

Systematic Review

Fault Detection, Sensing, and Intelligent Control in Soft Wearable Actuators for Rehabilitation and Motor Assistance: A Systematic Review

Cristina Floriana Pana ¹, Daniela Maria Pătrașcu-Pană ^{1,*}, Camelia Adela Maican ^{2,*} and Virginia Maria Rădulescu ³

¹ Department of Mechatronics and Robotics, University of Craiova, 200585 Craiova, Romania; cristina.pana@edu.ucv.ro

² Department of Automation and Electronics, University of Craiova, 200585 Craiova, Romania

³ Department of Medical Informatics and Biostatistics, Faculty of Medicine, University of Medicine and Pharmacy of Craiova, 200349 Craiova, Romania; virginia.radulescu@umfcv.ro

* Correspondence: daniela.pana@edu.ucv.ro (D.M.P.-P.); camelia.maican@edu.ucv.ro (C.A.M.)

Abstract

Soft wearable actuators offer compliant, lightweight assistance for rehabilitation and motor support, but their translation beyond controlled laboratories depends on reliable sensing, fault management, and adaptive control. This systematic review maps the evidence across three linked domains: fault detection and diagnosis (FDD), sensing, and intelligent control. Owing to marked heterogeneity in actuator types, validation settings, and reported outcomes, the evidence was synthesised narratively and described using publication counts and proportions rather than pooled performance estimates. The study-level supplementary appraisal covers all 106 publications included in the review. Four normative standards were retained within this total as normative context and were marked as not applicable for empirical methodological appraisal; they were not subtracted from the corpus count. Across the 106 included records, 40 were classified as direct, 57 as adjacent, five as indirect, and four as normative context. The FDD subset was especially limited: nine records provided adjacent evidence and five were indirect under the strict soft-wearable rehabilitation criterion. The review therefore identifies soft-actuator-specific FDD benchmarks, multimodal health-state estimation, and fault-aware control as actionable priorities, while distinguishing these structural gaps from constraints expected in a technologically young field. The completed review was retrospectively registered in the OSF Registries on 21 July 2026 using the Open-Ended Registration template.

Keywords: soft actuators; wearable robotics; rehabilitation; fault detection; sensing; intelligent control; machine learning; motor assistance; exoskeleton



Academic Editor: Gary M. Bone

Received: 29 June 2026

Revised: 24 July 2026

Accepted: 5 August 2026

Published: 7 August 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and

conditions of the [Creative Commons](https://creativecommons.org/licenses/by/4.0/)

[Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

1. Introduction

Neurological and musculoskeletal disorders often produce persistent motor limitations that require intensive, repetitive rehabilitation. Wearable robotic systems can increase the dose and consistency of task-oriented training and can quantify movement outside conventional therapist-led sessions [1–3]. Their value is particularly evident when assistance must be tailored to residual motor capacity and delivered across clinical and home settings [1,4].

Rigid exoskeletons have dominated wearable rehabilitation robotics and have demonstrated benefits in gait and upper-limb training [2,3,5]. Their fixed kinematic structures,

however, may be difficult to align with individual anatomy, add distal mass, and require careful management of physical human–robot interaction. These constraints have encouraged the development of compliant wearable systems that distribute forces over larger body areas [4,6,7].

Soft wearable actuators are fabricated from deformable elastomers, textiles, and composite laminates that conform to the body and accommodate anatomical variability [4,6,8]. Pneumatic and textile actuators are used widely in gloves, exosuits, and joint-assistance devices [8–11]. Electrically driven alternatives, including shape-memory-alloy and dielectric-elastomer actuators, may reduce noise or external pneumatic hardware, although thermal and high-voltage constraints remain relevant [12–14].

Compliance does not eliminate risk; it changes the failure physics. Pneumatic leakage, membrane damage, material fatigue, transmission failure, and sensor drift may develop gradually and can reduce assistance before a conventional safety threshold is reached [15–18]. State estimation is also difficult because large deformation limits the usefulness of rigid encoders. Flexible strain sensors, optical fibres, pressure sensors, force sensors, IMUs, and biosignals are therefore combined to estimate both actuator state and user intent [19–26]. Control must then accommodate nonlinear material behaviour, hysteresis, user variability, and safety constraints [27–30].

FDD, sensing, and control should consequently be considered as a coupled safety problem. Fault detection depends on the quality and redundancy of sensory information, while control performance depends on reliable estimates of both user state and actuator health. Conversely, model-based residuals may become unreliable when manufacturing variability, temperature, or fatigue shifts the actuator dynamics [15,17,18,31]. The literature has usually examined these functions separately.

Existing reviews have described soft actuator design, wearable architectures, sensing, or rehabilitation control [1,4,6,8,27,32–39]. Reviews of FDD have largely focused on rigid manipulators or general engineered systems [40–43]. An integrated assessment is therefore useful, provided that evidence transferred from non-wearable domains is identified explicitly and is not presented as direct validation in soft, human-coupled actuators.

This review has four objectives. It first characterises failure modes that are relevant to soft wearable rehabilitation. It then examines the sensing modalities used to estimate actuator state and human–device interaction, followed by the control approaches used to personalise assistance. Finally, it evaluates the directness of the available evidence and identifies research priorities that are actionable now, rather than limitations that mainly reflect the maturity of the field.

The remainder of this review is organised as follows. Section 3 summarises the main soft-actuator technologies, while Sections 4–6 examine FDD, sensing, and intelligent control. Section 7 presents a descriptive mapping of the reviewed literature. Section 8 discusses research gaps and future directions, and Section 9 presents the conclusions.

2. Materials and Methods

2.1. Search Strategy and Protocol

This systematic review was reported in accordance with the PRISMA 2020 statement [44]. Registration and protocol statement: The review methods were defined before the literature search and study selection process; however, the protocol was not prospectively registered. Following completion of the literature search, study selection, data extraction, critical appraisal, and narrative synthesis, the methods and supporting materials were retrospectively registered in the OSF Registries on 21 July 2026 using the Open-Ended Registration template [45]. This public, time-stamped record was created to strengthen methodological transparency and should not be interpreted as a prospective

preregistration. No major amendments to the predefined search strategy, eligibility criteria, or synthesis approach were made after screening began.

The review protocol was defined prior to the literature search and covers publications from January 2020 to June 2026, a window chosen to capture the period of most rapid development in soft wearable actuation and data-driven rehabilitation control while ensuring recency of the evidence base. Four publications predating 2020 were retained as seminal methodological sources: a material-level study of self-healing soft pneumatics, the foundational human-in-the-loop optimisation study, a soft-fault modelling study, and an early full-body soft sensing/control study [46–49]. Their retention is reported as a predefined exception to the principal date window rather than as an expansion of that window.

Searches were conducted across four electronic databases: Scopus, Web of Science (WoS), IEEE Xplore, and PubMed/MEDLINE. Google Scholar was used as a supplementary source to identify articles not indexed in the primary databases. Searches were performed in June 2026 using the following principal search string, adapted to the syntax of each database:

Primary search string (Scopus/WoS):

TITLE-ABS-KEY (

("soft actuator" OR "soft wearable" OR "soft exoskeleton" OR "soft exosuit"
OR "pneumatic actuator" OR "hydraulic actuator" OR "electroactive actuator"
OR "shape memory alloy" OR "dielectric elastomer" OR "tendon-driven"
OR "fabric actuator" OR "textile actuator")

AND

("rehabilitation" OR "motor assistance" OR "assistive device"
OR "wearable robot" OR "exoskeleton" OR "orthosis")

AND

("fault detection" OR "fault diagnosis" OR "fault tolerant" OR "leakage detection"
OR "anomaly detection" OR "EMG" OR "EEG" OR "intelligent control"
OR "machine learning" OR "deep learning" OR "adaptive control"
OR "bioinspired control" OR "reinforcement learning" OR "neural network")

)

AND PUBYEAR > 2019

Targeted sub-searches were conducted for each of the three thematic pillars of the review using focused strings for fault detection and diagnosis, sensing strategies, and intelligent control, respectively. Supplementary hand-searching of the reference lists of all included articles and of five high-impact review papers identified during screening was performed to ensure completeness.

The preserved search log identified 1217 records in aggregate, 389 duplicates removed, 828 records screened, 185 reports sought, 173 full texts assessed, and 106 publications included. Exact source-level result counts and complete interface-specific strings were not archived for every database. Accordingly, Figure 1 reports only the verified aggregate values and does not retrospectively allocate records to individual databases.

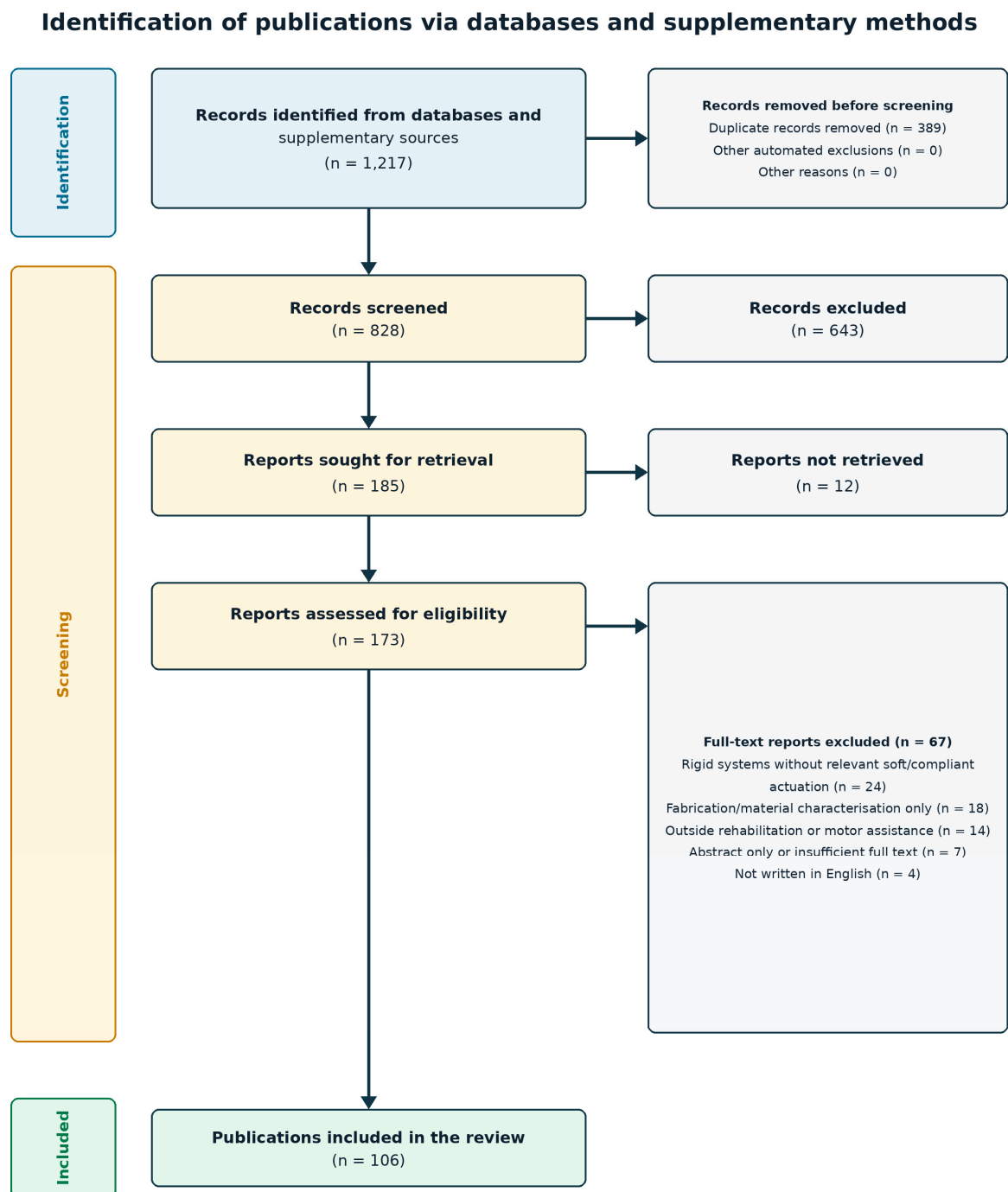


Figure 1. PRISMA 2020 [44] flow diagram based on the preserved search log. Counts are reported at the aggregate level because exact source-specific result totals were not archived for every database and supplementary search route. Full-text exclusions comprised rigid systems without relevant soft/compliant actuation ($n = 24$), fabrication or material characterisation only ($n = 18$), outside rehabilitation or motor assistance ($n = 14$), abstract only or insufficient full text ($n = 7$), and not written in English ($n = 4$). Adapted from the PRISMA 2020 flow diagram template under CC BY 4.0.

2.2. Inclusion and Exclusion Criteria

Articles were selected according to predefined criteria following the PICOS framework.

Population (P): Patients with locomotor impairments (post-stroke, spinal cord injury, Parkinson's disease, amyotrophic lateral sclerosis, or other neuromuscular conditions) or healthy subjects evaluated in the context of assistive or rehabilitative motor tasks.

Intervention (I): Soft wearable actuators, including pneumatic, hydraulic, shape memory alloy, dielectric elastomer, and tendon/cable-driven designs, integrated into wearable rehabilitation or motor assistance devices.

Comparison (C): Comparisons with rigid exoskeletons, conventional rehabilitation methods, or alternative soft actuator configurations, where reported.

Outcomes (O): At least one of the following: fault detection performance metrics (detection rate, false alarm rate, time to detection); sensing system characterisation (bandwidth, gauge factor, signal quality); control performance (tracking accuracy, metabolic cost reduction, clinical outcome measures); or safety indicators.

Study design (S): Original research articles, systematic reviews, and narrative reviews published in peer-reviewed journals or conference proceedings; experimental studies with quantitative data; case studies with device-level evaluation.

Articles were excluded if they: (i) addressed exclusively rigid robotic systems and offered no methodologically relevant FDD evidence for transferability to soft, human-coupled actuation; (ii) described actuator fabrication or material characterisation without any system-level control, sensing, or fault analysis; (iii) were conference abstracts without associated full-text data; (iv) were duplicates of a more complete publication; or (v) were not written in English.

Because methodological transferability was itself one of the review questions, a small and explicitly labelled adjacent/indirect evidence subset was retained when the originating platform was not soft or wearable but the study contributed a concrete FDD method relevant to fault-aware soft-actuator design. Such records were not treated as direct evidence of performance in soft wearable rehabilitation; they were appraised separately in Section 4.6 and Supplementary Table S1.

2.3. Study Selection Process

The selection process followed the four-stage PRISMA 2020 flow [44]. After removing duplicates across databases, titles and abstracts were independently screened by two reviewers against the eligibility criteria. Full texts were retrieved for all articles that passed abstract screening and were assessed for final inclusion; disagreements were resolved by consensus with a third reviewer. The PRISMA flow diagram is presented in Figure 1.

The verified flow counts were: 1217 records identified; 389 duplicates removed; 828 records screened; 643 records excluded at title/abstract screening; 185 reports sought; 12 not retrieved; 173 full-text reports assessed; 67 reports excluded after full-text assessment; and 106 publications included.

2.4. Data Extraction

Data were extracted from each included article using a standardised form capturing: (i) publication metadata (authors, year, journal, DOI); (ii) actuator type (pneumatic, hydraulic, SMA, DEA, tendon-driven, hybrid); (iii) anatomical target (hand, wrist, elbow, shoulder, ankle, knee, hip, or multi-joint); (iv) clinical population or user group; (v) primary thematic pillar(s) addressed (FDD, sensing, control, or combination); (vi) key methods or algorithms employed; (vii) performance metrics and quantitative outcomes reported; and (viii) validation context (bench, simulation, healthy subjects, or patients).

2.5. Quality Assessment

Because the corpus included bench experiments, algorithm-development studies, human-participant evaluations, clinical investigations, reviews, and normative documents, a single design-specific risk-of-bias instrument was not appropriate for every record. Two reviewers therefore used a structured critical appraisal focused on five domains: (1) direct relevance to soft wearable actuation; (2) relevance to rehabilitation or motor assistance;

(3) validation context, comprising simulation or bench testing, healthy participants, or patients; (4) reproducibility of the actuator, sensing, and control methods; and (5) relevance and completeness of the reported outcomes. Each domain was rated as adequate, partial, or inadequate/not reported. Evidence was additionally classified as direct, adjacent, or indirect for the claim being supported; normative standards were marked as not applicable for methodological appraisal. Disagreements were resolved by consensus. Appraisal did not determine eligibility because the objective was evidence mapping, but it governed the strength of the language used in the synthesis. Results from rigid manipulators, underwater thrusters, or general fault-diagnosis benchmarks were treated as transferability evidence rather than proof of performance in soft wearable devices. The 106 source-level ratings and verification status are reported in Supplementary Table S1; the operational definitions are in Supplementary Table S2. The authors subsequently reviewed and confirmed the D4 classifications using the corrected evidence corpus and the information captured in the manuscript extraction framework. The final D4 distribution comprised 33 publications rated as partial, 69 rated as inadequate/not reported, and four normative sources marked as not applicable; no publication was upgraded to adequate without explicit methodological support in the available evidence record. The source-level appraisal covers 106 of 108 references; the PRISMA 2020 reporting statement [44] and the methodological precedent [45] are retained as contextual references and are not included in the 106-row appraisal table.

2.6. Synthesis Approach

Marked heterogeneity in actuation principles, outcomes, and experimental settings precluded meta-analysis. We therefore used narrative synthesis and descriptive evidence mapping. Publications were grouped by thematic pillar and methodological family; counts and proportions describe publication year, actuator type, anatomical target, sensing modality, control framework, population, and validation context. These summaries characterise the composition of the literature and should not be interpreted as pooled estimates of technical or clinical performance.

For reproducibility, the five-category mapping variable used in the descriptive synthesis (FDD, sensing, intelligent control, background/design, and clinical) is distinguished from the seven-category primary-appraisal domain reported in Supplementary Table S1 (actuator/device design, cross-domain review, FDD, sensing, control, clinical, and safety). The variables serve different analytical purposes, and their category totals should not be interpreted as interchangeable.

3. Soft Wearable Actuator Technologies: An Overview

Soft wearable actuators constitute a broad and heterogeneous family of devices united by the common property of structural compliance. Unlike rigid robotic joints, soft actuators deform continuously under applied loads, distributing forces over large contact areas and accommodating the natural kinematic variability of the human body [6,8,9]. This compliance is both the primary advantage of soft systems and the root cause of the fault detection and control challenges examined in this review.

The following subsections describe the principal actuator technologies encountered in the rehabilitation literature, organised by working principle. Table 1 provides a comparative summary of actuator types, key materials, typical rehabilitation applications, and representative references. The fault detection, sensing, and control challenges specific to each technology are introduced here and developed in detail in Sections 4–6.

Table 1. Comparative overview of soft actuator technologies used in wearable rehabilitation devices.

Actuator Type	Working Principle	Key Materials	Typical Applications	Representative References
Soft Pneumatic Actuator (SPA)	Pressurised air inflates elastomeric chambers, producing bending, linear, or torsional motion	Silicone, PVC, fabric composites	Hand rehabilitation gloves, ankle exosuits, full-body exosuits	[12,13,22,34]
Hydraulic Soft Actuator	Incompressible fluid provides higher force density and reduced compressibility compared to pneumatic	Silicone, polyurethane, braided sleeves	High-force grip assistance, underwater rehabilitation	[20,34]
Shape Memory Alloy (SMA)	Phase transformation (martensite ↔ austenite) on heating/cooling generates contraction force	NiTi (Nitinol) wires or springs	Compact finger orthoses, tremor suppression	[7,10,50]
Dielectric Elastomer Actuator (DEA)	High-voltage electric field compresses elastomer film, producing in-plane expansion	VHB acrylic, silicone films, carbon electrodes	Lightweight assistive gloves, wrist orthoses	[15,16]
Tendon/Cable-Driven Soft Actuator	Motors or pneumatic actuators remotely transmit force via flexible tendons routed along the limb	Bowden cables, Dyneema fibres, textile sheaths	Dexterous hand exosuits, hip/ankle exosuits	[51–53]
Textile/Fabric Actuator (PAM)	Pressurised textile chambers or pneumatic artificial muscles woven into garments	Nylon, polyester, TPU-coated fabrics	Shoulder exomuscles, lower-back support, ankle exosuit	[54–57]

3.1. Soft Pneumatic Actuators

Soft pneumatic actuators (SPAs) are the most widely deployed technology in soft wearable rehabilitation systems [8]. In their most common form, SPAs consist of an elastomeric or textile chamber that inflates under positive gauge pressure, producing a prescribed bending, elongation, or torsional motion determined by geometric asymmetry or fibre reinforcement [8,11]. Fibre-reinforced pneumatic actuators, in which inextensible fibres wound helically or circumferentially around an elastomeric bladder constrain the inflation geometry, are particularly prevalent in hand rehabilitation gloves and ankle exosuits, where controlled bending moments are required [10,11].

Fabric-based SPAs replace monolithic elastomeric chambers with pneumatic pockets sewn or bonded into textile substrates, yielding actuators that are thinner, lighter, and more comfortable for prolonged wearable use [10,58–62]. Soft wearable systems studied by O'Neill et al. [63], Siviyy et al. [64], and Proietti et al. [65] illustrate how textile or fabric-based actuation can be integrated into garment-like devices for rehabilitation and assistance. Chai et al. [9] provide a recent review of fabric-based pneumatic actuator designs and their applications across flexible robotics and wearable assistance.

From a fault detection perspective, SPAs are predominantly subject to three failure modes: pneumatic leakage through membrane defects or fitting failures, material fatigue leading to progressive stiffness reduction, and sudden rupture under excessive pressure [15,16]. Because pressure is the primary control variable in most SPA systems, leakage is particularly insidious: a small leak reduces the pressure attained at a given pump output, causing the actuator to under-perform without triggering any immediate control

alarm [15]. The gradual nature of leakage-induced degradation motivates the development of model-based and data-driven fault detection methods discussed in Section 4.

3.2. Hydraulic Soft Actuators

Hydraulic soft actuators operate on the same chamber-inflation principle as SPAs but use an incompressible liquid, typically water or a biocompatible saline solution, as the working fluid [8,38]. The incompressibility of liquid media eliminates the energy storage associated with gas compression, yielding faster dynamic responses and higher force densities for a given actuator volume. These properties make hydraulic soft actuators attractive for applications demanding precise force control, such as finger individualisation in dexterous rehabilitation gloves.

The primary practical drawbacks of hydraulic systems for wearable applications are the need for fluid containment under dynamic loading conditions, which introduces the risk of leakage at seals and connections, and the increased mass of the fluid reservoir and pump. Research into miniaturised hydraulic drives and self-contained fluidic circuits has partially addressed these limitations [38], but hydraulic soft actuators remain less prevalent in wearable rehabilitation than their pneumatic counterparts. Their fault signatures are broadly similar to those of SPAs, leakage, delamination, and fitting failure, but the consequences of fluid release differ in nature, potentially introducing slip hazards or hygiene concerns in clinical environments.

3.3. Shape Memory Alloy Actuators

Shape memory alloy (SMA) actuators exploit the solid-state phase transformation of nickel–titanium (Nitinol) alloys between a low-temperature martensitic phase and a high-temperature austenitic phase [12]. When an SMA wire or spring is heated above the transformation temperature, typically by resistive Joule heating, it contracts, recovering a pre-programmed shape and exerting a substantial contraction force relative to its cross-sectional area. Cooling allows the wire to be re-extended by an antagonist element (spring or opposing SMA) for the return stroke.

SMA actuators are attractive for compact wearable devices because they are silent, require no pneumatic supply, and can be integrated into textile structures [12]. Shami et al. [12] review SMA-based wearable rehabilitation systems and discuss their potential for applications such as tremor management. Thermal bandwidth, heat dissipation, fatigue-induced plastic deformation, and drift in the transformation response remain important constraints. These mechanisms differ from pneumatic leakage and require diagnostic models that couple electrical, thermal, and mechanical measurements rather than relying on current or temperature thresholds alone.

3.4. Dielectric Elastomer Actuators

Dielectric elastomer actuators (DEAs) are electrically driven soft actuators in which a thin elastomeric membrane is sandwiched between two compliant electrodes [13,14]. When a high voltage (typically 1–10 kV) is applied across the electrodes, the resulting Maxwell stress compresses the elastomer in the thickness direction and expands it in-plane. By constraining the in-plane expansion in one direction, through pre-stretching or geometric patterning, useful out-of-plane displacements or bending motions can be produced.

DEAs offer extremely low mass, silent operation, and the potential for self-sensing (the capacitance of the DEA is directly related to its strain state), making them appealing for wearable applications [14]. However, the high operating voltages required raise significant safety concerns for human-contact applications, and the thin elastomeric films are susceptible to dielectric breakdown and electrode delamination, both of which can occur abruptly and without warning [13]. These safety and reliability challenges have limited

the clinical deployment of DEA-based wearable devices to date, though recent research on low-voltage DEA designs and encapsulation strategies is beginning to address them [14].

3.5. Tendon- and Cable-Driven Soft Actuators

Tendon-driven soft actuators separate the actuating motor from the limb-mounted mechanism, transmitting force via flexible cables or Bowden cable assemblies routed along textile guides [33]. This approach allows the heavy and rigid motor-gearbox units to be located remotely, at a waist pack, for example, while only lightweight cables and fabric attachment points remain at the limb, preserving the low distal mass that is critical for user comfort and biomechanical transparency [66,67].

Soft exosuits evaluated by Siviyy et al. [64] and the textile shoulder exomuscle studied by Georgarakis et al. [67] and Esser et al. [68] are representative wearable systems in which compliant transmissions or textile structures deliver assistance while limiting distal mass. Proietti et al. [66] further demonstrated that a multi-joint soft wearable could restore useful arm function in individuals with amyotrophic lateral sclerosis. These studies support the clinical potential of garment-like assistance, although their actuation and transmission architectures should not be treated as interchangeable.

The primary fault modes in tendon-driven systems are cable fraying or rupture, Bowden sheath kinking, and anchor point detachment, all of which cause sudden loss of transmission force and can result in abrupt withdrawal of assistive torque. Detection of these faults requires monitoring of cable tension and actuator-to-output force discrepancies, as described in Section 4 [33].

3.6. Hybrid and Emerging Actuator Configurations

Recent developments have explored hybrid actuator configurations that combine two or more working principles to exploit complementary advantages. Examples include pneumatic actuators with SMA-based variable stiffness elements [69], textile actuators with embedded DEA sensing layers [14], and fluidic soft actuators augmented with granular jamming for variable stiffness control. Pan et al. [38] provide a broad overview of soft actuator and robotic device combinations for rehabilitation and assistance, encompassing several emerging hybrid configurations.

From the perspective of this review, hybrid actuators present compounded fault detection challenges: each constituent actuation modality contributes its own characteristic failure modes, and the interactions between subsystems may give rise to novel fault signatures not anticipated by single-technology models. The data-driven and ensemble learning approaches reviewed in Section 4 are particularly well suited to these complex, multi-physics systems [16,43].

4. Fault Detection and Diagnosis in Soft Wearable Actuators

FDD comprises fault detection, isolation, and severity estimation. In a wearable rehabilitation device, it supports immediate protective action and longer-term maintenance. The evidence base is uneven. Supplementary Table S1 assigns nine of the 14 FDD records to adjacent evidence and five to indirect evidence under the strict target-domain definition; no record simultaneously combined a soft wearable rehabilitation platform, representative human coupling, and a complete device-level FDD validation. Rabiei et al. [15] and Duan et al. [16] provide the closest soft-actuator evidence at bench or platform level, while Sun et al. [70] addresses a rehabilitation exoskeleton. The remaining studies concern adjacent soft-robotic systems, rigid manipulators, or external actuator domains. This section therefore separates demonstrated actuator-level results from methods that remain candidates for transfer [15–18,31,40–43,46,48,70–73].

Table 2 summarises the principal failure modes of soft wearable actuators, the observable effects of each fault, and their clinical safety implications. The following subsections review the three main methodological families applied to FDD in soft wearable systems: model-based methods, signal-processing approaches, and data-driven methods. Figure 2 provides a schematic overview of the FDD pipeline for a generic soft wearable actuator system.

Table 2. Principal failure modes of soft wearable actuators and their safety implications.

Failure Mode	Actuator Type(s)	Observable Effect	Safety Implication	Representative References
Membrane puncture/rupture	SPA, Hydraulic	Sudden pressure loss, collapse of actuation	Loss of support force; risk of fall	[67,70]
Pneumatic leakage (gradual)	SPA, Textile PAM	Reduced pressure, position drift, increased compressor duty	Under-assistance; fatigue-induced compensatory movement	[70,71,74]
Material fatigue/delamination	SPA, DEA, Textile	Cyclic stiffness reduction, crack propagation, asymmetric deformation	Unpredictable kinematics; skin contact hazard	[17,71]
Tendon fraying/rupture	Tendon-driven	Sudden loss of transmission force	Abrupt drop in assistive torque; joint instability	[51]
SMA fatigue/plastic deformation	SMA	Reduced stroke, increased hysteresis, thermal drift	Reduced therapy efficacy; thermal burn risk	[7,50]
Valve/fitting failure	SPA, Hydraulic	Uncontrolled pressure release or flow blockage	Unsafe pressure surges or loss of control	[34,70]
Electrode delamination	DEA	Reduced electrostatic force, localised dielectric breakdown	Electrical hazard; loss of assistive function	[15,16]
Sensor drift/decalibration	All types	Incorrect state estimation, control instability	Erroneous torque commands; user discomfort	[41,46,71]

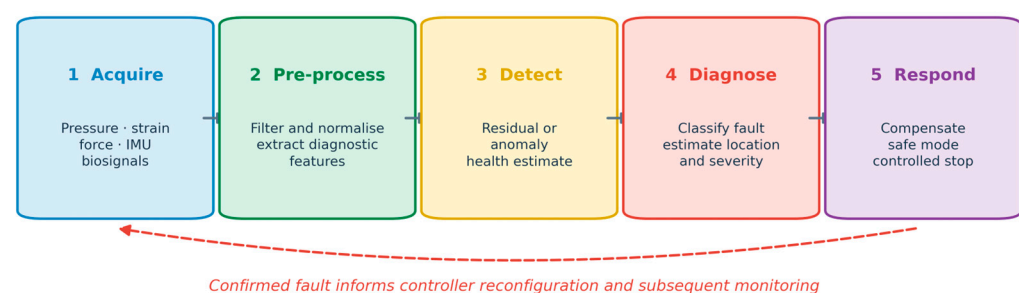


Figure 2. Fault detection and diagnosis workflow for a soft wearable actuator. Signals are acquired and pre-processed before residual or anomaly generation, fault classification, severity estimation, and a bounded protective response. Confirmed faults update subsequent monitoring and controller configuration.

4.1. Model-Based Fault Detection Methods

Model-based FDD methods construct an analytical or physical model of the actuator system and compare predicted outputs with measured signals to generate residuals. A residual that remains small under nominal conditions but grows significantly in the pres-

ence of a fault is used as a diagnostic indicator. These methods are well established in classical control theory and have been applied to soft actuators with varying degrees of adaptation to account for the nonlinear and hysteretic behaviour of compliant materials.

4.1.1. Observer-Based Methods

State observers, including Luenberger observers, extended Kalman filters (EKFs), and sliding mode observers, estimate the internal states of the actuator system from available measurements and generate residuals by comparing estimated and measured outputs. Cao et al. [31] proposed an observer-based continuous adaptive sliding mode control scheme for soft bending actuators, in which the observer simultaneously estimated external disturbances and actuator state, demonstrating robustness to modelling uncertainty that is characteristic of soft material behaviour. The same group [73] extended this approach to model-based robust tracking control without classical state observers, relying instead on an integral sliding surface to implicitly compensate for unmodelled dynamics.

Nguyen et al. [42] developed a third-order sliding-mode observer for a rigid robotic manipulator, and Hagh et al. [40] studied active fault-tolerant control for manipulator actuator faults. These studies establish observer and stability concepts, but they do not validate transfer to soft wearable systems. Application in human-coupled soft actuators would require online parameter adaptation, explicit representation of hysteresis and pressure–deformation drift, and testing under user-generated disturbances that can resemble fault residuals.

For lower limb rehabilitation exoskeletons equipped with soft or series-elastic actuators, Sun et al. [70] proposed a sliding mode-based fault reconstruction scheme capable of identifying both abrupt and incipient actuator faults, with demonstrated performance on a lower-limb rehabilitation platform. Zhang et al. [71] applied prescribed-performance sliding mode control to a series-elastic actuator-driven lower limb exoskeleton, incorporating adaptive compensation for actuator nonlinearity that implicitly provides robustness to mild fault conditions.

4.1.2. Pressure and Flow Model-Based Approaches

Pressure- and flow-based residuals are a natural starting point for pneumatic actuators because leakage changes the relation between supply input, chamber pressure, deformation, and delivered force [8,15]. Rabiei et al. [15] evaluated fault-tolerant position control for a leaking soft bending actuator. This provides direct actuator-level evidence, although transfer to a wearable rehabilitation device still requires validation during movement, variable external loading, and human interaction. We therefore do not infer a universal detection threshold or clinical safety benefit from this single experimental setting.

The key challenge for pressure-model-based methods in soft actuators is that the constitutive relationship between pressure and deformation is strongly nonlinear and subject to significant manufacturing variability, temperature dependence, and fatigue-induced drift [17,18]. Robust model-based FDD must therefore incorporate uncertainty bounds sufficiently wide to avoid false alarms under nominal variability, while remaining sensitive enough to detect real faults. This trade-off motivates the integration of model-based methods with adaptive or data-driven components, as described in Section 4.3.

4.1.3. Self-Healing and Fault-Tolerant Material Approaches

A distinct strand of research addresses actuator fault tolerance at the material level rather than the control level. Terryn et al. [46] demonstrated a self-healing soft pneumatic actuator based on a Diels–Alder thermoset elastomer capable of autonomously repairing puncture damage upon thermal activation. While this work predates the review window, it established the concept of intrinsic material-level fault recovery that has informed

subsequent research [17]. Bonard et al. [17] provide a comprehensive recent review of self-healing soft robots, covering self-healing elastomers, hydrogels, and liquid metal composites, as well as embedded sensing approaches that can detect damage and trigger healing responses. Li et al. [72] complemented these material-level approaches with position control strategies designed to maintain safe actuator behaviour in the presence of soft material nonlinearities.

4.2. Signal-Processing-Based Fault Detection

Signal-processing-based FDD methods analyse time-series measurements, typically pressure, flow, force, deformation, or acoustic emission signals, for features that indicate departing from nominal behaviour, without requiring an explicit physical model of the actuator. These methods are generally more computationally lightweight than model-based approaches and more robust to modelling uncertainty, but they require a reference characterisation of nominal signal behaviour and may be sensitive to operating-condition changes.

4.2.1. Statistical Process Control and Threshold Methods

The simplest signal-processing approach to FDD in soft actuators is threshold-based monitoring: a pressure, flow, or position signal is compared against a predefined bound, and a fault is declared if the signal remains outside the bound for a specified duration. While straightforward to implement, pure threshold methods suffer from poor sensitivity to gradual faults and high false alarm rates under variable operating conditions. Statistical process control (SPC) methods, including cumulative sum (CUSUM) charts and exponentially weighted moving averages (EWMAs), improve on simple thresholds by accumulating evidence of a distributional shift over time, achieving better detection sensitivity for incipient faults at the cost of increased detection latency [41].

Lovett et al. [18] reviewed sensor technologies and control challenges in soft robotics, noting that basic pressure monitoring with hysteresis-compensated thresholds remains the most commonly deployed FDD strategy in commercial soft rehabilitation devices, despite its recognised limitations. The review highlights the gap between academic FDD research and clinical deployment, where simplicity and regulatory compliance often constrain the sophistication of implemented methods.

4.2.2. Spectral and Time-Frequency Analysis

Spectral analysis methods decompose actuator signals in the frequency domain to identify fault-specific frequency components or changes in spectral shape. In pneumatic systems, leakage typically produces a characteristic increase in the high-frequency content of pressure oscillations due to turbulent flow through the defect orifice, while material fatigue manifests as a gradual reduction in the fundamental resonant frequency of the pneumatic circuit [15,16]. Wavelet transforms and empirical mode decomposition have been applied to separate fault-related transients from operating-condition-dependent background variations in soft actuator pressure signals, providing more robust fault indicators than purely spectral methods under non-stationary conditions [16].

4.3. Data-Driven Fault Detection Methods

Data-driven FDD methods learn fault signatures directly from operational data, without requiring an explicit physical model. The rapid growth of machine learning and deep learning techniques has made data-driven approaches increasingly prominent in the FDD literature across diverse engineered systems [41,43]. For soft wearable actuators, data-driven methods are particularly attractive because the complex, nonlinear, and history-dependent behaviour of soft materials is difficult to capture with analytical models of tractable complexity.

4.3.1. Classical Machine Learning Approaches

Classical classifiers can combine pressure, flow, deformation, and acoustic features. Duan et al. [16] examined multimodal spatiotemporal features and ensemble learning for faults in pneumatic soft actuators, providing direct evidence that complementary signals can improve fault discrimination. The wearable setting adds substantial domain shift: sensor placement, garment fit, user movement, and inter-device manufacturing variability may all alter the feature distribution. External validation across devices and users is therefore required before performance estimates can be generalised.

Nascimento and Valdenegro-Toro [48] used recurrent networks for soft-fault diagnosis in underwater thrusters. The study is methodologically relevant because it addresses gradual loss of performance, but the failure physics, loading environment, and safety response differ fundamentally from those of pneumatic, textile, or tendon-driven wearables. It is therefore cited as an example of a transferable modelling strategy, not as evidence that recurrent-network FDD is effective in rehabilitation devices.

4.3.2. Deep Learning and CNN-LSTM Architectures

Convolutional neural networks (CNNs) applied to time-series data can automatically extract hierarchical spatial features from raw actuator signals, bypassing the manual feature engineering required by classical machine learning methods. Long short-term memory (LSTM) networks capture temporal dependencies in sequential data, making them well suited to the detection of gradually evolving faults in soft actuators. Hybrid CNN-LSTM architectures combine both capabilities and have demonstrated state-of-the-art performance in fault diagnosis benchmarks across multiple domains [43].

CNN-LSTM architectures can extract local signal patterns while retaining temporal context, and they have performed well in general fault-diagnosis benchmarks [43]. Their suitability for soft wearables remains uncertain because available datasets are small and device-specific. Useful adaptations may include physics-informed features, uncertainty calibration, transfer learning, and evaluation on data acquired from multiple actuator batches and users.

Quamar and Nasir [41] reviewed AI, machine learning, and digital twin approaches for fault diagnosis and fault-tolerant control in robotic manipulators, identifying several architectural patterns, including physics-informed neural networks and attention-based transformer models, that have not yet been applied to soft wearable actuators but offer considerable promise, particularly for real-time FDD with limited training data.

4.3.3. Anomaly Detection and Unsupervised Methods

A significant practical limitation of supervised FDD methods, whether classical or deep learning-based, is the requirement for labelled training data covering the fault conditions of interest. For soft wearable rehabilitation devices, collecting labelled fault data in clinical settings is challenging, both ethically (fault conditions may be unsafe for users) and logistically (the diversity of fault types and severities is large). Unsupervised anomaly detection methods, which learn a model of nominal behaviour and flag deviations without requiring fault examples, are therefore particularly relevant.

Autoencoder-based anomaly detection, in which a neural network trained to reconstruct nominal data generates large reconstruction errors for out-of-distribution (faulty) inputs, has been applied to soft robotics monitoring [18]. One-class SVMs and isolation forests offer computationally lighter alternatives for resource-constrained wearable controllers. Alam et al. [75] reviewed neural network approaches for enhancing robot-assisted rehabilitation, including unsupervised learning methods for operational state monitoring,

and identified anomaly detection as an underexplored direction for improving the safety and reliability of soft rehabilitation systems.

4.4. Fault-Tolerant Control Strategies

Fault detection alone is insufficient for safe operation; detected faults must be followed by appropriate control responses. Fault-tolerant control (FTC) strategies for soft wearable actuators fall into two categories: passive FTC, in which the control design provides inherent robustness to a defined class of faults without requiring explicit detection; and active FTC, in which fault detection triggers a reconfiguration of the control law [15,40].

Passive fault-tolerant approaches for soft actuators typically employ robust control formulations, such as sliding mode or adaptive control, with disturbance bounds sufficiently wide to accommodate anticipated fault-induced degradation [31,73]. While simple and reliable, passive approaches necessarily sacrifice nominal performance to provide fault robustness, and they cannot accommodate faults that exceed the design disturbance bounds.

Active FTC changes the control response after a fault is detected. Rabiei et al. [15] studied leakage compensation in a soft bending actuator, whereas Sun et al. [70] investigated actuator fault reconstruction in a lower-limb rehabilitation exoskeleton. These studies support the feasibility of reconfiguration, but neither establishes a general strategy for soft wearable use. In a human-coupled device, compensation must be bounded so that an attempt to preserve tracking does not increase pressure, force, or interface load beyond safe limits.

For multi-actuator wearable systems assisting multiple joints, a fault in one actuator may be partially compensated by redistribution of assistive torques among the remaining functional actuators, an approach analogous to actuator redundancy management in aerospace systems [40]. This strategy requires a supervisory fault management layer that maintains a real-time model of system capability and adjusts the assistive torque allocation accordingly, a research direction that remains largely unexplored for soft wearable rehabilitation devices.

4.5. Benchmarking and Standardisation Challenges

A persistent challenge in the FDD literature for soft wearable actuators is the lack of standardised benchmarks and reporting conventions, which makes it difficult to compare results across studies [18,41]. Published studies vary widely in the fault types investigated, the actuator configurations used, the experimental conditions under which data are collected, and the performance metrics reported. Key metrics such as time-to-detection, minimum detectable fault amplitude, false alarm rate at clinically relevant thresholds, and performance under simultaneous fault and user movement artefact are rarely all reported in the same study.

The safety standards applicable to wearable rehabilitation devices, including ISO 13482 [76] for personal care robots, IEC 80601-2-78 [77] for medical rehabilitation robots, and ISO/TR 23482-1 [78] for safety testing methods, do not currently specify FDD performance requirements in quantitative terms, leaving validation methodologies largely to the discretion of individual research groups. Establishing community consensus on FDD benchmarking standards is identified in Section 8 as a priority research direction.

4.6. Transferability of FDD Methods to Soft, Human-Coupled Actuators

Transferability depends on whether the diagnostic signal is preserved when actuator physics and operating conditions change. Pressure residuals and observer-based methods are plausible for pneumatic wearables, but require adaptive baselines because temperature, garment fit, user loading, and fatigue alter nominal dynamics. Threshold and statistical-process methods are inexpensive to implement, yet voluntary movement may produce

transients that resemble leakage or blockage. Supervised learning can represent nonlinear signatures but is vulnerable to device and user domain shift. Unsupervised methods reduce the need for labelled faults, although they must distinguish actuator degradation from sensor displacement and changes in user effort.

Accordingly, a borrowed FDD method should be considered validated for soft wearable rehabilitation only after testing on the target actuator, during representative human movement, across more than one device or manufacturing batch, and with reporting of false alarms, detection latency, minimum detectable severity, and the safety consequence of the control response. Until those conditions are met, external-domain studies support methodological plausibility rather than clinical or device-level effectiveness.

5. Sensing Strategies for Soft Wearable Actuators

Effective sensing is a prerequisite for both fault detection and intelligent control in soft wearable rehabilitation systems. The sensing requirements of soft actuators differ fundamentally from those of rigid robotic systems: the large, continuous deformations produced by soft actuators preclude the use of conventional rigid-body encoders, and the intimate contact between device and human body demands sensors that are flexible, lightweight, biocompatible, and robust to the complex loading conditions of physical activity [18,23,24].

The sensing architecture of a soft wearable rehabilitation device encompasses three complementary categories [26]: proprioceptive sensors, which measure the internal state of the actuator; exteroceptive sensors, which measure interaction forces, kinematics, and environmental conditions at the human–device interface; and biosignal sensors, which acquire physiological signals, primarily from the muscular and nervous systems, to infer the user’s motor intent and effort. Table 3 provides a structured overview of the principal sensing modalities in each category, with key performance parameters and representative references. Figure 3 illustrates the integration of these three sensing layers in a representative soft wearable rehabilitation system.

Table 3. Sensing modalities used in soft wearable rehabilitation actuator systems.

Sensing Category	Modality/Sensor Type	Measured Quantity	Typical Performance	Representative References
Proprioceptive (Actuator State)	Pressure transducer	Chamber pressure (kPa)	Range: 0–300 kPa; accuracy $\pm 0.5\%$	[34,70]
	Resistive/capacitive strain gauge (flexible)	Bending angle, elongation (%)	GF: 2–10; bandwidth: DC–100 Hz	[18,41]
	Optical fibre sensor (FBG, intensity-based)	Curvature, bending angle	Resolution: 0.1° ; immune to EMI	[41,46]
	Pneumatic artificial muscle displacement sensor	Linear displacement (mm)	Range: 0–50 mm; linearity $\pm 2\%$	[34,79]
Exteroceptive (Interaction Forces)	Force/torque sensor (6-DOF)	Interaction forces and torques (N, Nm)	Resolution: 0.01 N; bandwidth: 0–500 Hz	[59,80]
	Capacitive/resistive pressure array (tactile)	Contact pressure distribution (kPa)	Spatial res.: 1–5 mm; temporal: 100 Hz	[12,22]
	IMU (accelerometer + gyroscope + magnetometer)	Segment orientation, angular velocity, acceleration	Drift: $<2^\circ/\text{min}$; update rate: 200 Hz	[36,60]

Table 3. Cont.

Sensing Category	Modality/Sensor Type	Measured Quantity	Typical Performance	Representative References
Biosignal (User Intent)	Surface EMG (sEMG)	Muscle activation amplitude and timing (μV)	Bandwidth: 10–500 Hz; SNR: 20–40 dB	[42,48,81]
	EEG (electroencephalography)	Cortical motor potentials (μV)	Bandwidth: 0.1–100 Hz; channels: 8–256	[66,69]
	fNIRS (functional near-infrared spectroscopy)	Cortical haemodynamic response	Temporal res.: 100 ms; spatial: 1–3 cm	[69]
Multimodal (Fusion)	sEMG + IMU fusion	Intent + kinematics combined	Improved robustness to artefacts	[60,82]
	Pressure + force + EMG fusion	Full interaction state	Clinical-grade intent detection	[80,83]

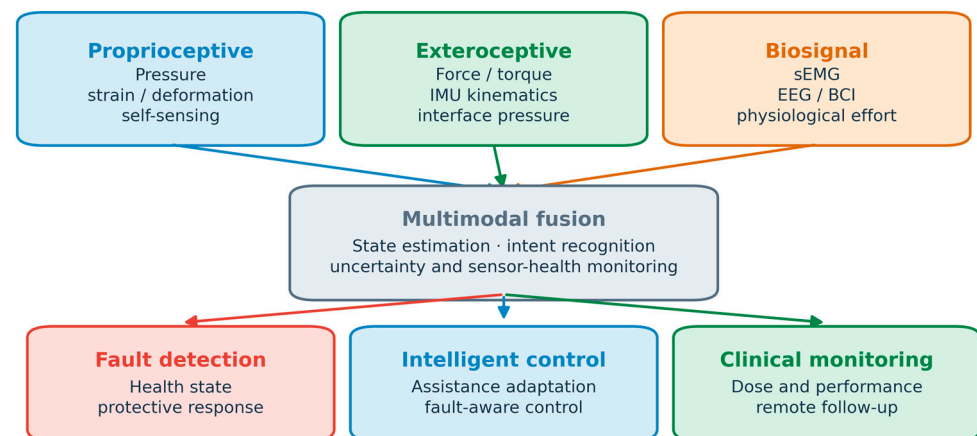


Figure 3. Multimodal sensing architecture for soft wearable rehabilitation. Proprioceptive, exteroceptive, and biosignal measurements are fused for actuator-health estimation, adaptive control, and clinical monitoring. Detailed sensor specifications are provided in Table 3.

5.1. Proprioceptive Sensing: Actuator State Monitoring

Proprioceptive sensors measure the internal state of the soft actuator, its deformation, pressure, force output, and temperature, providing the feedback signal required for closed-loop control and fault monitoring. The intrinsic softness and large deformability of soft actuators make proprioceptive sensing a uniquely challenging engineering problem.

5.1.1. Pressure Sensing

Pressure transducers are the most widely deployed proprioceptive sensors in pneumatic and hydraulic soft actuators, measuring the supply or chamber pressure that is the primary control variable in pressure-driven systems [8,15]. Modern miniaturised MEMS pressure sensors achieve measurement ranges of 0–300 kPa, accuracies of $\pm 0.5\%$ full scale, and response times below 1 ms, making them well suited for real-time control loops [8]. In the context of FDD, pressure signals are the primary input to model-based leakage detectors, as described in Section 4.1.2. However, pressure alone cannot distinguish between different deformation states of the actuator at the same pressure, a limitation that has driven interest in complementary deformation sensing.

5.1.2. Flexible Strain and Deformation Sensors

Flexible strain sensors measure the local deformation of the actuator body, providing a direct estimate of bending angle or elongation that complements pressure-based state estimation. The most widely used flexible strain sensing technologies in soft robotics are resistive sensors based on conductive composites, carbon black or graphene embedded in an elastomeric matrix, and capacitive sensors in which deformation changes the overlap area or separation of flexible electrode pairs [23,25].

Iqra et al. [25] demonstrated a flexible piezoresistive strain sensor fabricated by laser scribing of graphene oxide on polydimethylsiloxane (PDMS), achieving a gauge factor above 10, a measurement range of 0–50% strain, and hysteresis below 5% over 1000 cycles, performance characteristics relevant to the repetitive loading cycles of rehabilitation exercise. Wang et al. [23] reviewed soft polymer optical fibre sensors for elastomer deformation sensing and wearable applications, highlighting their immunity to electromagnetic interference and potential for integration into textile substrates as key advantages for wearable rehabilitation systems.

Kang et al. [24] developed a soft bending actuator with integrated fibre-jamming variable stiffness and fibre-optic proprioception, demonstrating that the embedded optical fibre could simultaneously serve as a deformation sensor and a structural stiffness modulation element. This dual functionality, actuation and sensing within the same fibre, is an example of the morphological computation paradigm in which soft robots exploit their material and structural properties to reduce sensor complexity.

5.1.3. Self-Sensing Actuation

Several soft actuator technologies offer inherent self-sensing capability in which the same physical element performs both actuation and state measurement. DEAs exhibit a capacitance that is directly related to the in-plane strain of the elastomeric membrane, enabling capacitance measurement between actuation pulses to estimate actuator deformation [14]. SMA actuators exhibit an electrical resistance that varies with phase composition and hence with contraction state, providing a self-sensing signal accessible via standard current and voltage measurements [12]. For SPAs, Li et al. [72] demonstrated position sensing based on the pressure–displacement model of the actuator, enabling position control without dedicated deformation sensors in constrained wearable deployments.

5.2. Exteroceptive Sensing: Interaction and Kinematics

Exteroceptive sensors measure quantities at the interface between the soft wearable device and the user's body, or in the environment. For rehabilitation applications, the most important exteroceptive measurements are interaction forces and torques, which determine whether the device is providing the intended assistive effort without causing discomfort or skin pressure injury, and limb kinematics, which characterise the user's movement for gait analysis, progress monitoring, and control.

5.2.1. Force and Torque Sensing

McCann et al. [84] developed an in-situ multi-axis torque measurement system for a soft shoulder wearable robot, embedding custom strain gauge assemblies within the fabric structure to measure the three-dimensional torques applied to the shoulder joint during assistive tasks. This approach demonstrated that accurate force sensing could be achieved within a soft wearable system without recourse to external measurement instruments, a critical step towards closed-loop force control in ambulatory rehabilitation.

Proietti et al. [65] described the sensing and control architecture of a multi-joint soft upper-limb exosuit for upper-limb assistance and rehabilitation, in which load cells

embedded in the cable transmission measured the tension exerted by each actuated degree of freedom, providing both control feedback and monitoring of asymmetric loading that could indicate actuator fault or misalignment. O'Neill et al. [63] incorporated interaction force sensing in a soft upper-limb wearable designed to reduce therapist fatigue during stroke rehabilitation, demonstrating the clinical utility of real-time force monitoring for both safety and therapy dose quantification.

5.2.2. Inertial Measurement Units

Inertial measurement units (IMUs), combining accelerometers, gyroscopes, and magnetometers, are widely used to estimate limb kinematics in wearable rehabilitation systems [49,85–87]. Their body-worn format is compatible with gait-phase detection and locomotion-mode classification outside an optical motion-capture laboratory. In a soft exosuit, however, sensor-to-segment motion and garment displacement must be considered because the textile structure may move relative to the underlying anatomy.

Zhang et al. [85] demonstrated real-time locomotion mode detection from a single IMU mounted on a soft exosuit, enabling automatic switching between walking, stair ascent, stair descent, and sitting control modes with a classification accuracy above 95% across ten subjects. Voisard et al. [86] evaluated automatic gait event detection from IMUs in both healthy subjects and patients with moderate-to-severe gait impairments, reporting that algorithms trained on healthy gait data showed significant performance degradation on pathological gait, motivating the development of population-specific or adaptive gait detection algorithms.

Prasanth et al. [87] systematically reviewed wearable-sensor methods for real-time gait detection. Their synthesis shows that reported algorithms differ in sensor placement, event definitions, participant populations, and validation protocols. These differences matter when gait-event detectors are transferred to a soft exosuit, because garment motion and compliant transmission can alter the relationship between segment kinematics and the timing of delivered assistance.

5.2.3. Tactile and Distributed Pressure Sensing

Distributed pressure sensing arrays at the human–device interface provide spatially resolved maps of contact pressure that are important both for comfort monitoring, identifying pressure concentrations that could cause skin injury during prolonged use, and for closed-loop control of interaction forces. O'Neill et al. [10] integrated capacitive pressure sensing elements within a textile pneumatic actuator to monitor the distribution of contact forces applied to the forearm during upper-limb rehabilitation assistance, enabling detection of interface misalignment that would otherwise produce localised pressure concentrations.

Ge et al. [11] incorporated flexible pressure sensors into the inner surface of a soft assistive glove to monitor the contact forces between the glove and individual finger segments during grasping tasks, using the sensor data to detect object contact and modulate gripping force in real time. This approach, in which distributed tactile sensing drives closed-loop grasping control, is representative of a broader trend towards sensor-rich soft wearable devices in which sensing and actuation are co-designed as integrated systems.

5.3. Bio-Signal Sensing: Motor Intent Estimation

Biosignal sensing acquires physiological signals generated by the user's neuromuscular system to infer motor intent, the desired movement that the wearable device should assist or facilitate. Accurate, low-latency intent estimation is essential for the naturalness and safety of the human–robot interaction: a device that responds after the intended movement has begun provides assistance that is too late to be biomechanically effective, while one that generates false intent detections may impose unexpected forces on the user [19,88].

5.3.1. Surface Electromyography

Surface electromyography (sEMG) measures the electrical activity generated by contracting muscles through electrodes placed on the skin surface, providing a non-invasive window into motor commands at the muscular level with latencies of 50–100 ms ahead of the resulting movement [19,21]. sEMG is the most widely used biosignal modality for intent detection in wearable rehabilitation systems, with reported applications spanning hand grasp intent [20], elbow flexion/extension [22], and lower limb locomotion mode [50,88].

Zhang et al. [19] provided a comprehensive review of sEMG-based motion intention recognition for exoskeleton robots, covering signal acquisition, feature extraction, and classification methods [89] with particular attention to the challenges of electrode placement variability, signal non-stationarity, and cross-session performance degradation. Sul et al. [21] reviewed EMG signal acquisition, filtering, and data analysis methods specifically for exoskeleton development, providing practical guidance on electrode configuration, amplification, and noise rejection for wearable deployment.

A significant challenge for sEMG-based intent detection in rehabilitation populations is the reduced signal quality arising from muscle weakness, spasticity, and co-contraction patterns characteristic of neurological injury [20]. Molinaro et al. [50] demonstrated a task-agnostic exoskeleton controller based on biological joint moment estimation from sEMG that generalised across locomotion tasks without task-specific training, reporting successful deployment in both healthy subjects and individuals with lower limb amputation. This task-agnostic approach is particularly relevant for rehabilitation, where the task repertoire changes over the course of therapy.

5.3.2. Electroencephalography and Brain–Computer Interfaces

Electroencephalography (EEG) measures cortical electrical activity through electrodes placed on the scalp, providing a signal that precedes muscle activation and can detect motor intent even in patients with severe muscle weakness or paralysis [22,51]. EEG-based brain–computer interfaces (BCIs) have been explored as control modalities for upper-limb soft exoskeletons in patients with spinal cord injury and ALS, where sEMG signals may be absent or insufficient for reliable intent detection.

Abdallah et al. [22] developed a hybrid EMG–EEG interface for robust intention detection and fatigue-adaptive control of an elbow rehabilitation robot, demonstrating that the combination of cortical and muscular signals outperformed either modality alone in terms of classification accuracy and robustness to muscle fatigue, a common confound in rehabilitation exercise sessions. Tang et al. [51] reviewed wearables-based motion intention prediction methods spanning the full hierarchy of the human nervous system, from cortical EEG through spinal cord potentials to peripheral nerve and muscle signals, identifying multi-level neural sensing as a future direction for high-fidelity intent estimation.

5.3.3. Multi-Modal Sensor Fusion

The complementary strengths of individual sensing modalities—sEMG provides high temporal resolution but is vulnerable to electrode shift and fatigue, IMUs provide robust kinematic information but cannot directly measure muscular effort, and force sensors measure interaction loads but not neural commands—motivate the integration of multiple modalities through sensor fusion algorithms [83,88].

Li et al. [83] proposed a multi-sensor fusion-based mirror adaptive assist-as-needed control strategy for a soft upper-limb exoskeleton that combined sEMG, force, and position signals through a fuzzy logic fusion layer, adapting the level of assistance in real time to the user's effort and fatigue state. Wang et al. [88] reviewed the sensing and algorithmic landscape for locomotion intention detection in lower limb exoskeletons, identifying

multimodal fusion, particularly sEMG combined with IMU and ground reaction force data, as the highest-performing approach for continuous locomotion mode classification in ambulatory conditions.

Kim et al. [90] integrated soft wearable flexible bioelectronics with an ankle-foot exoskeleton, combining metabolic cost estimation from wearable sensors with physical effort quantification from integrated strain gauges to provide a comprehensive picture of user state during exoskeleton-assisted walking. This multimodal physiological monitoring approach exemplifies the convergence of sensing, actuation, and clinical assessment in next-generation soft wearable rehabilitation systems.

6. Intelligent Control Frameworks for Soft Wearable Rehabilitation Devices

Control of soft wearable actuators must accommodate nonlinear material behaviour, uncertain human-limb impedance, and changes across users and sessions. No single control family resolves all of these constraints. The approaches identified in the literature are therefore compared according to modelling burden, adaptability, sensing requirements, and available validation rather than being ranked by isolated performance values [27,29,30,91]. Table 4 summarises the principal families.

Table 4. Intelligent control methods applied to soft wearable actuators for rehabilitation and motor assistance.

Control Family	Method	Key Feature	Actuator/Application	Representative References
Model-Based	PID/PID with feedforward	Simple, real-time; requires accurate model	SPA hand glove, ankle exosuit	[29,34]
	Model Predictive Control (MPC)	Constraint handling, preview horizon	Knee rehabilitation exoskeleton	[1,30]
	Impedance/admittance control	Transparent human–robot interaction	Multi-joint soft exosuit	[28,80]
Robust/Sliding Mode	Sliding mode control (SMC)	Robustness to model uncertainty	Lower limb exoskeleton, SPA	[19,91,92]
	Adaptive SMC + prescribed performance	Transient response guarantees	SEA-driven lower limb	[92,93]
Adaptive	Adaptive control (MRAC, APPC)	Online parameter update for nonlinear plant	Soft exo-suit ankle, hip	[47,88]
	Iterative Learning Control (ILC)	Trial-to-trial performance improvement	Hip and knee soft exoskeleton	[29]
Bioinspired	Central Pattern Generator (CPG)	Rhythmic gait generation, entrainment	Lower limb exoskeleton	[37]
	CPG + impedance hybrid	Smooth gait transitions + compliance	Ankle exosuit	[90]
Machine Learning	Supervised intent recognition (SVM, RF, DNN)	Pre-trained classifier for locomotion mode	Ankle/lower limb exoskeleton	[14,82]
	Convolutional Neural Network (CNN)	Spatial feature extraction from sEMG/IMU	Upper limb, hand exosuit	[48,65]
	LSTM/Temporal CNN	Sequential intent prediction	Multi-joint exoskeleton	[49,66]

Table 4. Cont.

Control Family	Method	Key Feature	Actuator/Application	Representative References
Reinforcement Learning	Deep RL (PPO, SAC, DDPG)	Reward-driven policy optimisation	Lower limb, tremor suppression	[31,38,39]
	RL in simulation + sim-to-real transfer	Large-scale training without patient data	Full-body exosuit	[43,72]
Human-in-the-Loop	Bayesian/Gaussian process optimisation	Personalised assistance with few trials	Hip soft exosuit	[27,73]
	Multi-sensor fusion adaptive assist-as-needed	Mirror therapy + progressive assistance	Upper limb soft exoskeleton	[83]

6.1. Model-Based Control

6.1.1. Impedance and Admittance Control

Impedance control regulates the dynamic relationship between position and force at the human–robot interface, allowing the wearable device to behave as a programmable mechanical impedance, spring, damper, and inertia, rather than imposing a fixed position or force trajectory [63,65]. This approach is particularly appropriate for rehabilitation applications because it allows the level of assistance to be modulated continuously from full guidance (low user effort required) to resistive training (high user effort required) by adjusting the impedance parameters, supporting the assist-as-needed paradigm that is central to evidence-based motor rehabilitation.

Proietti et al. [65] implemented impedance control in a multi-joint soft upper-limb exosuit, demonstrating that transparent interaction, in which the device exerts minimal forces when the user moves voluntarily, could be achieved despite the significant inertia and friction of the tendon-driven actuation system by combining impedance control with cable tension feedback. O'Neill et al. [63] applied admittance control to an inflatable soft upper-limb wearable for stroke rehabilitation, demonstrating clinically significant reductions in therapist physical effort during assisted reaching tasks without compromising the quality of movement assistance provided to severely impaired patients.

6.1.2. Model Predictive Control

Model predictive control (MPC) solves an online optimisation problem at each control step, selecting the control input that minimises a predicted cost over a finite time horizon while satisfying actuator and safety constraints [1,30]. The ability to handle multiple constraints explicitly, including joint range-of-motion limits, maximum interaction forces, and actuator pressure bounds, makes MPC particularly attractive for soft wearable rehabilitation devices, where safe operation within patient-specific biomechanical envelopes is essential.

Caulcrick et al. [30] developed a human-centred MPC framework for lower-limb robotic assistance that incorporated a musculoskeletal representation of the user. Jammeli et al. [29] proposed explicit MPC for a knee rehabilitation exoskeleton. Both studies illustrate how constraints can be embedded in controller design, although their results should not be generalised to soft wearable actuators without accounting for compliant transmission dynamics and device-specific computational limits.

6.2. Robust and Sliding Mode Control

Sliding mode control (SMC) drives the system state onto a designed sliding surface and maintains it there despite bounded disturbances and parameter uncertainty, making it inherently robust to the modelling errors that arise from soft material nonlinearity and hysteresis [31,71]. The principal limitation of classical SMC, high-frequency chattering due to discontinuous switching, has been addressed in soft actuator applications through higher-order SMC formulations and boundary layer methods that smooth the switching law at the cost of a small reduction in robustness.

Zhang et al. [71] applied prescribed-performance SMC to a series-elastic actuator-driven lower limb exoskeleton, ensuring that tracking errors remained within predefined time-varying bounds that tighten over the course of the rehabilitation session, a feature with direct clinical relevance as it provides formal guarantees on the quality of movement assistance. Hfaiedh et al. [54] combined reinforcement learning with sliding mode control for a passive upper-limb exoskeleton, using RL to adapt the SMC gains online in response to changing user biomechanics, demonstrating that the combination outperformed fixed-gain SMC in tracking accuracy across subjects with varying arm impedance.

Hasan and Alam [94] described adaptive sliding-mode control for a lower-extremity rehabilitation exoskeleton. Together with soft-actuator studies by Cao et al. [31,73], this work illustrates the robustness of sliding-mode formulations to bounded uncertainty. The remaining question is whether uncertainty bounds can represent fatigue, temperature drift, garment fit, and user-generated perturbations without producing excessive conservatism or chattering in a wearable system.

6.3. Adaptive and Iterative Learning Control

Adaptive control methods update their parameters online in response to measured discrepancies between model predictions and actual system behaviour, accommodating the slow time-varying changes in soft actuator characteristics due to material fatigue, temperature, and user biomechanical variability [28,95]. Model reference adaptive control (MRAC) adjusts the controller gains to minimise the error between actual and reference model outputs, while self-tuning regulators update an identified plant model and recompute the optimal control law at each step.

Li et al. [28] developed human-in-the-loop adaptive control for a soft exosuit with actuator dynamics and ankle-impedance adaptation. Such online adjustment is well matched to user variability, but clinical use requires safeguards on the rate and magnitude of parameter change. High-level locomotion planning and CPG-based adaptation may complement this approach [95], although these methods address gait generation rather than actuator-fault accommodation.

Iterative learning control uses the repeated structure of rehabilitation exercises to reduce systematic tracking error across trials. Chen et al. [74] applied ILC to a soft exoskeleton assisting the hip and knee. The method is attractive for repetitive therapy, but convergence reported for a specific device and task should not be interpreted as a general clinical performance threshold.

6.4. Bioinspired Control: Central Pattern Generators

Central pattern generator (CPG) models are biologically inspired oscillator networks that generate rhythmic motor commands analogous to those produced by spinal cord neural circuits during locomotion [27,95]. In wearable rehabilitation, CPG controllers offer several advantages: they generate smooth, continuous, and coordinated joint trajectories without requiring a detailed biomechanical model; they can entrain to the user's natural gait frequency through sensory feedback, producing assistance that is inherently synchronised

with the user's movement; and they can modulate gait parameters, speed, step length, and cadence, through high-level inputs without requiring trajectory replanning.

Duan et al. [95] implemented a CPG-based gait generation strategy for a lower limb exoskeleton, demonstrating that the oscillator network could generate physiologically realistic joint trajectories for walking, jogging, and stair climbing [96] by adjusting a small number of high-level parameters, and that entrainment to sensor-measured heel-strike events reduced gait phase error to below 5% of the gait cycle. Baud et al. [91] reviewed control strategies for lower-limb gait assistance exoskeletons, including CPG-based approaches, identifying bioinspired methods as particularly promising for their ability to generate natural inter-joint coordination without explicit trajectory specification.

6.5. Machine Learning-Based Control

6.5.1. Supervised Learning for Intent Recognition and Motion Control

Supervised machine learning classifiers trained on labelled sEMG, IMU, and force data have been extensively applied to locomotion mode recognition and motion intent classification for exoskeleton control [88,97]. Support vector machines, random forests, and, increasingly, deep neural networks trained on features extracted from multi-channel sEMG signals have achieved locomotion mode classification accuracies above 95% in controlled laboratory conditions [80].

Zaim et al. [20] reviewed machine learning and deep learning-based myoelectric control systems for upper limb rehabilitation, comprehensively comparing classical feature extraction with end-to-end deep learning approaches across multiple signal modalities including sEMG and EEG. The review identified convolutional architectures as the current best-performing approach for sEMG-based intent classification, while noting that cross-session and cross-subject generalisations remain significant open challenges for clinical deployment. Velez-Guerrero et al. [97] surveyed AI-based wearable robotic exoskeletons for upper limb rehabilitation, documenting the rapid transition from rule-based to data-driven control strategies that occurred between 2015 and 2021.

Molinaro et al. [50] achieved a particularly significant advance with a task-agnostic exoskeleton controller based on biological joint moment estimation from sEMG, which required no task-specific training and generalised across walking, stair climbing, and load-carrying conditions in both able-bodied subjects and lower-limb amputees. The biological joint moment estimation approach, in which a neural network maps sEMG features directly to joint moment, bypassing explicit task classification, represents a paradigm shift from discrete mode-switching to continuous biomechanical assistance that aligns more closely with natural human motor control.

6.5.2. Recurrent and Temporal Neural Networks

Recurrent neural networks, including LSTM and gated recurrent unit (GRU) architectures, capture temporal dependencies in sequential sensor data that are missed by frame-based classifiers operating on fixed-length windows [22,80]. In the context of soft wearable control, LSTM-based intent predictors have been applied to anticipatory control, predicting the intended movement before it begins from pre-movement neural or kinematic cues, allowing the exosuit to begin providing assistance with minimal perceptible delay.

Abdallah et al. [22] demonstrated that a hybrid EMG–EEG LSTM controller for elbow rehabilitation could detect movement intent from EEG motor imagery signals 200–350 ms before electromyographic activity onset, enabling the exoskeleton to initiate assistive forces synchronously with the voluntary movement command rather than reactively. Harris et al. [80] reviewed AI-based methodologies for exoskeleton-assisted lower limb rehabilitation, identifying recurrent architectures as particularly promising for continu-

ous gait control in patients with irregular or variable gait patterns where fixed-template controllers fail.

6.6. Reinforcement Learning for Soft Wearable Control

Reinforcement learning (RL) trains a control policy by maximising a cumulative reward signal through interaction with the environment, without requiring an explicit model of the system dynamics [52,53]. For soft wearable rehabilitation systems, RL offers the prospect of automatic policy optimisation that adapts to individual biomechanical variability and learns to minimise metabolic cost or maximise task performance without requiring manual tuning of control parameters, a compelling advantage given the large inter-individual variability in rehabilitation populations.

Luo et al. [52] developed deep-reinforcement-learning control for a lower-limb rehabilitation exoskeleton coupled to a musculoskeletal model. A later study demonstrated experiment-free exoskeleton assistance trained in simulation [98]. These results show the potential of simulation-based policy development, while also sharpening the need for independent safety validation, uncertainty testing, and explicit evaluation under actuator degradation before transfer to unsupervised rehabilitation.

Endrei et al. [53] applied deep RL to tremor suppression with a soft exoskeleton for Parkinson's disease patients, training a policy that learned to apply counter-phase assistive forces to attenuate pathological tremor while preserving voluntary movement, a challenging control problem that requires distinguishing between tremor and intentional motion in real time. Hfaiedh et al. [54] combined RL with sliding mode control for a passive upper-limb exoskeleton, using RL to adapt the SMC gains online and demonstrating improved robustness to parameter uncertainty compared to fixed-gain designs.

Huang et al. [55] proposed model-free reinforcement learning combined with dynamic movement primitives for adaptive lower-limb exoskeleton control. Gao et al. [56] examined autonomous motion and control in a lower-limb rehabilitation robot, while Wong Sang and Narayan [57] integrated reinforcement learning with finite-time sliding-mode control in a human-in-the-loop paediatric gait framework. Collectively, these studies illustrate the breadth of learning-based control, but device architecture, participant context, and safety validation determine whether their findings can be transferred to a soft wearable system.

6.7. Human-in-the-Loop Optimisation and Personalisation

Human-in-the-loop (HiTL) optimisation frameworks treat the user as part of the control loop and update assistive parameters from measured performance or physiological state [47,99]. These approaches are particularly relevant to soft wearable rehabilitation, where the most useful assistance profile varies between users and may change as motor function evolves. Their interpretation nevertheless depends on the optimisation objective, evaluation duration, participant population, and whether safety constraints were tested outside the calibration task.

Slade et al. [99] demonstrated real-world personalisation of exoskeleton assistance during walking using Bayesian optimisation of the assistive torque profile, achieving individual-specific metabolic cost reductions of 15–24% in community walking conditions without requiring laboratory calibration. Ding et al. [47] established the HiTL optimisation paradigm for soft exosuit control, using gradient-free optimisation of hip assistive timing parameters to minimise measured metabolic rate in real time, a seminal study that demonstrated the feasibility and clinical relevance of automated parameter personalisation [100].

Li et al. [83] extended HiTL concepts to upper-limb rehabilitation with a multi-sensor fusion-based mirror adaptive assist-as-needed control strategy, in which the level of robotic assistance was continuously modulated in response to the user's effort, estimated from

sEMG, to maintain the user at the desired therapeutic challenge level throughout the exercise session. Kokubu et al. [101] derived design rules for personalisation of soft rehabilitation gloves from a systematic study of inter-individual variability in hand anthropometry and grasping kinematics, providing a principled basis for the customisation of soft wearable hand rehabilitation devices to individual users.

6.8. Integration of Control and Fault-Tolerant Operation

The integration of intelligent control with fault detection and diagnosis, discussed in Section 4, is a nascent but critical research direction for soft wearable rehabilitation systems. Current practice largely treats FDD and control as separate subsystems: the FDD layer monitors actuator health and declares fault conditions, triggering a switch to a pre-designed safe mode, while the intelligent control layer operates under the assumption of nominal actuator behaviour [15,40].

Closer integration is possible if the controller maintains an estimate of actuator health and degrades assistance continuously as confidence falls [15,31,70,73]. Current rehabilitation-control reviews discuss adaptive and intelligent control in detail, but explicit fault accommodation remains uncommon [3,27,91]. This absence is more actionable than the limited number of large clinical trials: controller and FDD architectures can be co-designed now, even while the broader technology continues to mature.

Neural-network methods may support shared representations for state estimation, anomaly detection, and control [75]. At present, however, this remains a research proposition rather than a clinically validated architecture. Future studies should report whether joint learning improves detection robustness without allowing controller objectives to suppress or obscure emerging fault signals.

7. Descriptive Mapping of the Reviewed Literature

This section describes the composition of the mapped literature using counts and proportions. The mapping covers publication year, actuator technology, anatomical target, thematic pillar, population, and validation setting. These distributions identify concentrations of research activity; they are not pooled performance metrics or comparative-effectiveness estimates. Table 5 summarises the authors' descriptive classification dataset, while Supplementary Tables S1 and S2 provide source-level appraisal and explicitly distinguish empirical publications from normative context.

Table 5. Descriptive mapping of the literature included in the review (2020–2026). Counts describe the authors' classification dataset and do not represent pooled performance estimates.

Category	Sub-Category	N Articles	% of Total
Publication year	2020	13	12.3%
	2021	16	15.1%
	2022	15	14.2%
	2023	18	17.0%
	2024	14	13.2%
	2025–2026	26	24.5%
	Pre-2020 (seminal)	4	3.8%
Actuator type	Soft pneumatic (SPA/fabric)	52	49.1%
	Tendon/cable-driven	21	19.8%
	Shape memory alloy	8	7.5%
	Dielectric elastomer	6	5.7%
	Hydraulic soft	5	4.7%
	Hybrid/multi-technology	14	13.2%

Table 5. Cont.

Category	Sub-Category	N Articles	% of Total
Anatomical target	Hand/finger	28	26.4%
	Ankle/foot	22	20.8%
	Knee	12	11.3%
	Hip	11	10.4%
	Elbow/upper limb multi-joint	18	17.0%
	Shoulder	7	6.6%
	Full-body/trunk	8	7.5%
Primary thematic pillar	Fault detection & diagnosis	14	13.2%
	Sensing strategies	27	25.5%
	Intelligent control	38	35.8%
	Background/design review	18	17.0%
	Clinical application	9	8.5%
Clinical population	Stroke	24	22.6%
	Spinal cord injury	10	9.4%
	ALS/neuromuscular disease	6	5.7%
	Parkinson's disease/tremor	5	4.7%
	Healthy subjects (validation only)	41	38.7%
	Mixed/not specified	20	18.9%
Validation context	Bench/simulation only	31	29.2%
	Healthy human subjects	47	44.3%
	Patient/clinical	28	26.4%

7.1. Temporal Distribution of Publications

The temporal distribution in Figure 4 reveals a consistent and accelerating growth in research output on soft wearable actuators for rehabilitation over the review period. Publications from 2020 and 2021 account for 27.4% of the corpus ($n = 29$), reflecting the already substantial activity in the field at the start of the review window. The rate of publication increased progressively through 2022 and 2023, with 2023 representing the peak year of the 2020–2024 period ($n = 18$, 17.0%). The 2025–2026 segment, covering only 18 months of the review window, already accounts for 24.5% of all included articles ($n = 26$), indicating an acceleration of research activity that is consistent with broader trends in soft robotics and rehabilitation technology [6,8].

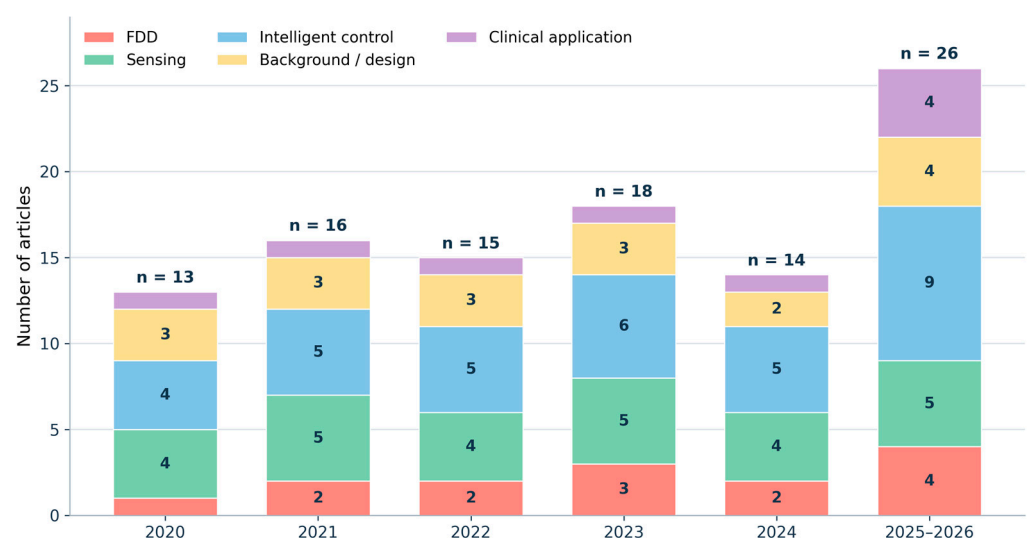


Figure 4. Annual distribution of the mapped publications by thematic pillar. Values are article counts; the chart describes research activity and not comparative performance.

The temporal growth is particularly pronounced in the intelligent control pillar, where deep reinforcement learning and simulation-based training approaches emerged as dominant themes in 2023–2025 [52,53,98]. The fault detection and diagnosis pillar, by contrast, shows a more modest growth trajectory, with the majority of FDD-specific publications concentrated in 2024–2025 [15,16,70]. This asymmetry, rapid growth in intelligent control relative to FDD, reflects the research gap identified in the present review and corroborates the abstract finding that fault-tolerant sensing and data-driven control remain underexplored relative to control performance optimisation.

7.2. Distribution by Actuator Technology

Soft pneumatic actuators, including both monolithic elastomeric and fabric-based designs, account for the largest share of included articles (49.1%, $n = 52$), consistent with their status as the most mature and widely deployed soft actuation technology in rehabilitation [8,9]. Tendon and cable-driven systems represent the second most prevalent category (19.8%, $n = 21$), reflecting the growing adoption of soft exosuit architectures based on Bowden cable transmission [66,67].

Figure 5 shows that shape memory alloy actuators (7.5%, $n = 8$) and dielectric elastomers (5.7%, $n = 6$) are substantially underrepresented relative to their potential, a finding consistent with the known barriers to clinical deployment of these technologies, thermal management challenges for SMAs and high-voltage safety concerns for DEAs [12,13]. Hydraulic soft actuators account for only 4.7% of included articles ($n = 5$), representing a particularly notable gap given the force density and control bandwidth advantages of hydraulic systems [38]. Hybrid and multi-technology configurations, while representing 13.2% of the corpus ($n = 14$), are growing rapidly in the 2024–2026 segment, suggesting increasing research interest in combining complementary actuation principles [14,69].

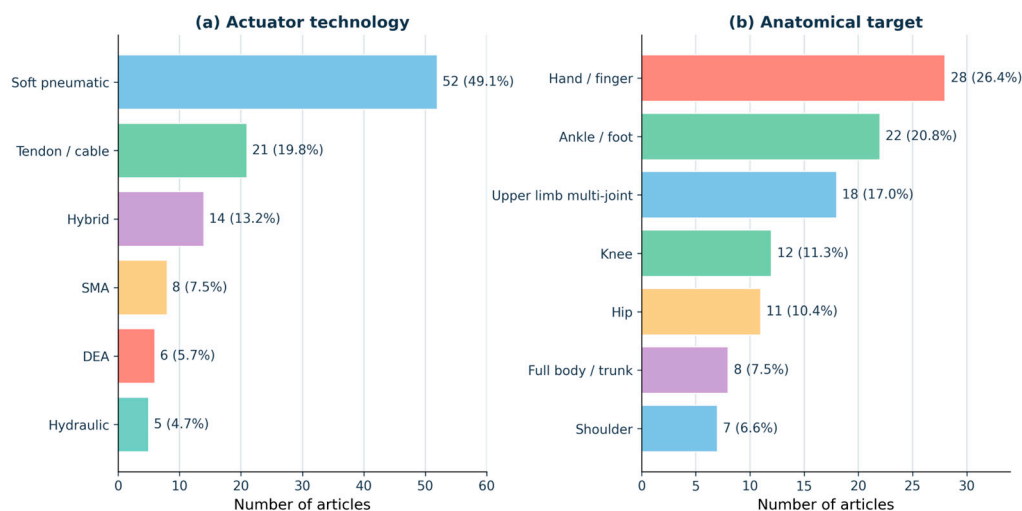


Figure 5. Distribution of the 106 mapped publications by (a) actuator technology and (b) anatomical target. Counts and percentages are based on the authors' classification dataset.

7.3. Distribution by Anatomical Target

Hand and finger rehabilitation constitutes the most studied anatomical application (26.4%, $n = 28$), driven by the large clinical need in post-stroke hand rehabilitation and the relative tractability of soft glove design [79,92,93,102]. Ankle and foot assistance is the second most prevalent target (20.8%, $n = 22$), reflecting the importance of ankle push-off power in gait rehabilitation and the availability of validated outcome measures for ankle exosuit evaluation [64,85].

Upper-limb multi-joint systems encompassing elbow and shoulder assistance account for 17.0% of the authors' classification dataset ($n = 18$), a category that includes soft wearables evaluated for ALS, neurological impairment, and spinal cord injury [66–68,103]. Knee and hip targets are comparably represented, while full-body and trunk systems form a smaller group. Device studies of hip assistance [104] and lower-back support [105] show that these less represented anatomical targets are technically feasible, although the strength of rehabilitation evidence varies between applications.

7.4. Distribution by Thematic Pillar

The intelligent control pillar accounts for the largest share of the authors' descriptive classification dataset (35.8%, $n = 38$), reflecting sustained activity in control algorithms for wearable assistance [27]. Sensing strategies constitute the second pillar by article count (25.5%, $n = 27$), encompassing the proprioceptive, exteroceptive, and biosignal modalities reviewed in Section 5 [19,88]. These frequencies describe research emphasis rather than the comparative maturity or effectiveness of either pillar.

Background and design review articles (17.0%, $n = 18$) provide the technological context for the three main pillars. Clinical application articles, those reporting outcome data from patient studies, account for 8.5% of the corpus ($n = 9$), a proportion that underscores the predominantly pre-clinical character of the current research landscape.

FDD is the smallest thematic pillar in the authors' descriptive dataset (13.2%, $n = 14$). The stricter source-level appraisal in Supplementary Table S1 classified nine FDD records as adjacent and five as indirect. Rabiei et al. [15] and Duan et al. [16] studied faults in soft actuators, but not complete validation during representative wearable rehabilitation; Sun et al. [70] studied a rehabilitation exoskeleton whose architecture is adjacent to, rather than identical to, the target soft-wearable setting. Other records concerned rigid manipulators [40,42], general fault-diagnosis methods [41,43], or soft-robotic platforms without the full human-coupled rehabilitation context [17,18,31,46,72,73]. These studies identify candidate methods, but they cannot establish diagnostic accuracy, safety benefit, or transferability in soft wearable rehabilitation.

7.5. Clinical Populations and Validation Contexts

Stroke is the most frequently represented clinical condition in the descriptive dataset, with evidence spanning controlled evaluation, soft-glove assistance, and home-oriented rehabilitation [81,92,106]. Spinal cord injury, ALS and other neuromuscular diseases, and Parkinsonian tremor are represented by smaller but clinically important bodies of literature. These frequencies describe where studies have been conducted; they should not be interpreted as comparative treatment effects or as evidence that less represented populations are unsuitable for soft wearable intervention.

Healthy-participant validation accounted for 38.7% of the corpus, while 18.9% involved mixed or unspecified populations. Patient-level validation was reported in 26.4% of the included publications. This distribution is consistent with an emerging technology field and should not, by itself, be interpreted as deficient research practice. It does, however, limit the certainty of claims about clinical effectiveness and long-term usability [1,79,92,93,106].

As shown in Figure 6, validation settings comprised healthy-participant experiments (44.3%, $n = 47$), patient or clinical studies (26.4%, $n = 28$), and bench or simulation studies (29.2%, $n = 31$). Designs and outcomes varied markedly. We therefore report these categories as indicators of evidence maturity and refrain from presenting a pooled sample-size estimate or a general statement about clinical efficacy without a verified study-level dataset.

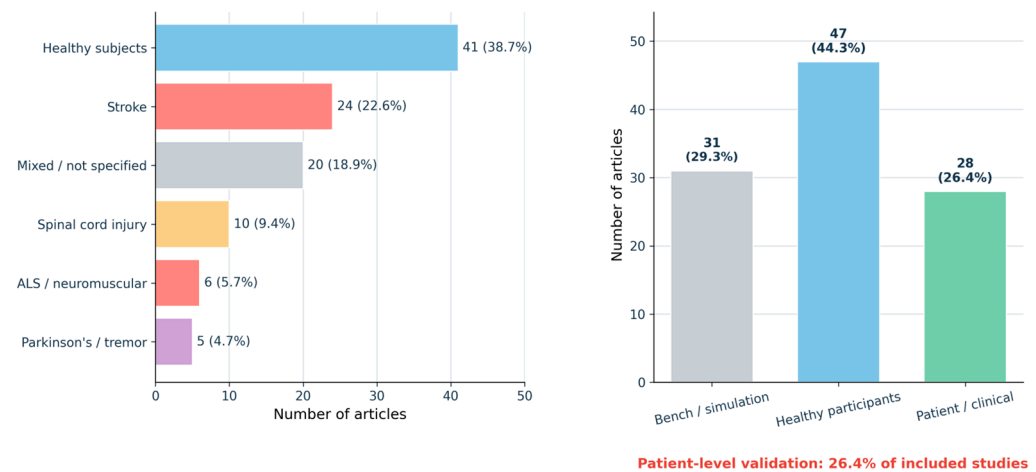


Figure 6. Clinical population and validation context distributions: **(Left)** clinical population; **(Right)** validation context. Patient-level validation: $n = 28$ (26.4%); totals may differ from 100% due to rounding.

7.6. Critical Appraisal and Confidence in the Evidence

Supplementary Table S1 contains 106 unique source records reconstructed from the original bibliography. Forty were classified as direct evidence for the broad review scope, 57 as adjacent, five as indirect, and four as normative context. This distribution supports greater confidence in statements that describe the existence or technical feasibility of soft-wearable sensing, actuation, and control than in claims of comparative performance or clinical effectiveness. The FDD subset warrants the greatest caution: all 14 records were adjacent or indirect under the strict target-domain definition. Accordingly, Sections 4 and 8 use external-domain FDD studies to explain methodological plausibility and transfer conditions, not to claim validated performance in a soft, human-coupled rehabilitation device. The four standards inform safety and risk-management context but are not treated as empirical evidence. Following author verification, D4 comprised 33 partial and 69 inadequate/not reported ratings, with four normative sources marked as not applicable. This conservative distribution indicates that reproducibility is constrained chiefly by incomplete methodological reporting and therefore limits the strength of comparative and translational claims.

8. Discussion and Future Research Directions

The literature shows rapid development in actuator design, sensing, and control, but the identified limitations do not have equal implications. Some are maturity-driven: small samples, single-session evaluations, and a predominance of healthy-participant studies are common during early device development and should be described without implying avoidable methodological failure. Other gaps reflect choices that can be addressed immediately. These include the imbalance between control and FDD research, reliance on models that do not represent soft-material variability, weak integration between health monitoring and control, and the absence of shared FDD benchmarks. Table 6 separates these categories and prioritises the latter group.

Table 6. Identified research gaps, current limitations, recommended directions, and priorities.

Research Gap	Current Limitation	Recommended Direction	Priority
Integrated FDD + control	FDD and control designed independently; discrete mode-switching	Unified fault-aware control architectures; continuous degradation compensation	High

Table 6. *Cont.*

Research Gap	Current Limitation	Recommended Direction	Priority
FDD in clinical populations	FDD validated on bench or healthy subjects only; no patient data	FDD evaluation with stroke, SCI, and PD patients; clinically relevant fault thresholds	High
Standardised FDD benchmarks	No consensus on metrics, fault types, or test protocols	Community benchmark dataset; reporting checklist for FDD papers	High
Sensing in home environments	Most sensing validated in lab; real-world variability underexplored	Long-duration ambulatory studies; drift-compensation for wearable sensors	High
Transfer learning for intent recognition	Cross-session and cross-subject generalisation poor; retraining required	Domain adaptation and transfer learning for sEMG/EEG control; few-shot personalisation	Medium
RL safety in rehabilitation	RL policies validated in simulation; sim-to-real gap and safety constraints underexplored	Safe RL with formal constraint satisfaction; Lyapunov-based safety certificates	Medium
Hydraulic soft actuators	Underrepresented in literature vs. pneumatic; FDD underdeveloped	FDD methods specific to hydraulic systems; seal and fluid integrity monitoring	Medium
Regulatory and standardisation	ISO/IEC standards do not specify quantitative FDD performance requirements	Engagement with standards bodies; evidence base for FDD performance thresholds	Medium
Self-healing integration with control	Self-healing materials demonstrated in isolation; no integration with FDD/control	Self-healing actuators with embedded damage detection and healing-state estimation	Low–Medium
Paediatric and geriatric populations	Most studies on adults; age-specific biomechanics underexplored	Device design and control adaptation for paediatric gait and geriatric frailty	Low–Medium

8.1. The FDD Gap: Safety-Critical but Underinvested

The clearest structural imbalance is the limited attention given to FDD relative to intelligent control (13.2% versus 35.8% of the mapped corpus). More importantly, most FDD evidence is indirect. This does not show that current wearable devices are unsafe; rather, it shows that the published literature provides insufficient device-specific evidence to quantify fault-detection performance during soft, human-coupled operation [15,16,18,40–42,46,48,70].

Borrowed methods differ in their likely transferability. Observer-based approaches can be computationally efficient, but their residuals are vulnerable to hysteresis, temperature, fatigue, and manufacturing variation [17,31,73]. Supervised classifiers can represent nonlinear fault signatures, yet require labelled and externally validated datasets [16,43]. Unsupervised anomaly detection reduces dependence on fault labels but may confuse user variability, sensor shift, or task transitions with actuator degradation [18,75]. These trade-offs should be tested rather than assumed.

We identify three priority directions for FDD research: First, the development of population-specific fault detection benchmarks using data collected from wearable devices during rehabilitation exercise in patient populations, the operating conditions that matter clinically. Second, the development of unsupervised and semi-supervised anomaly detection methods that can learn a model of nominal device behaviour from unlabelled operational data, eliminating the need for labelled fault examples that are difficult and ethically problematic to collect in clinical settings [75]. Third, the integration of self-healing

material strategies [17,46] with embedded FDD, creating actuators that can detect, quantify, and autonomously repair damage, represents a long-term but high-impact research direction that has received minimal attention to date.

8.2. Towards Integrated Fault-Aware Intelligent Control

The current practice of designing FDD and intelligent control as separate subsystems, with FDD triggering discrete mode-switching to a pre-designed safe mode upon fault detection, is a pragmatic but suboptimal architecture [15,40]. Discrete mode-switching introduces discontinuities in the assistive force profile that are biomechanically disruptive and potentially uncomfortable for the user; it also places a high burden on the FDD threshold, since any threshold setting is simultaneously too sensitive (causing false alarms that trigger unnecessary mode switches) and too insensitive (allowing faults to progress before detection) [41].

A more principled approach is fault-aware control, in which the control policy maintains a probabilistic estimate of actuator health state and modulates assistive parameters continuously in response to this estimate, providing graceful performance degradation rather than abrupt mode switching [31,73]. Approaches from the robust control and stochastic control literature, including tube MPC with state uncertainty, risk-sensitive optimal control, and chance-constrained programming, provide formal frameworks for this integration that have not yet been applied to soft wearable systems. The parallel development of physics-informed neural networks and Bayesian deep learning methods that provide calibrated uncertainty estimates alongside control outputs [41] offers a promising pathway towards data-driven fault-aware control architectures.

For reinforcement learning-based controllers, the integration of fault tolerance requires extending the reward function and safety constraints to account for actuator degradation. Safe RL methods that provide formal guarantees on constraint satisfaction during both training and deployment [52,57] are particularly relevant here, as they can be adapted to treat actuator fault conditions as safety constraint violations to be avoided rather than disturbances to be compensated post-hoc.

8.3. Sensing: From Laboratory to Clinical Deployment

The sensing technologies reviewed in Section 5 demonstrate impressive laboratory performance, flexible strain sensors with gauge factors above 10, optical fibre systems immune to electromagnetic interference, and sEMG classifiers with intent recognition accuracies above 95%, yet the translation of these capabilities to real-world clinical performance remains challenging [18,23].

The primary barriers to clinical sensing deployment are sensor drift and recalibration requirements, electrode–skin interface variability for biosignal sensing, and the difficulty of maintaining consistent sensor-to-skin contact during the large deformations associated with soft actuator operation [19,21]. Long-duration studies investigating sensor performance over multi-week rehabilitation programmes, rather than the single-session experiments that dominate the current literature, are needed to characterise drift rates and establish recalibration protocols compatible with clinical workflows [86,87].

For biosignal-based intent recognition, the cross-session and cross-subject generalisation problem is the most significant barrier to clinical deployment [20]. Transfer learning and domain adaptation methods that can rapidly adapt a pre-trained intent recognition model to a new user or session with minimal additional labelled data offer a promising solution [50,80]. Few-shot and zero-shot learning approaches, in which generalisation to new users is achieved from very few or no user-specific examples, represent the frontier of this research direction and are beginning to appear in the rehabilitation control literature.

8.4. Clinical Translation: Bridging the Lab-to-Clinic Gap

The proportion of patient studies is best interpreted as a marker of technological maturity. Small samples and short evaluations are expected while devices and algorithms are still being stabilised. They become a more consequential limitation when authors make clinical-effectiveness claims or when systems are proposed for unsupervised home use. Future clinical studies should therefore be aligned with the maturity and intended use of the device, progressing from safety and feasibility to repeated-session effectiveness and comparative trials [1,79,92,93,106].

Translating soft wearable rehabilitation technology from laboratory demonstrations to clinically deployable devices requires progress on several fronts simultaneously. Regulatory pathways for soft wearable medical devices vary significantly across jurisdictions and are not yet fully defined for devices combining soft actuation, embedded AI, and autonomous operation [76,77]. The applicable standards, ISO 13482 for personal care robots and IEC 80601-2-78 for medical rehabilitation robots, provide safety frameworks but do not specify performance requirements for FDD or intelligent control that would constitute a quantitative basis for regulatory clearance [78,107]. Engagement between the research community and standards bodies to develop evidence-based quantitative FDD and control performance thresholds for soft wearable rehabilitation devices is identified as a priority.

Home-based rehabilitation is an important deployment context for soft wearable devices because it may increase therapy dose beyond supervised clinical sessions [4,6,108]. The requirements are more demanding than in a laboratory: devices must operate safely without continuous clinician oversight, detect anomalous behaviour, guide the user through setup and calibration, and retain enough information for remote review. These conditions place sensing robustness, transparent protective responses, and fault-aware control at the centre of home-device design.

8.5. Standardisation of Reporting and Benchmarking

A recurring limitation identified throughout this review is the absence of standardised reporting conventions and benchmarks that would allow direct comparison of results across studies. This limitation affects all three thematic pillars: FDD papers report heterogeneous metrics (detection rate, false alarm rate, time-to-detection) under different fault conditions and operating scenarios [41]; sensing papers report different performance characterisation protocols and evaluation conditions [18]; and control papers use different performance metrics, evaluation tasks, and subject populations [27,91].

We propose the following minimum reporting checklist for future soft wearable actuator studies addressing FDD, sensing, or intelligent control in rehabilitation contexts:

- Actuator specification: type, working pressure/force range, nominal stroke, and compliance characteristics;
- Fault characterisation (FDD studies): fault type, severity range, injection method, and operating conditions during evaluation;
- FDD metrics: detection rate, false alarm rate, time-to-detection, and minimum detectable fault amplitude at a specified threshold;
- Sensing characterisation: bandwidth, accuracy, drift rate over session duration, and performance under actuator operation (crosstalk);
- Control performance: tracking error (RMSE), assist-as-needed ratio, and metabolic cost reduction where applicable;
- Validation context: subject population (healthy/patient, n, age, condition), task repertoire, session duration, and number of sessions;
- Safety events: any unplanned stops, fault-triggered interventions, or adverse events during testing.

Adoption of such a reporting checklist by journals and conferences publishing in this area would substantially improve the comparability and reproducibility of results across the field, accelerating progress towards clinical translation [18,41].

8.6. Emerging Opportunities

Beyond the priority gaps identified above, several emerging research directions offer substantial long-term opportunities for the field. Digital twin frameworks, in which a real-time computational model of the soft wearable device is maintained in parallel with the physical system and updated by sensor data, provide a natural platform for integrating FDD, sensing, and control [41]. The digital twin can serve simultaneously as the model for model-based FDD residual generation, as the plant model for MPC, and as the basis for offline reinforcement learning, eliminating the need for separate modelling efforts for each function.

Data-efficient learning and probabilistic state estimation may reduce the amount of labelled fault data required for deployment. Their near-term value lies in calibrated uncertainty, domain adaptation, and transparent detection limits rather than in unrestricted use of general-purpose foundation models. Evaluation should remain anchored to actuator physics, clinically plausible disturbances, and predefined protective responses.

Finally, the convergence of soft wearable actuation with advanced materials science, including stretchable electronics, conductive hydrogels, and 4D-printed structures with programmed shape-change responses, offers the prospect of devices in which actuation, sensing, and self-monitoring functions are fully integrated at the material level, eliminating the interfaces between subsystems that are the primary loci of fault occurrence in current devices [17,82].

9. Conclusions

This systematic review examines FDD, sensing, and intelligent control in soft wearable actuators for rehabilitation and motor assistance. The corrected supplementary appraisal maps all 106 publications included in the review. Four normative standards are retained within this total as normative context and are marked as not applicable for empirical methodological appraisal. The literature documents substantial progress in soft exosuits, multimodal sensing, adaptive assistance, and simulation-based control. It also reveals an uneven evidentiary structure. Technical innovation is concentrated in sensing and control, whereas FDD evidence that directly combines soft actuation, wearable human coupling, and rehabilitation validation is not yet available in the mapped source set.

The following principal conclusions are drawn from the review:

First, soft pneumatic actuators remain the dominant technology for wearable rehabilitation, accounting for nearly half of all included studies, but alternative modalities, tendon-driven systems, SMAs, DEAs, and hybrid configurations, are growing in representation and offer complementary capabilities that may prove superior for specific anatomical targets and patient populations [6,8,9].

Second, FDD is underrepresented relative to its role in safety assurance. Of the 14 FDD records, Supplementary Table S1 classified nine as adjacent and five as indirect under the strict target-domain criterion. The appropriate conclusion is not that borrowed methods are ineffective, nor that they are already transferable. It is that soft-actuator-specific benchmarks and validation studies are required before diagnostic performance can be quantified in wearable rehabilitation [15–18,31,40–43,46,48,70–73].

Third, sensing technology has advanced rapidly, with flexible strain sensors, optical fibre proprioception, IMU-based gait phase detection, and multimodal sEMG/EEG interfaces all demonstrating laboratory performance sufficient for rehabilitation control. The

primary challenge is no longer sensor physics but sensor deployment: achieving consistent, drift-free, and comfortable sensing over multi-week rehabilitation programmes in diverse patient populations [19,23,86].

Fourth, intelligent control has seen the most dynamic development of the three pillars, with deep reinforcement learning and human-in-the-loop optimisation emerging as leading paradigms for personalised assistance. The key challenge for clinical translation is safety assurance: demonstrating that learned control policies behave safely across the full range of patient conditions, device degradation states, and environmental perturbations that arise in real-world deployment [47,52,99].

Fifth, the three pillars of FDD, sensing, and control are interdependent in ways that current research largely fails to exploit. Integrated fault-aware control architectures, in which the control policy accounts explicitly for uncertainty in actuator state arising from detected or suspected faults, offer substantially better safety guarantees than the current practice of separate FDD and control design with discrete mode-switching. Developing such architectures is identified as a priority research direction for the field.

Sixth, the limited proportion of patient-level studies primarily reflects the developmental stage of the field. This constrains conclusions about clinical effectiveness but should not be conflated with a remediable design flaw in early prototypes. As systems approach home or unsupervised use, validation should progress to repeated-session studies, standardised clinical outcomes, and adequately powered comparative trials [1,79,92,93,106].

This review has limitations. Searches were completed in June 2026 and may not capture records indexed subsequently. Heterogeneity in devices, outcomes, and validation settings precluded meta-analysis, so the reported counts describe the literature rather than effect magnitude. The English-language restriction may have excluded relevant evidence. Inclusion of adjacent and indirect FDD studies broadens the methodological landscape but lowers confidence in transferability claims; we addressed this by labelling such evidence explicitly and avoiding quantitative extrapolation to soft wearable devices. Supplementary Table S1 was reconstructed from the corrected bibliography and manuscript-level information, after which the authors reviewed and confirmed the D4 classifications using the available evidence record and manuscript extraction framework. Incomplete methodological reporting across the corpus remains a substantive limitation on reproducibility and direct cross-study comparison.

Despite these limitations, we believe the present review provides the most comprehensive and integrated examination to date of fault detection, sensing, and intelligent control as an interconnected system for soft wearable rehabilitation actuators, and that the research gaps and future directions identified here offer a useful roadmap for the community working to translate these remarkable technologies into clinical practice.

Supplementary Materials: The following supporting information can be downloaded at <https://www.mdpi.com/article/10.3390/act15080431/s1>, Supplementary Tables S1 and S2 provide the individual appraisal and its rubric. Table S1. individual appraisal of the evidence corpus. Table S2. appraisal rubric and verification protocol.

Author Contributions: Conceptualization, C.F.P. and D.M.P.-P.; methodology, C.F.P. and C.A.M.; investigation, C.F.P. and D.M.P.-P.; data curation, C.F.P.; writing—original draft preparation, C.F.P. and D.M.P.-P.; writing—review and editing, C.A.M. and V.M.R.; visualization, C.F.P.; supervision, C.F.P. and V.M.R. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable. This study is a systematic review of publicly available literature and did not involve the collection of new human-participant or animal data.

Informed Consent Statement: Not applicable.

Data Availability Statement: The retrospective registration record and supporting materials, including the protocol record, preserved search strategy, PRISMA 2020 [44] flow diagram, and individual appraisal of the 106 included publications, are publicly available through the OSF Registries at <https://doi.org/10.17605/OSF.IO/KPXH5>. No individual participant-level data were generated or analysed in this review.

Acknowledgments: During the preparation of this manuscript, the authors used Claude (Anthropic, San Francisco, CA, USA, claude.ai) for the purposes of generating the schematic figures (Figures 2–6) and for drafting and editing portions of the manuscript text. The authors have reviewed and edited all outputs and take full responsibility for the content of this publication.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

ALS	Amyotrophic lateral sclerosis
BCI	Brain–computer interface
CNN	Convolutional neural network
CPG	Central pattern generator
DEA	Dielectric elastomer actuator
DNN	Deep neural network
EEG	Electroencephalography
EMG/sEMG	Electromyography/surface electromyography
FDD	Fault detection and diagnosis
FTC	Fault-tolerant control
GRU	Gated recurrent unit
HiTL	Human-in-the-loop
ILC	Iterative learning control
IMU	Inertial measurement unit
LSTM	Long short-term memory
MPC	Model predictive control
MRAC	Model reference adaptive control
PD	Parkinson’s disease
pHRI	Physical human–robot interaction
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
RL	Reinforcement learning
SCI	Spinal cord injury
SMC	Sliding mode control
SMA	Shape memory alloy
SPA	Soft pneumatic actuator
SVM	Support vector machine

References

1. Bardi, E.; Gandolla, M.; Braghin, F.; Resta, F.; Pedrocchi, A.L.G.; Ambrosini, E. Upper Limb Soft Robotic Wearable Devices: A Systematic Review. *J. Neuroeng. Rehabil.* **2022**, *19*, 87. [[CrossRef](#)] [[PubMed](#)]
2. Rodriguez-Fernandez, A.; Lobo-Prat, J.; Font-Llagunes, J.M. Systematic Review on Wearable Lower-Limb Exoskeletons for Gait Training in Neuromuscular Impairments. *J. Neuroeng. Rehabil.* **2021**, *18*, 22. [[CrossRef](#)] [[PubMed](#)]
3. de Miguel-Fernandez, J.; Lobo-Prat, J.; Prinsen, E.; Font-Llagunes, J.M.; Marchal-Crespo, L. Control Strategies Used in Lower Limb Exoskeletons for Gait Rehabilitation after Brain Injury: A Systematic Review and Analysis of Clinical Effectiveness. *J. Neuroeng. Rehabil.* **2023**, *20*, 23. [[CrossRef](#)] [[PubMed](#)]
4. Sharma, B.; Phan, P.T.; Davies, J.; Hoang, T.T.; Nguyen, C.C.; Ji, A.; Zhu, K.; Nicotra, E.; Lovell, N.H.; Do, T.N. Soft Upper-Limb Wearable Robotic Devices: Technology and Applications. *Adv. Intell. Syst.* **2024**, *6*, 2400266. [[CrossRef](#)]

5. Plaza, A.; Hernandez, M.; Puyuelo, G.; Garces, E.; Medina, E.; Martinez-Pascual, M.; de la Torre, R. Lower-Limb Medical and Rehabilitation Exoskeletons: A Review of the Current Designs. *IEEE Rev. Biomed. Eng.* **2021**, *16*, 278–291. [[CrossRef](#)] [[PubMed](#)]
6. Shi, Y.; Dong, W.; Lin, W.; Gao, Y. Soft Wearable Robots: Development Status and Technical Challenges. *Sensors* **2022**, *22*, 7584. [[CrossRef](#)] [[PubMed](#)]
7. Sivi, C.; Baker, L.M.; Quinlivan, B.T.; Porciuncula, F.; Swaminathan, K.; Awad, L.N.; Walsh, C.J. Opportunities and Challenges in the Development of Exoskeletons for Locomotor Assistance. *Nat. Biomed. Eng.* **2023**, *7*, 456–472. [[CrossRef](#)] [[PubMed](#)]
8. Xavier, M.S.; Tawak, C.D.; Zolfagharian, A.; Pinski, J.; Howard, D.; Young, T.; Lai, J.; Harrison, S.M.; Yong, Y.K.; Bodaghi, M.; et al. Soft Pneumatic Actuators: A Review of Design, Fabrication, Modeling, Sensing, Control and Applications. *IEEE Access* **2022**, *10*, 59442–59485. [[CrossRef](#)]
9. Chai, Y.; Qin, Y.; Xu, Z.; Zheng, X.; Jia, H. Advances in Fabric-Based Pneumatic Soft Actuators for Flexible Robotics: Design and Applications. *Sensors* **2025**, *25*, 3665. [[CrossRef](#)] [[PubMed](#)]
10. O'Neill, C.T.; McCann, C.M.; Hohimer, C.J.; Bertoldi, K.; Walsh, C.J. Unfolding Textile-Based Pneumatic Actuators for Wearable Applications. *Soft Robot.* **2022**, *9*, 163–172. [[CrossRef](#)] [[PubMed](#)]
11. Ge, L.; Chen, F.; Wang, D.; Zhang, Y.; Han, D.; Wang, T.; Gu, G. Design, Modeling, and Evaluation of Fabric-Based Pneumatic Actuators for Soft Wearable Assistive Gloves. *Soft Robot.* **2020**, *7*, 583–596. [[CrossRef](#)] [[PubMed](#)]
12. Shami, Z.; Arslan, T.; Lomax, P. Wearable Soft Robots: Case Study of Using Shape Memory Alloys in Rehabilitation. *Bioengineering* **2025**, *12*, 276. [[CrossRef](#)] [[PubMed](#)]
13. Novelli, G.L.; Vargas, G.G.; Andrade, R.M. Dielectric Elastomer Actuators as Artificial Muscles for Wearable Robots. *J. Intell. Mater. Syst. Struct.* **2023**, *34*, 1007–1025. [[CrossRef](#)]
14. Ma, Z.; Sameoto, D. A Review of Electrically Driven Soft Actuators for Soft Robotics. *Micromachines* **2022**, *13*, 1881. [[CrossRef](#)] [[PubMed](#)]
15. Rabiei, S.; Sadeghi Nalkenani, S.; Sharifi, I.; Talebi, H.A. Fault Tolerant Position Control of Soft Bending Actuator in the Presence of Actuator Leakage. *Robot. Auton. Syst.* **2025**, *188*, 104944. [[CrossRef](#)]
16. Duan, T.; Lv, Y.; Wang, L.; Li, H.; Yi, T.; He, Y.; Lv, Z. Diagnosing Faults of Pneumatic Soft Actuators Based on Multimodal Spatiotemporal Features and Ensemble Learning. *Machines* **2025**, *13*, 749. [[CrossRef](#)]
17. Bonard, S.; Moreno-Serna, V.; Kortaberria, G.; Díaz Díaz, D. Self-Healing Polymeric Soft Actuators. *Chem. Rev.* **2023**, *123*, 736–810. [[CrossRef](#)] [[PubMed](#)]
18. Lovett, E.; Hammond, M.; Seyfi, N.; Golestaneh, A.F.; Cichella, V.; Lamuta, C. A Review on Sensor Technologies, Control Approaches, and Emerging Challenges in Soft Robotics. *Adv. Robot. Res.* **2025**, *1*, 202500085. [[CrossRef](#)]
19. Zhang, X.; Zhang, W.; Cao, J.; Zheng, J.; Dong, D.; Zhu, L.; Hua, Z.; Xie, H. Review of sEMG for Exoskeleton Robots: Motion Intention Recognition Techniques and Applications. *Sensors* **2025**, *25*, 2448. [[CrossRef](#)] [[PubMed](#)]
20. Zaim, T.; Abdel-Hadi, S.; Mahmoud, R.; Khandakar, A.; Rakhtala, S.M.; Chowdhury, M.E.H. Machine Learning- and Deep Learning-Based Myoelectric Control System for Upper Limb Rehabilitation Utilizing EEG and EMG Signals: A Systematic Review. *Bioengineering* **2025**, *12*, 144. [[CrossRef](#)] [[PubMed](#)]
21. Sul, J.-H.; Piyathilaka, L.; Moratuwage, D.; Dunu Arachchige, S.; Jayawardena, A.; Kahandawa, G.; Preethichandra, D.M.G. Electromyography Signal Acquisition, Filtering, and Data Analysis for Exoskeleton Development. *Sensors* **2025**, *25*, 4004. [[CrossRef](#)] [[PubMed](#)]
22. Abdallah, I.B.; Bouteraa, Y.; Alotaibi, A. A Hybrid EMG–EEG Interface for Robust Intention Detection and Fatigue-Adaptive Control of an Elbow Rehabilitation Robot. *Sci. Rep.* **2025**, *15*, 40895. [[CrossRef](#)] [[PubMed](#)]
23. Wang, N.; Yao, Y.; Wu, P.; Zhao, L.; Chen, J. Soft Polymer Optical Fiber Sensors for Intelligent Recognition of Elastomer Deformations and Wearable Applications. *Sensors* **2024**, *24*, 2253. [[CrossRef](#)] [[PubMed](#)]
24. Kang, J.; Lee, S.; Park, Y.-L. Soft Bending Actuator with Fiber-Jamming Variable Stiffness and Fiber-Optic Proprioception. *IEEE Robot. Autom. Lett.* **2023**, *8*, 7344–7351. [[CrossRef](#)]
25. Iqra, M.; Anwar, F.; Jan, R.; Mohammad, M.A. A Flexible Piezoresistive Strain Sensor Based on Laser Scribed Graphene Oxide on Polydimethylsiloxane. *Sci. Rep.* **2022**, *12*, 4911. [[CrossRef](#)] [[PubMed](#)]
26. Hegde, C.; Su, J.; Tan, J.M.R.; He, K.; Chen, X.; Magdassi, S. Sensing in Soft Robotics. *ACS Nano* **2023**, *17*, 15277–15307. [[CrossRef](#)] [[PubMed](#)]
27. Wang, J.; Chortos, A. Control Strategies for Soft Robot Systems. *Adv. Intell. Syst.* **2022**, *4*, 2100165. [[CrossRef](#)]
28. Li, Z.; Li, Q.; Huang, P.; Xia, H.; Li, G. Human-in-the-Loop Adaptive Control of a Soft Exo-Suit with Actuator Dynamics and Ankle Impedance Adaptation. *IEEE Trans. Cybern.* **2023**, *53*, 7920–7932. [[CrossRef](#)] [[PubMed](#)]
29. Jammeli, I.; Chemori, A.; Moon, H.; Elloumi, S.; Mohammed, S. An Assistive Explicit Model Predictive Control Framework for a Knee Rehabilitation Exoskeleton. *IEEE/ASME Trans. Mechatron.* **2022**, *27*, 3636–3647. [[CrossRef](#)]
30. Caulcrick, C.; Huo, W.; Franco, E.; Mohammed, S.; Hoult, W.; Vaidyanathan, R. Model Predictive Control for Human-Centred Lower Limb Robotic Assistance. *IEEE Trans. Med. Robot. Bionics* **2021**, *3*, 980–991. [[CrossRef](#)]

31. Cao, G.; Liu, Y.; Jiang, Y.; Zhang, F.; Bian, G.; Owens, D.H. Observer-Based Continuous Adaptive Sliding Mode Control for Soft Actuators. *Nonlinear Dyn.* **2021**, *105*, 371–386. [\[CrossRef\]](#)
32. Ortiz, J.; Grioli, G.; Rossiter, J.; Helps, T.; Sadeghi, A.; Xiloyannis, M. Editorial: Actuation, Sensing and Control Systems for Soft Wearable Assistive Devices. *Front. Robot. AI* **2022**, *9*, 992699. [\[CrossRef\]](#) [\[PubMed\]](#)
33. Mahmoudi Khomami, A.; Najafi, F. A Survey on Soft Lower Limb Cable-Driven Wearable Robots without Rigid Links and Joints. *Robot. Auton. Syst.* **2021**, *144*, 103846. [\[CrossRef\]](#)
34. Sun, Y.; Tang, Y.; Zheng, J.; Dong, D.; Chen, X.; Bai, L. From Sensing to Control of Lower Limb Exoskeleton: A Systematic Review. *Annu. Rev. Control.* **2022**, *53*, 83–96. [\[CrossRef\]](#)
35. He, G.; Huang, X.; Li, F.; Wang, H. Review of Power-Assisted Lower Limb Exoskeleton Robot. *J. Shanghai Jiaotong Univ. Sci.* **2024**, *29*, 1–15. [\[CrossRef\]](#)
36. Chen, Y.; Yang, Y.; Li, M.; Chen, E.; Mu, W.; Fisher, R.; Yin, R. Wearable Actuators: An Overview. *Textiles* **2021**, *1*, 283–321. [\[CrossRef\]](#)
37. Xiloyannis, M.; Alicea, R.; Georgarakis, A.-M.; Haufe, F.L.; Wolf, P.; Masia, L.; Riener, R. Soft Robotic Suits: State of the Art, Core Technologies, and Open Challenges. *IEEE Trans. Robot.* **2022**, *38*, 1343–1362. [\[CrossRef\]](#)
38. Pan, M.; Yuan, C.; Liang, X.; Dong, T.; Liu, T.; Zhang, J.; Zou, J.; Yang, H.; Bowen, C. Soft Actuators and Robotic Devices for Rehabilitation and Assistance. *Adv. Intell. Syst.* **2022**, *4*, 2100140. [\[CrossRef\]](#)
39. Bulea, T.C.; Sharma, N.; Sikdar, S.; Su, H. Editorial: Next Generation User-Adaptive Wearable Robots. *Front. Robot. AI* **2022**, *9*, 920655. [\[CrossRef\]](#) [\[PubMed\]](#)
40. Hagh, Y.S.; Asl, R.M.; Fekih, A.; Wu, H.; Handroos, H. Active Fault-Tolerant Control Design for Actuator Fault Mitigation in Robotic Manipulators. *IEEE Access* **2021**, *9*, 47912–47929. [\[CrossRef\]](#)
41. Quamar, M.M.; Nasir, A. Review on Fault Diagnosis and Fault-Tolerant Control Scheme for Robotic Manipulators: Recent Advances in AI, Machine Learning, and Digital Twin. *arXiv* **2024**, arXiv:2402.02980. [\[CrossRef\]](#)
42. Nguyen, V.C.; Tran, X.T.; Kang, H.J. A Novel High-Speed Third-Order Sliding Mode Observer for Fault-Tolerant Control Problem of Robot Manipulators. *Actuators* **2022**, *11*, 259. [\[CrossRef\]](#)
43. Huang, T.; Zhang, Q.; Tang, X.; Zhao, S.; Lu, X. A Novel Fault Diagnosis Method Based on CNN and LSTM and Its Application in Fault Diagnosis for Complex Systems. *Artif. Intell. Rev.* **2022**, *55*, 1289–1315. [\[CrossRef\]](#)
44. Page, M.J.; McKenzie, J.E.; Bossuyt, P.M.; Boutron, I.; Hoffmann, T.C.; Mulrow, C.D.; Shamseer, L.; Tetzlaff, J.M.; Akl, E.A.; Brennan, S.E.; et al. The PRISMA 2020 Statement: An Updated Guideline for Reporting Systematic Reviews. *BMJ* **2021**, *372*, n71. [\[CrossRef\]](#) [\[PubMed\]](#)
45. Rădulescu, V.M.; Pană, C.F.; Pătrașcu-Pană, D.M.; Maican, C.A. *Fault Detection, Sensing, and Intelligent Control in Soft Wearable Actuators for Rehabilitation and Motor Assistance: A Retrospectively Registered Systematic Review*; OSF Registries: Washington, DC, USA, 2026. [\[CrossRef\]](#)
46. Terryn, S.; Brancart, J.; Lefeber, D.; Van Assche, G.; Vanderborght, B. Self-Healing Soft Pneumatic Robots. *Sci. Robot.* **2017**, *2*, ea4268. [\[CrossRef\]](#) [\[PubMed\]](#)
47. Ding, Y.; Kim, M.; Kuindersma, S.; Walsh, C.J. Human-in-the-Loop Optimization of Hip Assistance with a Soft Exosuit during Walking. *Sci. Robot.* **2018**, *3*, ea45438. [\[CrossRef\]](#) [\[PubMed\]](#)
48. Nascimento, S.; Valdenegro-Toro, M. Modeling and Soft-Fault Diagnosis of Underwater Thrusters with Recurrent Neural Networks. *IFAC-PapersOnLine* **2018**, *51*, 80–85. [\[CrossRef\]](#)
49. Kim, J.; Kwon, J.; Han, S.; Park, Y.-L.; Jo, S. Deep Full-Body Motion Network for a Soft Wearable Motion Sensing Suit. *IEEE/ASME Trans. Mechatron.* **2019**, *24*, 56–66. [\[CrossRef\]](#)
50. Molinaro, D.D.; Scherpereel, K.L.; Schonhaut, E.B.; Evangelopoulos, G.; Shepherd, M.K.; Young, A.J. Task-Agnostic Exoskeleton Control via Biological Joint Moment Estimation. *Nature* **2024**, *635*, 337–344. [\[CrossRef\]](#) [\[PubMed\]](#)
51. Tang, C.; Xu, Z.; Occhipinti, E.; Yi, W.; Xu, M.; Kumar, S.; Virk, G.S.; Gao, S.; Occhipinti, L.G. From Brain to Movement: Wearables-Based Motion Intention Prediction across the Human Nervous System. *Nano Energy* **2023**, *115*, 108712. [\[CrossRef\]](#)
52. Luo, S.; Androwis, G.; Adamovich, S.; Nunez, E.; Su, H.; Zhou, X. Robust Walking Control of a Lower Limb Rehabilitation Exoskeleton Coupled with a Musculoskeletal Model via Deep Reinforcement Learning. *J. Neuroeng. Rehabil.* **2023**, *20*, 34. [\[CrossRef\]](#) [\[PubMed\]](#)
53. Endrei, T.; Földi, S.; Makk, Á.; Cserey, G. Learning to Suppress Tremors: A Deep Reinforcement Learning-Enabled Soft Exoskeleton for Parkinson's Patients. *Front. Robot. AI* **2025**, *12*, 1537470. [\[CrossRef\]](#) [\[PubMed\]](#)
54. Hfaiedh, A.; Jellali, A.; Khraief, N.; Belghith, S. A Reinforcement Learning Based Sliding Mode Control for Passive Upper-Limb Exoskeleton. *Int. J. Adv. Robot. Syst.* **2024**, *21*, 17298806241279777. [\[CrossRef\]](#)
55. Huang, L.; Zheng, J.; Gao, Y.; Song, Q.; Liu, Y. A Lower Limb Exoskeleton Adaptive Control Method Based on Model-Free Reinforcement Learning and Improved Dynamic Movement Primitives. *J. Intell. Robot. Syst.* **2025**, *111*, 24. [\[CrossRef\]](#)
56. Gao, X.; Zhang, P.; Peng, X.; Zhao, J.; Liu, K.; Miao, M.; Zhao, P.; Luo, D.; Li, Y. Autonomous Motion and Control of Lower Limb Exoskeleton Rehabilitation Robot. *Front. Bioeng. Biotechnol.* **2023**, *11*, 1223831. [\[CrossRef\]](#) [\[PubMed\]](#)

57. Wong Sang, M.; Narayan, J. Reinforcement Learning-Based Finite-Time Sliding-Mode Control in a Human-in-the-Loop Framework for Pediatric Gait Exoskeleton. *Machines* **2025**, *13*, 668. [\[CrossRef\]](#)
58. Natividad, R.F.; Miller-Jackson, T.; Chen-Hua, R.Y. A 2-DOF Shoulder Exosuit Driven by Modular, Pneumatic, Fabric Actuators. *IEEE Trans. Med. Robot. Bionics* **2021**, *3*, 166–178. [\[CrossRef\]](#)
59. Nassour, J.; Hamker, F.H.; Cheng, G. High-Performance Perpendicularly-Enfolded-Textile Actuators for Soft Wearable Robots: Design and Realization. *IEEE Trans. Med. Robot. Bionics* **2020**, *2*, 309–319. [\[CrossRef\]](#)
60. Kim, W.; Park, H.; Kim, J. Compact Flat Fabric Pneumatic Artificial Muscle (FFPAM) for Soft Wearable Robotic Devices. *IEEE Robot. Autom. Lett.* **2021**, *6*, 2603–2610. [\[CrossRef\]](#)
61. Wirekoh, J.; Parody, N.; Riviere, C.N.; Park, Y.-L. Design of Fiber-Reinforced Soft Bending Pneumatic Artificial Muscles for Wearable Tremor Suppression Devices. *Smart Mater. Struct.* **2021**, *30*, 015013. [\[CrossRef\]](#)
62. Elmoughni, H.M.; Yilmaz, A.F.; Ozlem, K.; Khalilbayli, F.; Cappello, L.; Atalay, A.T.; Ince, G.; Atalay, O. Machine-Knitted Seamless Pneumatic Actuators for Soft Robotics: Design, Fabrication, and Characterization. *Actuators* **2021**, *10*, 94. [\[CrossRef\]](#)
63. O'Neill, C.T.; Proietti, T.; Nuckols, K.; Clarke, M.E.; Hohimer, C.J.; Cloutier, A.; Lin, D.J.; Walsh, C.J. Inflatable Soft Wearable Robot for Reducing Therapist Fatigue during Upper Extremity Rehabilitation in Severe Stroke. *IEEE Robot. Autom. Lett.* **2020**, *5*, 3899–3906. [\[CrossRef\]](#)
64. Sivi, C.; Bae, J.; Baker, L.; Porciuncula, F.; Grimmer, M.; Walsh, C.J. Offline Assistance Optimization of a Soft Exosuit for Augmenting Ankle Power of Stroke Survivors During Walking. *IEEE Robot. Autom. Lett.* **2020**, *5*, 828–835. [\[CrossRef\]](#) [\[PubMed\]](#)
65. Proietti, T.; O'Neill, C.T.; Hohimer, C.J.; Nuckols, K.; Clarke, M.E.; Zhou, Y.M.; Lin, D.J.; Walsh, C.J. Sensing and Control of a Multi-Joint Soft Wearable Robot for Upper-Limb Assistance and Rehabilitation. *IEEE Robot. Autom. Lett.* **2021**, *6*, 2381–2388. [\[CrossRef\]](#)
66. Proietti, T.; O'Neill, C.; Gerez, L.; Cole, T.; Mendelowitz, S.; Nuckols, K.; Hohimer, C.; Lin, D.; Paganoni, S.; Walsh, C. Restoring Arm Function with a Soft Robotic Wearable for Individuals with Amyotrophic Lateral Sclerosis. *Sci. Transl. Med.* **2023**, *15*, eadd1504. [\[CrossRef\]](#) [\[PubMed\]](#)
67. Georgarakis, A.-M.; Xiloyannis, M.; Wolf, P.; Riener, R. A Textile Exomuscle That Assists the Shoulder during Functional Movements for Everyday Life. *Nat. Mach. Intell.* **2022**, *4*, 574–582. [\[CrossRef\]](#)
68. Esser, A.; Müller, F.; Manczurowsky, J.; Hasson, C.J.; Unger, T.; Awai, C.E.; Wolf, P.; Riener, R. Impact of a Shoulder Exosuit on Range of Motion, Endurance, and Task Execution in Users with Neurological Impairments. *Wearable Technol.* **2025**, *6*, e42. [\[CrossRef\]](#) [\[PubMed\]](#)
69. Zahedi, A.; Zhang, B.; Yi, A.; Zhang, D. A Soft Exoskeleton for Tremor Suppression Equipped with Flexible Semiactive Actuator. *Soft Robot.* **2021**, *8*, 432–447. [\[CrossRef\]](#) [\[PubMed\]](#)
70. Sun, Z.; Li, Z.; Wu, G.; Zheng, J.; Man, Z. Sliding Mode-Based Actuator Fault Reconstruction and Fault-Tolerant Control of Lower Limb Rehabilitation Exoskeleton Robots. *Control. Eng. Pract.* **2026**, *167*, 106659. [\[CrossRef\]](#)
71. Zhang, F.; Wang, T.; Zhang, L.; Shi, E.; Wang, C.; Li, N.; Lu, Y.; Zhang, B. Sliding-Mode Control Based on Prescribed Performance Function and Its Application to a SEA-Based Lower Limb Exoskeleton. *Front. Robot. AI* **2025**, *12*, 1534040. [\[CrossRef\]](#) [\[PubMed\]](#)
72. Li, D.; Dornadula, V.; Lin, K.; Wehner, M. Position Control for Soft Actuators, Next Steps toward Inherently Safe Interaction. *Electronics* **2021**, *10*, 1116. [\[CrossRef\]](#)
73. Cao, G.; Huo, B.; Yang, L.; Zhang, F.; Liu, Y.; Bian, G. Model-Based Robust Tracking Control Without Observers for Soft Bending Actuators. *IEEE Robot. Autom. Lett.* **2021**, *6*, 5175–5182. [\[CrossRef\]](#)
74. Chen, C.J.; Zhang, Y.; Li, Y.J.; Xu, B. Iterative Learning Control for a Soft Exoskeleton with Hip and Knee Joint Assistance. *Sensors* **2020**, *20*, 4333. [\[CrossRef\]](#) [\[PubMed\]](#)
75. Alam, N.; Hasan, S.; Mashud, G.A.; Bhujel, S. Neural Network for Enhancing Robot-Assisted Rehabilitation: A Systematic Review. *Actuators* **2025**, *14*, 16. [\[CrossRef\]](#)
76. ISO 13482:2014; Robots and Robotic Devices—Safety Requirements for Personal Care Robots. International Organization for Standardization: Geneva, Switzerland, 2014.
77. IEC 80601-2-78:2019; Medical Electrical Equipment—Part 2-78: Particular Requirements for the Basic Safety and Essential Performance of Medical Robots for Rehabilitation, Assessment, Compensation or Alleviation. International Electrotechnical Commission: Geneva, Switzerland, 2019.
78. ISO/TR 23482-1:2020; Robotics—Application of ISO 13482—Part 1: Safety-Related Test Methods. International Organization for Standardization: Geneva, Switzerland, 2020.
79. Su, Y.; Xu, J.; Chen, Y.; Chen, T.; Mo, L. The Application of Soft Robotic Gloves in Stroke Patients: A Systematic Review and Meta-Analysis of Randomized Controlled Trials. *Brain Sci.* **2023**, *13*, 900. [\[CrossRef\]](#) [\[PubMed\]](#)
80. Harris, A.; Nguyen, J.; Park, S.W.; Ngo, V.; Bramble, J. AI-Based Methodologies for Exoskeleton-Assisted Rehabilitation of the Lower Limb: A Review. *Front. Robot. AI* **2024**, *11*, 1341580. [\[CrossRef\]](#) [\[PubMed\]](#)

81. Wang, T.; Liu, Z.; Gu, J.; Tan, J.; Hu, T. Effectiveness of Soft Robotic Glove versus Repetitive Transcranial Magnetic Stimulation in Post-Stroke Patients with Severe Upper Limb Dysfunction: A Randomised Controlled Trial. *Front. Neurol.* **2023**, *13*, 887205. [[CrossRef](#)] [[PubMed](#)]
82. Fu, C.; Xia, Z.; Hurren, C.; Nilghaz, A.; Wang, X. Textiles in Soft Robots: Current Progress and Future Trends. *Biosens. Bioelectron.* **2022**, *196*, 113690. [[CrossRef](#)] [[PubMed](#)]
83. Li, N.; Yang, Y.; Li, G.; Yang, T.; Wang, Y.; Chen, W.; Yu, P.; Xue, X.; Zhang, C.; Wang, W.; et al. Multi-Sensor Fusion-Based Mirror Adaptive Assist-as-Needed Control Strategy of a Soft Exoskeleton for Upper Limb Rehabilitation. *IEEE Trans. Autom. Sci. Eng.* **2024**, *21*, 475–487. [[CrossRef](#)]
84. McCann, C.M.; Hohimer, C.J.; O'Neill, C.T.; Young, H.T.; Bertoldi, K.; Walsh, C.J. In-Situ Measurement of Multi-Axis Torques Applied by Wearable Soft Robots for Shoulder Assistance. *IEEE Trans. Med. Robot. Bionics* **2023**, *5*, 363–374. [[CrossRef](#)]
85. Zhang, X.; Tricomi, E.; Missiroli, F.; Lotti, N.; Masia, L. Real-Time Assistive Control via IMU Locomotion Mode Detection in a Soft Exosuit. *IEEE/ASME Trans. Mechatron.* **2024**, *29*, 1201–1212. [[CrossRef](#)]
86. Voisard, C.; de l'Escalopier, N.; Ricard, D.; Petitjean, C. Automatic Gait Events Detection with Inertial Measurement Units: Healthy Subjects and Moderate to Severe Impaired Patients. *J. Neuroeng. Rehabil.* **2024**, *21*, 104. [[CrossRef](#)] [[PubMed](#)]
87. Prasanth, H.; Caban, M.; Keller, U.; Courtine, G.; Ijspeert, A.; Vallery, H.; von Zitzewitz, J. Wearable Sensor-Based Real-Time Gait Detection: A Systematic Review. *Sensors* **2021**, *21*, 2727. [[CrossRef](#)] [[PubMed](#)]
88. Wang, D.; Yao, J.; Zhao, Z.; Chen, Y. Sensors and Algorithms for Locomotion Intention Detection of Lower Limb Exoskeletons. *Med. Eng. Phys.* **2023**, *113*, 103960. [[CrossRef](#)] [[PubMed](#)]
89. Yang, X.; Fu, Z.; Li, B.; Liu, J. An sEMG-Based Human-Exoskeleton Interface Fusing Convolutional Neural Networks with Hand-Crafted Features. *Front. Neurorobotics* **2022**, *16*, 938345. [[CrossRef](#)] [[PubMed](#)]
90. Kim, J.; Kantharaju, P.; Yi, H.; Jacobson, M.; Jeong, H.; Kim, H. Soft Wearable Flexible Bioelectronics Integrated with an Ankle-Foot Exoskeleton for Estimation of Metabolic Costs and Physical Effort. *npj Flex. Electron.* **2023**, *7*, 3. [[CrossRef](#)]
91. Baud, R.; Manzoori, A.R.; Ijspeert, A.; Bouri, M. Review of Control Strategies for Lower-Limb Exoskeletons to Assist Gait. *J. Neuroeng. Rehabil.* **2021**, *18*, 119. [[CrossRef](#)] [[PubMed](#)]
92. Heung, H.-L.; Tang, Z.-Q.; Shi, X.-Q.; Tong, K.-Y.; Li, Z. A Bidirectional Fabric-Based Soft Robotic Glove for Hand Function Assistance in Patients with Chronic Stroke. *J. Neuroeng. Rehabil.* **2023**, *20*, 131. [[CrossRef](#)] [[PubMed](#)]
93. Proulx, C.E.; Beaulac, M.; David, M.; Deguire, C.; Haché, C.; Klug, F.; Kupnik, M.; Higgins, J.; Gagnon, D.H. Review of the Effects of Soft Robotic Gloves for Activity-Based Rehabilitation in Individuals with Reduced Hand Function and Manual Dexterity Following a Neurological Event. *J. Rehabil. Assist. Technol. Eng.* **2020**, *7*, 2055668320918130. [[CrossRef](#)] [[PubMed](#)]
94. Hasan, S.K.; Alam, N. Biomechanical Design and Adaptive Sliding Mode Control of a Human Lower Extremity Exoskeleton for Rehabilitation Applications. *Robotics* **2025**, *14*, 146. [[CrossRef](#)]
95. Duan, W.; Chen, W.; Wang, J.; Liu, J.; Pei, Z.; Chen, J. Gait-Generation Strategy for Lower Limb Exoskeleton Based on Central Pattern Generator. *IEEE/ASME Trans. Mechatron.* **2024**, *29*, 4191–4202. [[CrossRef](#)]
96. Kou, J.; Wang, Y.; Chen, Z.; Shi, Y.; Guo, Q. Gait Planning and Multimodal Human-Exoskeleton Cooperative Control Based on Central Pattern Generator. *IEEE/ASME Trans. Mechatron.* **2025**, *30*, 2598–2608. [[CrossRef](#)]
97. Velez-Guerrero, M.A.; Callejas-Cuervo, M.; Mazzoleni, S. Artificial Intelligence-Based Wearable Robotic Exoskeletons for Upper Limb Rehabilitation: A Review. *Sensors* **2021**, *21*, 2146. [[CrossRef](#)] [[PubMed](#)]
98. Luo, S.; Jiang, M.; Zhang, S.; Zhu, J.; Yu, S.; Dominguez Silva, I.; Wang, T.; Rouse, E.; Zhou, B.; Yuk, H. Experiment-Free Exoskeleton Assistance via Learning in Simulation. *Nature* **2024**, *630*, 353–359. [[CrossRef](#)] [[PubMed](#)]
99. Slade, P.; Kochenderfer, M.J.; Delp, S.L.; Collins, S.H. Personalizing Exoskeleton Assistance While Walking in the Real World. *Nature* **2022**, *610*, 277–282. [[CrossRef](#)] [[PubMed](#)]
100. Monteiro, S.; Figueiredo, J.; Fonseca, P.; Vilas-Boas, J.P.; Santos, C.P. Human-in-the-Loop Optimization of Knee Exoskeleton Assistance for Minimizing User's Metabolic and Muscular Effort. *Sensors* **2024**, *24*, 3305. [[CrossRef](#)] [[PubMed](#)]
101. Kokubu, S.; Nishimura, R.; Yu, W. Deriving Design Rules for Personalization of Soft Rehabilitation Gloves. *IEEE Access* **2024**, *12*, 14474–14486. [[CrossRef](#)]
102. Lai, J.; Song, A.; Wang, J.; Shi, K.; Ji, Q.; Lu, Y.; Li, H. Design and Evaluation of a Bidirectional Soft Glove for Hand Rehabilitation-Assistance Tasks. *IEEE Trans. Med. Robot. Bionics* **2023**, *5*, 965–976. [[CrossRef](#)]
103. Ferroni, R.; D'Avola, G.; Sciarrone, G.; Righi, G.; De Santis, C.; Carpaneto, J.; Gandolla, M.; Del Popolo, G.; Micera, S.; Proietti, T. A Multi-Joint Soft Exosuit Improves Shoulder and Elbow Motor Functions in Individuals with Spinal Cord Injury. *Nat. Mach. Intell.* **2025**, *7*, 1390–1402. [[CrossRef](#)]
104. Miller-Jackson, T.M.; Natividad, R.F.; Lim, D.Y.L.; Yeow, R.C.-H. A Wearable Soft Robotic Exoskeleton for Hip Flexion Rehabilitation. *Front. Robot. AI* **2022**, *9*, 835237. [[CrossRef](#)] [[PubMed](#)]
105. Cuttilan, A.N.; Natividad, R.E.F.; Yeow, R.C. Fabric-Based, Pneumatic Exosuit for Lower-Back Support in Manual-Handling Tasks. *Actuators* **2023**, *12*, 273. [[CrossRef](#)]

106. Osuagwu, B.A.C.; Timms, S.; Peachment, R.; Dowie, S.; Thrussell, H.; Cross, S.; Shirley, R.; Segura-Fragoso, A.; Taylor, J. Home-Based Rehabilitation Using a Soft Robotic Hand Glove Device Leads to Improvement in Hand Function in People with Chronic Spinal Cord Injury: A Pilot Study. *J. Neuroeng. Rehabil.* **2020**, *17*, 40. [[CrossRef](#)] [[PubMed](#)]
107. *ISO 12100:2010*; Safety of Machinery—General Principles for Design—Risk Assessment and Risk Reduction. International Organization for Standardization: Geneva, Switzerland, 2010.
108. Akbari, A.; Haghverd, F.; Behbahani, S. Robotic Home-Based Rehabilitation Systems Design: From a Literature Review to a Conceptual Framework for Community-Based Remote Therapy During COVID-19 Pandemic. *Front. Robot. AI* **2021**, *8*, 612331. [[CrossRef](#)] [[PubMed](#)]

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.