modes, the contribution of the user's joint torque was greater than in the passive mode. This allows for more effective and targeted rehabilitation, avoiding complete dependence on the exoskeleton. The human-to-robot torque ratio (Rh), which represents the contribution of human effort, was very low in the passive mode (0.036 in extension and 0.042 in flexion) and higher in the assistive modes (0.46 for the extension phase of extension assist and 0.18 for the flexion phase of flexion assist. This supports that the controller operated as 'assist-as-needed': in assistive mode, the robot transferred part of the workload to the subject. Under 'resistance' conditions, when the patient intentionally opposed the movement, Rh increased (0.23 and 0.59 for extension and flexion phases, respectively).

In the end, in the solution presented by Shim *et al* [105], the system was tested and evaluated by fifteen users: eight able-bodied individuals (control group) and seven lower-limb amputees (real patients), aged between 30 and 60 years. In the initial EMG recognition and muscle activation phase, patients performed 'Ankle Up' and 'Ankle Down' movements to evaluate muscular control. The system distinguishes between static (no signal) and dynamic (muscle activation) states, and the presence of EMG activity above a threshold was used to determine the response of the virtual prosthesis. The system counted a movement as successful only if it was performed correctly within a predefined time window, requiring patients to exceed a minimum muscle strength threshold to complete an exercise. Each amputee was asked to complete a total of 10 movements. The system guided patients through the exercises by displaying a 'Complete' message after each successful action. The results indicated that patients could reactivate their residual muscles and use EMG signals to control the virtual prosthesis. Muscle contraction recognition improved over time, allowing for greater precision and control of the prosthetic limb. Analysis of EMG signal variation revealed a progressive reduction in motor response latency. The study shows the feasibility of using EMG signals acquired at the amputation site to drive the virtual prosthesis actions in the XR environment. The system and its reactivity/usability were evaluated by the users, and the experiment was reported as highly rated in terms of perceived muscle rehabilitation effect and motivation.

4. Discussions and conclusions

This review highlights the innovation of biosignal-controlled robotic rehabilitation, emphasising its potential to improve rehabilitative processes.

Robotic rehabilitation technologies are increasingly used in the care of individuals with motor impairments and have been studied across several clinical populations. Although not part of the studies included in this systematic review, different papers reported benefits as:

- Improved outcomes. Improvements on functional and clinically relevant outcomes are reported in [106–108];
- Safety. Most systems are generally reported as well tolerated and have shown a good safety profile in patient use [109];
- Personalisation. Assistance level and task difficulty can be adjusted to the individual's deficits and goals, allowing graded progression over the course of therapy [110];
- Accessibility. These systems can be configured for different care settings, including inpatient clinics, outpatient services, and even home-based use [111, 112].

A recurring objective across recent studies is to deliver repetitive, intensive, and individualised practice, features that can be difficult to achieve consistently with conventional therapy alone.

The literature spans different timescales and aims: from immediate assistive control (e.g. MRAC or ML-based systems) to longer-term motor reorganisation (e.g. hybrid or home-based solutions), suggesting an integrated framework in which robotic systems not only assist movement but also support processes associated with neuroplasticity. It should also be noted that this review was intentionally scoped to examine biosignal-controlled robotic rehabilitation systems across emerging technological paradigms rather than to provide a disease-specific synthesis. Accordingly, highly investigated disease-specific populations, such as stroke, spinal cord injury, and other neurological or neuromuscular conditions, were not systematically pooled because disease-specific impairments, compensatory mechanisms, and rehabilitation protocols could confound the analysis of the role of biosignals in robotic control.

Most of the included studies consist of exploratory or proof-of-concept trials involving a limited number of participants, often healthy volunteers, and primarily aim to demonstrate the system's functional principles rather than evaluate its large-scale clinical effectiveness, as initial testing on healthy subjects represents an essential step in the development and validation of biosignal-controlled robotic strategies prior to clinical translation.

From a technical point of view, the analysed technologies here, including model-based controllers (Toro-Ossaba *et al* [91]), robot-FES hybrids (Takenaka *et al* [92, 93]), ML-driven exoglove systems (Sierotowicz [94]), and extended prosthesis use (Osborn *et al* [96]), converge on a shared design rationale: reduce physical effort (e.g. lower EMG amplitude, lower required torque, reduced co-contraction) while preserving motor learning and functional recovery. Although these systems address different rehabilitation contexts and stages, the overall pattern suggests that combining robotic assistance with user-driven intent and meaningful feedback is more likely to support durable improvements than assistance alone. A key point across these systems is the integration of the user into the control loop via biosignals, mainly sEMG. In this paradigm, the subject is not treated as a passive recipient of motion but as an active contributor to control. This represents a shift from the earlier generations of rehabilitation robots [113, 114], which successfully provided passive motor support [115], but did not necessarily promote voluntary motor relearning. In contrast, more recent approaches recognise the importance of combining assisted movement with voluntary (or at least stimulated) muscle activation. All EMG-based systems, although through different methods, are designed to promote active participation, either through intention-driven signals (e.g. movement initiation) or through modulation based on internal states (e.g. fatigue, pain) [99], which are detected by the robot and used to dynamically adapt the therapy. The common goal is to fine-tune the intervention to the subject's specific needs. Nevertheless, EMG control is not without problems, including electrode displacement, noise sensitivity, response latency, and intra/inter-subject variability [23, 116, 117]. To overcome these limitations, some systems may incorporate additional biosignals, such as HRV and electrodermal activity, to estimate user states, including stress, fatigue, or attention. These signals can act as adaptive feedback parameters [39, 118], leading to more personalised rehabilitation approaches. In the study by [119], the ECG signal is not used to directly control the robot through biosignal, but to estimate the user's energy consumption related to walking intensity. Regarding EEG signals, none of the articles screened considered them directly in a rehabilitation context. During the screening phases, several studies involving EEG were analysed; however, they mainly emphasised system performance rather than rehabilitation outcomes, as seen in brain-computer interface applications [120, 121], or they focused on classification parameters derived from EEG data, as in [122–124]. Modularity and portability are other common priorities among the reviewed systems. Several prototypes, such as the one of [95] and home-use prostheses [96], are designed to be compact and usable outside the hospital, aligning with trends in telerehabilitation and home care. Patient compliance was high, with some users even expressing enthusiasm, particularly in long-term prosthesis use [96]. Between studies, notable differences emerge, reflecting different technological maturity levels and approaches. These include:

- Device complexity: From multi-joint exoskeletons (e.g. anthropomorphic prosthetic hands [96]) to simpler systems targeting a single joint (e.g. wrist actuators [100] or manual resistance plates [125]). This naturally impacts the scope, which ranges from complete upper-limb recovery to more localised goals (e.g. improving wrist strength vs hand dexterity).
- Control system: systems that include EMG interfaces report improved motor control and reduced perceived effort [126, 127].
- Rehabilitation outcomes: results range from variation in muscle activation, expressed via sEMG, which is one of the main expressions of the rehabilitation efficacy [128], to the achieved RoM, active torque and the reduction of passive stiffness [91, 100].

In upper-limb applications, improvements have been observed both in performance metrics and in indicators consistent with reduced user contribution during assisted movement. For instance, during elbow training, a myoelectric adaptive controller reduced the user torque by approximately 34%–40% (RMS), while maintaining tracking errors of 4.5° in passive conditions and 10° during active-assisted trials, suggesting a lower mechanical load without a major loss in functional accuracy [91]. This pattern is consistent with reduced loading without a proportional loss of task accuracy. An EMG-driven ML controller implemented in a soft exoglove reduced muscle activity by up to 50% at higher force levels (>10 N), supporting the idea that proportional myoelectric assistance can reduce effort and maintain voluntary engagement [94]. Similarly, a soft elbow sleeve tested during repetitive pitching showed decreased biceps/triceps activation (60% and 40% in steady passive assistance and by 50% and 30% in EMG-activated assistance). The CCI also decreased from 0.31 to 0.12, suggesting improved muscular coordination rather than pure passive unloading [95]. Importantly, hybrid approaches that combine robotic support with FES appear to produce more durable learning-related effects than single-modality feedback, as indicated by better retention in wrist pointing tasks when training included robot+FES compared with visual-feedback-only control conditions (two independent studies by the same group, with retention assessed up to one week) [92, 93]. These findings are consistent with a motor learning-oriented rehabilitation framework, in which assisted movement paired with endogenous and/or exogenous muscle activation may enhance sensorimotor coupling and support consolidation of motor memory, particularly under multimodal feedback conditions. The clearest clinically oriented evidence within the upper-limb domain comes from telerehabilitation studies in fracture subjects, where EMG-driven adaptive control was associated with large improvements in RoM. In a clinical cohort undergoing a 10 d remote protocol, wrist RoM increased by up to 73 % [99]. A subsequent protocol reported an increase in RoM after 10 days, with concurrent changes in joint mechanics (e.g. passive stiffness reduced from 0.26 to 0.09 Nm, passive resistance reduced by 30%) and, in the best-recovering patient, active torque increasing from 0.93 to 2.09 Nm, possibly indicating an increase in muscle activation as therapy progressed through active functional participation [100].

Lower-limb systems also show similar benefit in terms of motor function and physiologically relevant changes. For example, during treadmill training with an exoskeleton controlled via EMG-driven admittance, subjects modulated gait parameters, with walking speed varying from 0.110 to 0.120 m s^{-1} under trajectory adaptation; during these phases, muscle activation was significantly higher than fixed-trajectory walking ($p < 0.05$), indicating also increased user engagement rather than fully passive guidance [102]. In a knee exoskeleton study, results showed reductions in the EMG of quadriceps and biceps femoris during assisted motion (about 55%–58% reduction, depending on subject and muscle), consistent with unloading effects [103]. In fact, the results suggest a reduction of muscle effort during assisted movement, with possible application to patients with knee weakness during swing. Along the same line, an ‘assist-as-needed’ controller showed a human-to-robot torque ratio 3%–4% in passive mode but increased up to 46% (extension) and 18% (flexion) in assistive modes, illustrating how biosignal-guided control can limit over-assistance and promote active participation. Finally, an XR-based amputee rehabilitation platform [105] tested in 7 amputees showed improved EMG recognition across repeated trials (10 movements), reduced latency for motor responses, and higher engagement, supporting usability and adherence-related factors, which may serve as important contributors to long-term functional outcomes. In fact, the test was highly rated in terms of muscle rehabilitation effect and motivation. Repetitive training can help at maintaining/increasing muscle movement memory. In conclusion, the direction of effects is promising, but the current state of clinical evidence remains preliminary: many studies involve small samples and/or healthy participants, there is no standardised reporting of outcome measures, and long-term follow-up is rarely con.ducted beyond simple retention tasks

Some systems are clearly in early prototype phases (e.g. small sample sizes, tests on healthy volunteers, primarily engineering metrics), while others have begun clinical translation. Pain-adaptive telerehabilitation systems, for example, have already been tested in real-world clinical settings [99]. A further distinction lies in the use, or omission, of additional stimulation. Only a minority of systems (e.g. Abdallah & Bouteraa's OSCS [101], Takenaka *et al* [92, 92]) combine robotic actuation with FES, aiming to simultaneously engage both muscles and joints. Most studies, however, focus on mechanical assistance combined with voluntary intent, employing adaptive or assist-as-needed myoelectric controllers to stimulate intrinsic activation without external stimulation. While robotic systems augmented rehabilitation using technique as FES have shown encouraging performance, reporting outcomes comparable to voluntary training [93]), they also introduce additional technical complexity. Nevertheless, the therapist remains central to the intervention, overseeing device calibration, guiding task execution, and evaluating progress.

Artificial intelligence has also been explored to improve control accuracy and adaptive assistance, with ML and DL methods increasingly applied to biosignals and kinematic data. In particular, DL applied to EMG has been proposed to enhance human–robot interaction and fine motor control [97]. These models can learn from the inputs of the therapist to detect when assistance is needed, using the analysis of time-series of movement trajectories to predict and deliver timely support [129, 130]. However, many studies were conducted on young, healthy volunteers, so the systems were not tested in a clinical setting or with conditions such as spasticity, muscular weakness, or pathological movement patterns. Most of the authors highlight the need for future trials on clinical populations to better validate these systems and guide their refinement. Another promising potential direction is the use of VR and XR environments [105]. These technologies aim to increase motivation, engagement and motor outcomes, offering immersive, interactive, and customisable therapy [131–134]. VR can increase motor learning without requiring the patient to wear a physical rehabilitative device, offering an alternative method for functional training. In parallel, several of the analysed articles [99, 100] rely on IoT-based architectures to enable remote and distributed rehabilitative applications. For the studies included in this review, IoT is not treated as an independent therapeutic component but rather as an enabling infrastructure that facilitates a constant transmission of data among patients, robotic devices, and therapists. This connectivity supports real-time monitoring of biosignals, remote supervision of sessions, and adaptive tuning of the rehabilitation parameter.

In conclusion, the 15 reviewed studies in general show the rapidly evolving field in robotic rehabilitation, with different but converging strategies that support the shift toward more intelligent, patient-centred therapy. In addition, the screened literature mainly supports feasibility, early clinical applicability, and promising preliminary trends. A common theme is that robotic systems increase the quantity and quality of therapy, and that biosignal integration, particularly EMG, allows more adaptive, personalised interventions, facilitating both guided movement and motor relearning.

Despite differences in device type (exoskeleton vs glove vs end-effector), control strategy (e.g. fuzzy logic vs DL), development stage (feasibility vs clinical application), and rehabilitation metrics, the available evidence suggests promising but still preliminary effects. Improvements in strength, muscle activation, RoM, coordination, and reductions in perceived effort and pain have been reported, potentially associated with the real-time adaptability of these technologies.

Nevertheless, robust clinical validation has not yet been achieved; so that, future directions include large-scale, controlled clinical trials comparing robotic solutions with standard therapy, the integration of additional biosignals (e.g. EEG for detecting motor intention in patients with no residual EMG activity), and improvement in usability for routine clinical and home use. The integration of engineering and clinical expertise, evident throughout this body of research, will be key to helping to inform the future development of clinically applicable robotic rehabilitation solutions, with the potential to significantly improve motor recovery and independence for people with neurological conditions.

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Data availability statement

The data cannot be made publicly available upon publication because no suitable repository exists for hosting data in this field of study. The data that support the findings of this study are available upon reasonable request from the authors.

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References

[1] Parisi A, Bellinzona F, Di Lernia D, Repetto C, De Gaspari S, Brizzi G, Riva G and Tuena C 2022 Efficacy of multisensory technology in post-stroke cognitive rehabilitation: a systematic review *J. Clin. Med.* **11** 6324

[2] Everard G, Declerck L, Detrembleur C, Leonard S, Bower G, Dehem S and Lejeune T 2022 New technologies promoting active upper limb rehabilitation after stroke: an overview and network meta-analysis *Eur. J. Phys. Rehabil. Med.* **58** 530

[3] Wu X, Qiao X, Xie Y, Yang Q, An W, Xia L, Li J and Lu X 2025 Rehabilitation training robot using mirror therapy for the upper and lower limb after stroke: a prospective cohort study *J. NeuroEng. Rehabil.* **22** 54

[4] Susanto E A, Tong R K, Ockenfeld C and Ho N S 2015 Efficacy of robot-assisted fingers training in chronic stroke survivors: a pilot randomized-controlled trial *J. NeuroEng. Rehabil.* **12** 1–9

[5] Hwang C H, Seong J W and Son D-S 2012 Individual finger synchronized robot-assisted hand rehabilitation in subacute to chronic stroke: a prospective randomized clinical trial of efficacy *Clin. Rehabil.* **26** 696–704

[6] Bhattacharjee S, Barman A, Patel S and Sahoo J 2024 The combined effect of robot assisted therapy and activities of daily living training on upper limb recovery in persons with subacute stroke: a randomized controlled trial *Arch. Phys. Med. Rehabil.* **105** 1041–9

[7] Dehem S, Gilliaux M, Stoquart G, Detrembleur C, Jacquemin G, Palumbo S, Frederick A and Lejeune T 2019 Effectiveness of upper-limb robotic-assisted therapy in the early rehabilitation phase after stroke: A single-blind, randomised, controlled trial *Ann. Phys. Rehabil. Med.* **62** 313–20

[8] Daly J J, McCabe J P, Holcomb J, Monkiewicz M, Gansen J and Pundik S 2019 Long-dose intensive therapy is necessary for strong, clinically significant, upper limb functional gains and retained gains in severe/moderate chronic stroke *Neurorehabil. Neural Repair* **33** 523–37

[9] Maranesi E, Riccardi G R and Mercante O 2018 La riabilitazione robotica nel grande anziano: il punto di vista dell'ingegnere biomedico *Menti Attive* **48** 69

[10] Kiyono K, Tanabe S, Hirano S, Ii T, Nakagawa Y, Tan K, Saitoh E and Otaka Y 2024 Effectiveness of robotic devices for medical rehabilitation: an umbrella review *J. Clin. Med.* **13** 6616

[11] Feigin V L, Vos T, Nichols E, Owolabi M O, Carroll W M, Dichgans M, Deuschl G, Parmar P, Brainin M and Murray C 2020 The global burden of neurological disorders: translating evidence into policy *Lancet Neurol.* **19** 255–65

[12] Lee M H, Siewiorek D P, Smailagic A, Bernardino A and i Badia S B 2023 Design, development and evaluation of an interactive personalized social robot to monitor and coach post-stroke rehabilitation exercises *User Model. User-Adapt. Interact.* **33** 545–69

[13] Nijenhuis S M *et al* 2015 Feasibility study into self-administered training at home using an arm and hand device with motivational gaming environment in chronic stroke *J. NeuroEng. Rehabil.* **12** 1–13

[14] Molteni F, Gasperini G, Cannaviello G and Guanziroli E 2018 Exoskeleton and end-effector robots for upper and lower limbs rehabilitation: narrative review *Phys. Med. Rehabil.* **10** S174–88

[15] Bruni M F, Melegari C, De Cola M C, Bramanti A, Bramanti P and Calabrò R S 2018 What does best evidence tell us about robotic gait rehabilitation in stroke patients: a systematic review and meta-analysis *J. Clin. Neurosci.* **48** 11–17

[16] Iosa M, Morone G, Cherubini A and Paolucci S 2016 The three laws of neurorobotics: a review on what neurorehabilitation robots should do for patients and clinicians *J. Med. Biol. Eng.* **36** 1–11

[17] Banyai A D and Brisan C 2024 Robotics in physical rehabilitation: systematic review *Healthcare* **12** 1720

[18] Budhota A *et al* 2021 Robotic assisted upper limb training post stroke: a randomized control trial using combinatory approach toward reducing workforce demands *Front. Neurol.* **12** 622014

[19] Liu L, Illian M, Leonhardt S and Misgeld B J 2023 Iterative learning control for cascaded impedance-controlled compliant exoskeleton with adaptive reaction to spasticity *IEEE Trans. Instrum. Meas.* **72** 1–11

[20] Kuo L-C, Yang K-C, Lin Y-C, Lin Y-C, Yeh C-H, Su F-C and Hsu H-Y 2023 Internet of things (IoT) enables robot-assisted therapy as a home program for training upper limb functions in chronic stroke: a randomized control crossover study *Archi. Phys. Med. Rehabil.* **104** 363–71

[21] Moghbelan Y *et al* 2024 A smart motor rehabilitation system based on the internet of things and humanoid robotics *Appl. Sci.* **14** 11489

[22] Khan M M R, Swapnil A A Z, Ahmed T, Rahman M M, Islam M R, Brahmi B, Fareh R and Rahman M H 2022 Development of an end-effector type therapeutic robot with sliding mode control for upper-limb rehabilitation *Robotics* **11** 98

[23] Mahfouz D M, Shehata O M, Morgan E I and Arrichiello F 2024 A comprehensive review of control challenges and methods in end-effector upper-limb rehabilitation robots *Robotics* **13** 181

[24] Huo W, Mohammed S, Moreno J C and Amirat Y 2014 Lower limb wearable robots for assistance and rehabilitation: a state of the art *IEEE Syst. J.* **10** 1068–81

[25] Martinez-Hernandez U, Metcalfe B, Assaf T, Jabban L, Male J and Zhang D 2021 Wearable assistive robotics: a perspective on current challenges and future trends *Sensors* **21** 6751

[26] Laut J, Porfiri M and Raghavan P 2016 The present and future of robotic technology in rehabilitation *Curr. Phys. Med. Rehabil. Rep.* **4** 312–9

[27] Gopura R A and Kiguchi K 2009 Mechanical designs of active upper-limb exoskeleton robots: state-of-the-art and design difficulties *2009 IEEE Int. Conf. Rehabilitation Robotics* (IEEE) pp 178–87

[28] Díaz I, Gil J J and Sánchez E 2011 Lower-limb robotic rehabilitation: literature review and challenges *J. Robot.* **2011** 759764

[29] Alonso A C, Brech G C, Bourquin A M and Greve J M D 2011 The influence of lower-limb dominance on postural balance *Sao Paulo Med. J.* **129** 410–3

[30] Basteris A, Nijenhuis S M, Stienen A H, Buurke J H, Prange G B and Amirabdollahian F 2014 Training modalities in robot-mediated upper limb rehabilitation in stroke: a framework for classification based on a systematic review *J. NeuroEng. Rehabil.* **11** 1–15

[31] Oña E D, Garcia-Haro J M, Jardón A and Balaguer C 2019 Robotics in health care: perspectives of robot-aided interventions in clinical practice for rehabilitation of upper limbs *Appl. Sci.* **9** 2586

[32] Dillen A *et al* 2022 Deep learning for biosignal control: insights from basic to real-time methods with recommendations *J. Neural Eng.* **19** 011003

[33] Palumbo A, Vizza P, Calabrese B and Ielpo N 2021 Biopotential signal monitoring systems in rehabilitation: a review *Sensors* **21** 7172

[34] Klein C, Li S, Hu X and Li X 2018 Editorial: electromyography (EMG) techniques for the assessment and rehabilitation of motor impairment following stroke *Front. Neurol.* **9** 1122

[35] Brambilla C, Pirovano I, Mira R M, Rizzo G, Scano A and Mastropietro A 2021 Combined use of EMG and EEG techniques for neuromotor assessment in rehabilitative applications: a systematic review *Sensors* **21** 7014

[36] Khairuddin I M, Sidek S N, Majeed A P, Razman M, Puzi A A and Yusof H 2021 The classification of movement intention through machine learning models: the identification of significant time-domain EMG features *Peer J. Comput. Sci.* **7** e379

[37] Luo J, Zhang C, Si W, Jiang Y, Yang C and Zeng C 2025 A physical human-robot interaction framework for trajectory adaptation based on human motion prediction and adaptive impedance control *IEEE Trans. Automat. Sci. Eng.* **22** 5072–83

[38] Toro-Ossaba A, Tejada J C and Sanín-Villa D 2025 Myoelectric control in rehabilitative and assistive soft exoskeletons: a comprehensive review of trends, challenges and integration with soft robotic devices *Biomimetics* **10** 214

[39] Santoriello V *et al* 2024 New paradigm in postural control response: a dual approach using center of pressure and electroencephalography *2024 E-Health and Bioengineering Conference (EHB)* (IEEE) pp 1–6

[40] Marino M and Mantini D 2024 Human brain imaging with high-density electroencephalography: techniques and applications *J. Physiol.* **604** 783-812

[41] Araujo R S, Silva C R, Netto S P, Morya E and Brasil F L 2021 Development of a low-cost EEG-controlled hand exoskeleton 3D printed on textiles *Frontiers Neurosci.* **15** 661569

[42] Tang Z, Cui Z, Wang H, Liu P, Xu X and Yang K 2024 A 4-dof exosuit using a hybrid EEG-based control approach for upper-limb rehabilitation *IEEE J. Trans. Eng. Health Med.* **12** 622–34

[43] Wu Y 2023 Applications of EEG-based brain-computer interface devices in rehabilitation *Highlights Sci. Eng. Technol.* **39** 809–15

[44] Al-Quraishi M S, Elamvazuthi I, Daud S A, Parasuraman S and Borboni A 2018 Eeg-based control for upper and lower limb exoskeletons and prostheses: a systematic review *Sensors* **18** 3342

[45] Saikia A and Paul S 2019 EEG signal processing and its classification for rehabilitation device control *Application of Biomedical Engineering in Neuroscience* (Springer) pp 173–96

[46] Task Force of the European Society of Cardiology and the North American Society of Pacing and Electrophysiology 1996 Heart rate variability: standards of measurement, physiological interpretation and clinical use *Circulation* **93** 1043–65

[47] Nuuttila O-P, Uusitalo A, Kokkonen V-P, Weerarathna N and Kyröläinen H 2024 Monitoring fatigue state with heart rate-based and subjective methods during intensified training in recreational runners *Eur. J. Sport Sci.* **24** 857–69

[48] Kim H-G, Cheon E-J, Bai D-S, Lee Y H and Koo B-H 2018 Stress and heart rate variability: a meta-analysis and review of the literature *Psychiatry Invest.* **15** 235

[49] Zhao S, Liu J, Gong Z, Lei Y, OuYang X, Chan C C and Ruan S 2020 Wearable physiological monitoring system based on electrocardiography and electromyography for upper limb rehabilitation training *Sensors* **20** 4861

[50] Cisnal A, Antolínez D, Turiel J P, Fraile J C and Fuente E D L 2023 A versatile embedded platform for implementation of biocooperative control in upper-limb neuromotor rehabilitation scenarios *IEEE Access* **11** 35726–36

[51] Ke L, Li J, Du Q and Shen Z 2018 Study on the application of cardiac impedance and ECG in medical robot *2018 IEEE Int. Conf. Intelligence and Safety for Robotics (ISR)* (IEEE) pp 563–8

[52] Fernández-Lázaro D, Mielgo-Ayuso J, Adams D P, González-Bernal J J, Fernández Araque A, García A C and Fernández-Lázaro C I 2020 Electromyography: a simple and accessible tool to assess physical performance and health during hypoxia training. a systematic review *Sustainability* **12** 9137
[53] Ramani P K, Lui F and Arya K 2025 Nerve conduction studies and electromyography *Statpearls [Internet]* (StatPearls Publishing)
[54] Meng W, Liu Q, Zhou Z, Ai Q, Sheng B and Xie S S 2015 Recent development of mechanisms and control strategies for robot-assisted lower limb rehabilitation *Mechatronics* **31** 132–45
[55] Tian J, Wang H, Zheng S, Ning Y, Zhang X, Niu J and Vladareanu L 2022 sEMG-based gain-tuned compliance control for the lower limb rehabilitation robot during passive training *Sensors* **22** 7890
[56] Nguyen N-K *et al* 2024 An sEMG signal-based robotic arm for rehabilitation applying fuzzy logic *Eng. Technol. Appl. Sci. Res.* **14** 14287–94
[57] Li Z, Wang B, Sun F, Yang C, Xie Q and Zhang W 2013 sEMG-based joint force control for an upper-limb power-assist exoskeleton robot *IEEE J. Biomed. Health Inform.* **18** 1043–50
[58] Kiguchi K and Hayashi Y 2012 An EMG-based control for an upper-limb power-assist exoskeleton robot *IEEE Trans. Syst. Man Cybern. B* **42** 1064–71
[59] Yin G, Zhang X, Chen D, Li H, Chen J, Chen C and Lemos S 2020 Processing surface EMG signals for exoskeleton motion control *Front. Neurorobot.* **14** 40
[60] Liu Y, Li X, Zhu A, Zheng Z and Zhu H 2021 Design and evaluation of a surface electromyography-controlled lightweight upper arm exoskeleton rehabilitation robot *Int. J. Adv. Robot. Syst.* **18** 17298814211003461
[61] Song T, Yan Z, Guo S, Li Y, Li X and Xi F 2023 Review of sEMG for robot control: techniques and applications *Appl. Sci.* **13** 9546
[62] Dzewaltowski A and Malcolm P 2024 Enhanced muscle activation using robotic assistance within the electromechanical delay: implications for rehabilitation? *IEEE Trans. Neural Syst. Rehabil. Eng.* **32** 2432–40
[63] Zhang X, Qu Y, Zhang G, Wang Z, Chen C and Xu X 2025 Review of sEMG for exoskeleton robots: motion intention recognition techniques and applications *Sensors* **25** 2448
[64] Retnaningsih R, Budiyono A, Ismail R, Tugasworo D, Danuaji R, Syahrul S and Gunawan H 2023 Robotics applications in neurology: a review of recent advancements and future directions (arXiv:2312.06956)
[65] Qassim H M and Hasan W W 2020 A review on upper limb rehabilitation robots *Appl. Sci.* **10** 6976
[66] Baniqued P D E, Stanyer E C, Awais M, Alazmani A, Jackson A E, Mon-Williams M A, Mushtaq F and Holt R J 2021 Brain–computer interface robotics for hand rehabilitation after stroke: a systematic review *J. NeuroEng. Rehabil.* **18** 15
[67] Huo Y, Wang X, Zhao W, Hu H and Li L 2023 Effects of EMG-based robot for upper extremity rehabilitation on post-stroke patients: a systematic review and meta-analysis *Front. Physiol.* **14** 1172958
[68] Lennon O *et al* 2020 A systematic review establishing the current state-of-the-art, the limitations and the desired checklist in studies of direct neural interfacing with robotic gait devices in stroke rehabilitation *Front. Neurosci.* **14** 578
[69] Holanda L J, Silva P M, Amorim T C, Lacerda M O, Simão C R and Morya E 2017 Robotic assisted gait as a tool for rehabilitation of individuals with spinal cord injury: a systematic review *J. NeuroEng. Rehabil.* **14** 126
[70] Bardi E, Gandolla M, Braghin F, Resta F, Pedrocchi A L and Ambrosini E 2022 Upper limb soft robotic wearable devices: a systematic review *J. NeuroEng. Rehabil.* **19** 87
[71] Rzyman G, Szkopek J, Redlarski G and Palkowski A 2020 Upper limb bionic orthoses: general overview and forecasting changes *Appl. Sci.* **10** 5323
[72] Fu J, Choudhury R, Hosseini S M, Simpson R and Park J-H 2022 Myoelectric control systems for upper limb wearable robotic exoskeletons and exosuits-a systematic review *Sensors* **22** 8134
[73] Yang J, He Y, Shi P and Yu H 2022 A review on human intent understanding and compliance control strategies for lower limb exoskeletons *Proc. Inst. Mech. Eng. I* **236** 1067–86
[74] Plessis T D, Djouani K and Oosthuizen C 2021 A review of active hand exoskeletons for rehabilitation and assistance *Robotics* **10** 40
[75] Singh J, Ali F, Gill R, Shah B and Kwak D 2023 A survey of eeg and machine learning-based methods for neural rehabilitation *IEEE Access* **11** 114155–71
[76] Sherif O, Bassuoni M M and Mehrez O 2024 A survey on the state of the art of force myography technique (FMG): analysis and assessment *Med. Biol. Eng. Comput.* **62** 1313–32
[77] Xu H and Xiong A 2021 Advances and disturbances in sEMG-based intentions and movements recognition: a review *IEEE Sens. J.* **21** 13019–28
[78] Lu C, Qi Q, Liu Y, Li D, Xian W, Wang Y, Chen C and Xu X 2024 Exoskeleton recognition of human movement intent based on surface electromyographic signals *IEEE Access* **12** 53986–4004
[79] Carvalho C R, Fernández J M, Del-Ama A J, Barroso F O and Moreno J C 2023 Review of electromyography onset detection methods for real-time control of robotic exoskeletons *J. NeuroEng. Rehabil.* **20** 141
[80] Luo S, Meng Q, Li S and Yu H 2024 Research of intent recognition in rehabilitation robots: a systematic review *Disability Rehabil. Assist. Technol.* **19** 1307–18
[81] Alam N, Hasan S, Mashud G A and Bhujel S 2025 Neural network for enhancing robot-assisted rehabilitation: a systematic review *Actuators* **14** 16
[82] Esposito D, Centracchio J, Andreozzi E, Gargiulo G D, Naik G R and Bifulco P 2021 Biosignal-based human–machine interfaces for assistance and rehabilitation: a survey *Sensors* **21** 6863
[83] Zongxing L, Jie Z, Ligang Y, Jinshui C and Hongbin L 2024 The human–machine interaction methods and strategies for upper and lower extremity rehabilitation robots: a review *IEEE Sens. J.* **24** 13773–87
[84] Torres F, Puente S and Ubeda A 2020 *Assistance Robotics and Biosensors 2019* (MDPI)
[85] Nath R K and Somasundaram C 2023 Double fascicular nerve transfer restored nearly normal functional movements in a completely paralyzed upper extremity resulting from an ACDF surgery: a case report and review of recent literature *Am. J. Case Rep.* **24** e938650–1
[86] Luo M, Wu X, Yu N, Wang K and Cao W 2024 *Biomechanics, Sensing and bio-Inspired Control in Rehabilitation and Wearable Robotics* (Frontiers Media SA) p 1487075
[87] Diotaiuti P, Marotta G, Vitiello S, Di Siena F, Palombo M, Langiano E, Ferrara M and Mancone S 2025 Biofeedback for motor and cognitive rehabilitation in Parkinson's disease: a comprehensive review of non-invasive interventions *Brain Sci.* **15** 720
[88] Zhou L, Zhang B, Kang R, Wang Y, Qin J, Xiao Q and Hui V 2025 Efficacy of the conventional rehabilitation robot and biosignal feedback-based rehabilitation robot on upper-limb function in patients with stroke: a systematic review and network meta-analysis *NeuroRehabilitation* **57** 169–80

[89] Selçuk A A 2019 A guide for systematic reviews: PRISMA *Turk. Arch. Otorhinol.* **57** 57

[90] Page M J *et al* 2021 The PRISMA 2020 statement: an updated guideline for reporting systematic reviews *Brit. Med. J.* **372** n71

[91] Toro-Ossaba A, Tejada J C, Rúa S, Núñez J D and Peña A 2024 Myoelectric model reference adaptive control with adaptive Kalman filter for a soft elbow exoskeleton *Control Eng. Pract.* **142** 105774

[92] Takenaka K, Shima K and Shimatani K 2023 Hybrid rehabilitation system with motion estimation based on EMG signals *2023 Int. Conf. Rehabilitation Robotics (ICORR)* (IEEE) pp 1–6

[93] Takenaka K, Shima K and Shimatani K 2024 Investigation of motor learning effects using a hybrid rehabilitation system based on motion estimation *Sensors* **24** 3496

[94] Sierotowicz M *et al* 2022 EMG-driven machine learning control of a soft glove for grasping assistance and rehabilitation *IEEE Robot. Automat. Lett.* **7** 1566–73

[95] Khan M U A, Ajmal H M S, Hassan H A, Azam A and Malik E 2025 A soft robotic sleeve for physiotherapy: improving elbow rehabilitation in baseball pitchers *Physiotherapy Res. Int.* **30** e70025

[96] Osborn L E *et al* 2021 Extended home use of an advanced osseointegrated prosthetic arm improves function, performance and control efficiency *J. Neural Eng.* **18** 026020

[97] Yang D and Liu H 2021 An EMG-based deep learning approach for multi-DOF wrist movement decoding *IEEE Trans. Ind. Electron.* **69** 7099–108

[98] Zheng J, Li Z, Xu T and Song R 2025 An electromyographic-based control using Gaussian mixture model on an upper-limb cable-driven rehabilitation robot *Adv. Intell. Syst.* **7** 2400505

[99] Bouteraa Y, Abdallah I B, Alnowaiser K and Ibrahim A 2021 Smart solution for pain detection in remote rehabilitation *Alexandria Eng. J.* **60** 3485–500

[100] Bouteraa Y, Abdallah I B, Alnowaiser K, Islam M R, Ibrahim A and Gebali F 2022 Design and development of a smart IoT-based robotic solution for wrist rehabilitation *Micromachines* **13** 973

[101] Abdallah I B and Bouteraa Y 2024 An optimized stimulation control system for upper limb exoskeleton robot-assisted rehabilitation using a fuzzy logic-based pain detection approach *Sensors* **24** 1047

[102] Chen W, Lyu M, Ding X, Wang J and Zhang J 2023 Electromyography-controlled lower extremity exoskeleton to provide wearers flexibility in walking *Biomed. Signal Process. Control* **79** 104096

[103] Han Y, Zhu S, Gao H, Wu Z, Xu Y and Zhou W 2020 The swing control of knee exoskeleton based on admittance model and nonlinear oscillator *J. Intell. Robot. Syst.* **99** 747–56

[104] Caulcrick C, Huo W, Franco E, Mohammed S, Hoult W and Vaidyanathan R 2021 Model predictive control for human-centred lower limb robotic assistance *IEEE Trans. Med. Robot. Bionics* **3** 980–91

[105] Shim W *et al* 2022 Implementation of the XR rehabilitation simulation system for the utilization of rehabilitation with robotic prosthetic leg *Appl. Sci.* **12** 12659

[106] Alashram A R, Annino G and Padua E 2021 Robot-assisted gait training in individuals with spinal cord injury: a systematic review for the clinical effectiveness of lokomat *J. Clin. Neurosci.* **91** 260–9

[107] Amirbekova M, Kispayeva T, Adomaviciene A, Eszhanova L, Bolshakova I and Ospanova Z 2025 Systematic review and meta-analysis of effectiveness of robotic therapy in the recovery of motor functions after stroke *Front. Hum. Neurosci.* **19** 1622661

[108] Bonanno M, De Luca R, De Nunzio A M, Quartarone A and Calabrò R S 2022 Innovative technologies in the neurorehabilitation of traumatic brain injury: a systematic review *Brain Sci.* **12** 1678

[109] Park G-M, Cho S-H, Hong J-T, Kim D-H and Shin J-C 2023 Effects and safety of wearable exoskeleton for robot-assisted gait training: a retrospective preliminary study *J. Personalized Med.* **13** 676

[110] Gasperina S D, Roveda L, Pedrocchi A, Braghin F and Gandolla M 2021 Review on patient-cooperative control strategies for upper-limb rehabilitation exoskeletons *Front. Robot. AI* **8** 745018

[111] Germanotta M, Mauro M C, Falchini F, Di Luzio F S, Vollero L, Zollo L and Aprile I G 2025 A robotic rehabilitation intervention in a home setting during the Covid-19 outbreak: a feasibility pilot study in patients with stroke *J. NeuroEng. Rehabil.* **22** 93

[112] Aprile I, Gallotti M, Schirru M, Insalaco S, Germanotta M, di Luzio F S, Vollero L and Zollo L 2022 Robotic telerehabilitation: a feasibility study in patients with stroke *Gait Posture* **97** 25–26

[113] Krebs H I, Hogan N, Volpe B, Aisen M, Edelstein L and Diels C 1999 Overview of clinical trials with MIT-MANUS: a robot-aided neuro-rehabilitation facility *Technol. Health Care* **7** 419–23

[114] Jezernik S, Colombo G, Keller T, Frueh H and Morari M 2003 Robotic orthosis lokomat: a rehabilitation and research tool *Neuromodulation Technol. Neural Interface* **6** 108–15

[115] Lum P S, Burgar C G, Shor P C, Majmundar M and Van der Loos M 2002 Robot-assisted movement training compared with conventional therapy techniques for the rehabilitation of upper-limb motor function after stroke *Arch. Phys. Med. Rehabil.* **83** 952–9

[116] Abdikenov B, Zholtayev D, Suleimenov K, Assan N, Ozhikenov K, Ozhikenova A, Nadirov N and Kapsalyamov A 2025 Emerging frontiers in robotic upper-limb prostheses: mechanisms, materials, tactile sensors and machine learning-based EMG control: a comprehensive review *Sensors* **25** 3892

[117] Mohebbian M R, Nosouhi M, Fazilati F, Esfahani Z N, Amiri G, Malekifar N, Yusefi F, Rastegari M and Marateb H R 2021 A comprehensive review of myoelectric prosthesis control (arXiv:2112.13192)

[118] Santoriello V, Granata R, Ponsiglione A M, D'Antò M, D'Agostino G, Cuomo A, Cascella M, Romano M and Amato F Effects of virtual reality and respiratory biofeedback on heart rate variability and skin conductance

[119] Lopes J M, Figueiredo J, Fonseca P, Cerqueira J J, Vilas-Boas J P and Santos C P 2022 Deep learning-based energy expenditure estimation in assisted and non-assisted gait using inertial, EMG and heart rate wearable sensors *Sensors* **22** 7913

[120] Mahmoudi A, Khosrotabar M, Gramann K, Rinderknecht S and Sharbafi M A 2025 Using passive BCI for personalization of assistive wearable devices: a proof-of-concept study *IEEE Trans. Neural Syst. Rehabil. Eng.* **33** 476–87

[121] Albán-Escobar M, Navarrete-Arroyo P, De la Cruz-Guevara D R and Tobar-Quevedo J 2024 Assistance device based on SSVEP-BCI online to control a 6-DOF robotic arm *Sensors* **24** 1922

[122] Vaghei Y, Park E J and Arzanpour S 2022 Decoding brain signals to classify gait direction anticipation *2022 44th Annual Int. Conf. IEEE Engineering in Medicine & Biology Society (EMBC)* (IEEE) pp 309–12

[123] Ortega P and Faisal A A 2021 Deep learning multimodal fnirs and EEG signals for bimanual grip force decoding *J. Neural Eng.* **18** 0460e6

[124] Hooda N, Das R and Kumar N 2020 Fusion of EEG and EMG signals for classification of unilateral foot movements *Biomed. Signal Process. Control* **60** 101990

[125] Ullah A, Waris A, Shafiq U, Khan N B, Saeed Q, Tassadaq N, Qasim O and Ali H T 2024 ExoMechHand prototype development and testing with EMG signals for hand rehabilitation *Med. Eng. Phys.* **124** 104095

[126] Rong W, Li W, Pang M, Hu J, Wei X, Yang B, Wai H, Zheng X and Hu X 2017 A neuromuscular electrical stimulation (NMES) and robot hybrid system for multi-joint coordinated upper limb rehabilitation after stroke *J. NeuroEng. Rehabil.* **14** 34

[127] Abdallah I B, Bouteraa Y and Alotaibi A 2025 Hybrid EMG–NMES control for real-time muscle fatigue reduction in bionic hands *Sci. Rep.* **15** 22467

[128] Xu J, Xu L, Li Y, Cheng G, Shi J, Liu J and Chen S 2020 A multi-channel reinforcement learning framework for robotic mirror therapy *IEEE Robot. Automat. Lett.* **5** 5385–92

[129] Martínez-Pascual D, Catalán J M, Lledó L D, Blanco-Ivorra A and Aracil N G 2024 Deep learning for assistive decision-making in robot-aided rehabilitation therapy pp 65–74

[130] Martínez-Pascual D, Catalán J M, Lledó L D, Blanco-Ivorra A and García-Aracil N 2025 A deep learning model for assistive decision-making during robot-aided rehabilitation therapies based on therapists' demonstrations *J. NeuroEng. Rehabil.* **22** 18

[131] Zhang B, Wong K, Kang R, Fu S-Y, Qin J and Xiao Q 2023 Efficacy of robot-assisted and virtual reality interventions on balance, gait and daily function in patients with stroke: a systematic review and network meta-analysis *Arch. Phys. Med. Rehabil.* **104** 1711–9

[132] Mubin O, Alnajjar F, Jishtu N, Alsinglawi B and Mahmud A A 2019 Exoskeletons with virtual reality, augmented reality and gamification for stroke patients' rehabilitation: systematic review *JMIR Rehabil. Assist. Technol.* **6** e12010

[133] Lu M, Saeys W, Maryam M, Gjeleshi I, Nazarahari H, Truijen S and Scataglini S 2025 Using 3D and 4D digital human modeling in extended reality-based rehabilitation: a systematic review *Front. Bioeng. Biotechnol.* **13** 1496168

[134] Zanatta F, Giardini A, Pierobon A, D'addario M and Steca P 2022 A systematic review on the usability of robotic and virtual reality devices in neuromotor rehabilitation: patients' and healthcare professionals' perspective *BMC Health Serv. Res.* **22** 523