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# A Comprehensive Review of Control Challenges and Methods in End-Effector Upper-Limb Rehabilitation Robots

**Dalia M. Mahfouz [1,2,†], Omar M. Shehata [1,2,3,†], Elsayed I. Morgan [1,2] and Filippo Arrichiello [4,*,†]**

1 Mechatronics Department, Faculty of Engineering and Materials Science, German University in Cairo (GUC), Cairo 11835, Egypt; dalia.mahfoz@guc.edu.eg (D.M.M.); omar.mohamad@guc.edu.eg or mrs.research.lab@gmail.com (O.M.S.); elsayed.morgan@guc.edu.eg (E.I.M.)
2 Multi-Robot Systems (MRS) Research Group, Cairo 11835, Egypt
3 Mechatronics Department, Faculty of Engineering, Ain Shams University (ASU), Cairo 11517, Egypt
4 Electrical and Information Engineering Department, University of Cassino and Southern Lazio (UNICAS), 03043 Cassino, Italy
* Correspondence: f.arrichiello@unicas.it; Tel.: +39-0776-2993391
† These authors contributed equally to this work.

**Abstract:** In the last decades, there has been an increasing number of human patients who suffer from upper-limb disorders limiting their motor abilities. One of the possible solutions that gained extensive research interest is the development of robot-aided rehabilitation training setups, including either end-effector or exoskeleton robots, which showed various advantages compared to traditional manual rehabilitation therapy. One of the main challenges of these systems is to control the robot's motion to track a desirable rehabilitation training trajectory while being affected by either voluntary or involuntary human forces depending on the patient's recovery state. Several previous studies have been targeting exoskeleton robotic systems focusing on their structure, clinical features, and control methods, with limited review on end-effector-based robotic rehabilitation systems. In this regard, an overview of the most common end-effector robotic devices used for upper-limb rehabilitation is provided in this paper, describing their mechanical structure, features, clinical application, commercialization, advantages, and shortcomings. Additionally, a comprehensive review on possible control methods applied to end-effector rehabilitation exploitation is presented. These control methods are categorized as conventional, robust, intelligent, and most importantly, adaptive controllers implemented to serve for diverse rehabilitation control modes, addressing their development, implementation, findings, and possible drawbacks.

**Keywords:** review; end-effector; upper limb; rehabilitation; control; adaptive



**Citation:** Mahfouz, D.M.; Shehata, O.M.; Morgan, E.I.; Arrichiello, F. A Comprehensive Review of Control Challenges and Methods in End-Effector Upper-Limb Rehabilitation Robots. *Robotics* **2024**, *13*, 181. https://doi.org/10.3390/robotics13120181

Academic Editor: Dan Zhang

Received: 5 November 2024
Revised: 28 November 2024
Accepted: 14 December 2024
Published: 18 December 2024



## 1. Introduction

According to a global study jointly developed by the World Health Organization (WHO) and the Institute for Health Metrics and Evaluation (IHME) provided in 2021, one third of the world's population were living with a health condition [1]. Globally, there was an increase of about 79.4% in the number of people living with disabilities between 1990 and 2021. The recorded disability conditions were classified as musculoskeletal disorders (MSDs), neurological disorders, sensory impairments, mental disorders, and others. Most of the disabilities were classified as musculoskeletal and neurological disorders. MSDs are composed of more than 150 different diseases/conditions and impairments that include muscles, nerves, tendons, joints, and other injuries and postural disorders [2]. About 1.71 billion people encounter musculoskeletal conditions worldwide [3]. Moreover, neurological disorders are defined as diseases of the central and peripheral nervous system [4]. It can occur due to cerebrovascular conditions, such as strokes and other severe diseases. About 12 million people are recorded to suffer from strokes yearly worldwide [5].

Thus, the need for rehabilitation is increasing all over the world due to the presence of the aforementioned health conditions. Rehabilitation is crucial as it can help in preventing, reducing, or managing complications associated with many health conditions, such as postural disorders, spinal cord injury, stroke, accidents, or fractures that can extensively limit humans' motor abilities and activities of daily living (ADL) [6,7]. These patients are dramatically affected in terms of physical, financial, and mental issues.

In the last decades, extensive research interest has been directed towards robot-aided rehabilitation training solutions, which have shown various advantages compared to traditional manual rehabilitation therapy [7]. This is mainly due to their ability to perform the rehabilitation task in a repetitive and efficient manner, improving the patient's motor abilities [7]. The main challenge is to design and implement a robotic system structure that is capable of performing rehabilitation therapy in an effective and safe manner.

In this regard, several robotic systems have been built to serve as upper or lower extremity rehabilitation robots. These robots are mainly classified as end-effector robots or exoskeletons [8–12]. End-effector robots are said to have a simple structure that can be easily adapted to diverse patients' configurations and health conditions. However, exoskeletons are considered to reproduce the kinematics of the human limb and support its motion through controlling each joint separately [8,10]. This makes exoskeletons more complex to develop but more precise in terms of joint control [13].

One of the prime challenges of rehabilitation robotic system development is its control structure, as the control system should be designed to consider the human configuration, recovery stage, motor ability, intentions, and safety. Various controllers were reviewed by previous papers including conventional, intelligent, and robust controllers with a limited number of reviews on adaptive control methods, which are considered to be vital for robotic rehabilitation. Adaptive control methods are used to adjust the control parameters based on the patient's real-time performance and health condition. This ensures personalized, safe, and effective therapy that evolves with the patient's progress and changing capabilities [8–11]. Moreover, to the best of the authors' knowledge, various studies focus on reviewing these control systems for exoskeleton robots without listing the possible controllers for the end-effector ones [8–11].

Thus, this paper aims to provide a comprehensive review on rehabilitation robots focusing on upper-limb rehabilitation systems. The main reason behind presenting this comprehensive review paper is to serve as a positive guiding value for future researchers in upper-limb rehabilitation robotics field. One of the study objectives is to review several end-effector and exoskeleton robotic system structures, discussing their functional differences in terms of mechanical structure, targeted joints, clinical applications, commercialization, advantages, and drawbacks. In addition, unlike previous reviews, this study reviews and summarizes several diverse control methods used for upper-limb rehabilitation utilizing end-effector robots. These control methods are categorized as conventional, robust, intelligent, and most importantly, adaptive controllers implemented to serve for diverse rehabilitation control modes. The control methods are further classified as model-based and data-driven-based non-adaptive or adaptive control methods, which are used to handle multi degrees of freedom (DoF) end-effector robotic systems. Furthermore, the adaptive control methods introduced are further decomposed into several categories, listing the development, findings, and possible drawbacks of each controller in each category.

The paper is organized as follows: Section 2 includes the literature search strategy and information sources used to build the structure of the review. Section 3 presents an overview of upper-limb rehabilitation robots including the end-effector and exoskeleton robots investigated in the previous literature. In addition, it includes the possible clinical and functional requirements needed for an efficient and safe rehabilitation process. Section 4 discusses the control modes and challenges available in upper-limb rehabilitation robotics. The end-effector control methods are reviewed in Section 5. Finally, Section 6 summarizes the work of the paper and recommends future endeavors.

## 2. Literature Search Methodology

In order to find several articles related to upper-limb robotic rehabilitation systems, three platforms; IEEE Xplore, Scopus, and PubMed, were searched. These platforms are the databases for this review. Three sets of keywords were used to search through the aforementioned databases, as this paper is mainly presented to serve two objectives.

The first is to examine a multitude of end-effector and exoskeleton robotic systems used for upper-limb rehabilitation in previous review papers. Thus, the keywords used were (Rehabilitation AND Robot AND Upper AND (Review OR Survey)). The second is focused on the control algorithms implemented in end-effector robots utilized for upper-limb rehabilitation. As a result, the keywords used were (Rehabilitation AND Robot AND Upper AND Control AND End AND Effector).

For a more focused review on adaptive controllers, the keywords were modified to include “Adaptive”: (Rehabilitation AND Robot AND Upper AND Control AND End AND Effector AND Adaptive). Articles published since 2009 were included. A diagram is presented in Figure 1 to demonstrate the search methodology.

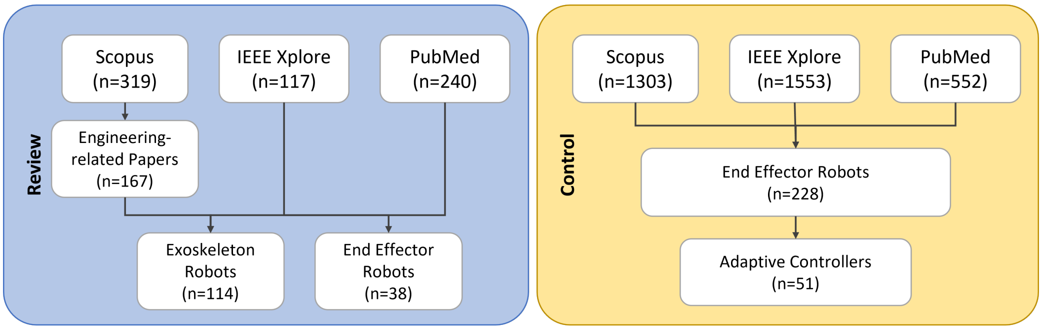



**Figure 1.** Search methodology diagram.

## 3. Overview of Upper-Limb Rehabilitation Robots

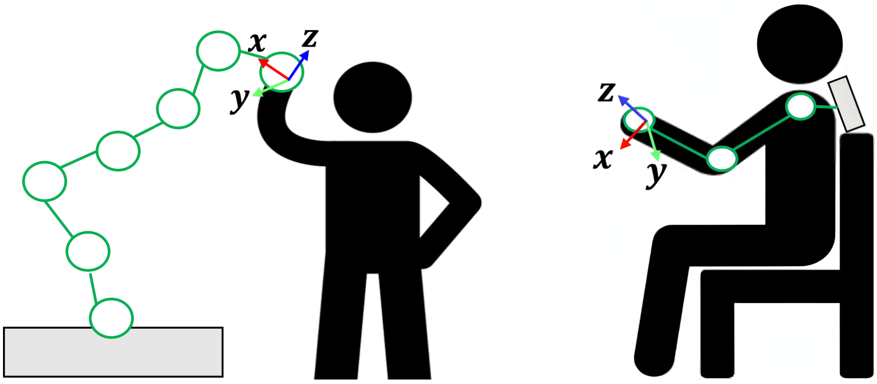
Recently, various robotic systems for upper-limb rehabilitation have been developed. These systems are designed to perform task-oriented repetitive movements which in turn enhance the muscle strength and expand the range of motion of the patient’s affected limb [10,14]. This section provides a comprehensive overview of upper-limb rehabilitation robot mechanisms, discussing their functional differences in terms of mechanical structure, targeted joints, clinical applications, commercialization, advantages, and drawbacks. In addition, the clinical and functional requirements that such systems have to meet are covered to support an effective and efficient rehabilitation process.

### *3.1. Rehabilitation Robot Mechanisms*

Generally, rehabilitation robots can be classified as end-effector and exoskeleton mechanisms [8–12] as shown in Figure 2. The end-effector robotic system interacts with the patient through the most distal segment of the human limb (e.g., human wrist) without direct alignment between the patient and the robot’s joints. These systems are said to have a simple structure that can be easily adapted to diverse patients’ configurations and health conditions. In addition end-effector robots are contemplated to have convenient control approaches with high precision [8,10,14].

Focusing on upper-limb end-effector robots, various robotic manipulators have been developed for patients suffering from musculoskeletal and neurological disorders [10]. One of the early developed end-effector robots for upper-limb rehabilitation was the MIT Manus [15]. It was designed to determine whether repetitive reaching exercises using a robotic device could enhance the recovery of the upper-limb function in hemiparetic stroke survivors [16]. Other robotic systems such as ARM (Assisted Rehabilitation and Measurement) Guide [17], MIME (Mirror-Image Movement Enabler) [18], Bi-Manu-Track [19], GENTLE/s [20], and Italian NeReBot [21] neurorehabilitation robots, as well as ACT$^{3D}$ [22]

and ACT$^{4D}$ [23] (Arm Coordination Training Robot) and many others, have previously been utilized. A summary of the frequently addressed upper-limb end-effector robots in the previous literature and their main features is provided in Table 1 [8,10,12,24]. The table includes each robot's mechanical structure in terms of motion classification, DoF, and targeted joints. In addition to the disease handled and clinical tests performed. It takes into account the number of subjects and therapy sessions details. Moreover, the software origin is highlighted. It is worth mentioning that most software tools used are closed access, only available for developers and the entities that acquire the robot. Finally, the commercialization status of each setup is also given. Along with end-effector robots, exoskeletons are also used to handle neurological and musculoskeletal disorders. Contrary to end-effector robots, exoskeletons reproduce the kinematics of the human limb and support its motion through controlling the position and orientation of each joint separately [8,10]. This makes the exoskeleton robots more complex in terms of control and more expensive as right-limb exoskeletons cannot be used for left-limb treatment [13]. Thus, exoskeletons are considered to be hard and expensive to use for bilateral rehabilitation.




(**a**) End-effector structure (**b**) Exoskeleton structure

**Figure 2.** End-effector and exoskeleton robotic structures for upper-limb rehabilitation process.

Several exoskeleton robots have been developed for upper-limb rehabilitation, such as RUPERT (Robotic Upper Extremity Repetitive Trainer) [25], MAHI EXO-II [26], MyoPro [27], CADEN (Cable-Actuated Dextrous Exoskeleton for Neurorehabilitation) [28,29], ARMin [30,31], SUEFUL [32], EXO-UL7 [33], ARMEO Power [34], HAL-SJ (Hybrid Assistive Limb—Single Joint) [35] and many others [36,37]. It is worth mentioning that most of the presented exoskeleton robots do not provide actuation for all the limb's DoF [10]. Table 2 provides a summary for some of the upper-limb exoskeletons and their prime features [8,10,12,13,24,36,37]. Due to the complex structure of exoskeletons and their inability to be adapted to serve diverse patients with distinct postural configurations and health conditions, this study focuses on the end-effector robotic structure. End-effector robots are considered for their simplicity and ability to interact more easily with the human subject.

It is then crucial to mention the clinical and functional requirements of the end-effector robotic systems to achieve the desirable rehabilitation task while considering the patient's health conditions, comfort and safety.

### *3.2. Requirements for Upper-Limb Rehabilitation*

When considering end-effector robots for upper-limb rehabilitation, several requirements should be considered in order to ensure that the application adheres to multiple stakeholders, including patients, therapists, as well as the robots. Patients' requirements are crucial to achieve healthy motor recovery, safety, adaptability, and engagement.

On the other hand, therapists are required to be well trained to use the rehabilitation robot's equipment in an efficient and effective way. In addition, the patients' status needs to be monitored and analyzed continuously [16].

**Table 1.** Main features of frequently addressed upper-limb end-effector robots.

| EE Robot | Year | Classification | DoF | Targeted Joints | Type of Disease | Clinical Testing | Software Origin | Commercial |
|---|---|---|---|---|---|---|---|---|
| MIT Manus [15] | 1994 | Planar motion | 2 | Shoulder + elbow | Stroke, CP, MS, TBI | 1000++ [38] from 1999 till 2004, 250 strokes, 3 h/wk for 12 wks [15] | Massachusetts Institute of Technology (MIT) [15] | ✓ |
| ARM-Guide [17] | 1995 | Linear motion | 1 | Shoulder + elbow | Stroke | In 2000, 3 chronic strokes, 3 h/wk for 8 wks [39] | Rehab Inst. of Chicago, University of California [40] | ✗ |
| NeReBot [21] | 1995 | Cable-driven motion | 2 | Shoulder + elbow + wrist | Stroke | In 2007, 12 early strokes and 12 unimpaired upper limbs ≈5 h/wk for 4 wks [41] | Robotics Lab, University of Padua [42] | ✗ |
| MIME [18] | 1997 | Bi-manual motion | 6 | Shoulder + elbow | Stroke | In 2004, 13 chronic strokes, 3 h/wk for 8 wks [43] In 2011, 54 hemipareses, up to 30 h [44] | Stanford University [18] | ✗ |
| Bi-Manu-Track [19] | 2001 | Bi-manual motion | 2 | Adaptive | Stroke | In 2016, 34 chronic strokes ≈20 h, for 4 wks [45] In 2023, 70 hemiplegic strokes, 6 h/wk for 3 wks [45] | Reha-Stim Co., Germany [46] | ✓ |
| GENTLE-/s [20] | 2002 | 3D motion | 3 | Shoulder + elbow + wrist | Stroke | In 2007, 31 strokes, 3 h/wk for 9 wks [47] | Moog Inc. [48] | ✗ |
| HAPTIC MASTER [49] | 2002 | 3D motion | 3 | Forearm | Stroke, dystonia | In 2014, 22 chronic strokes, 4 h/wk for 8 wks [50] | Moog Inc. [48] | ✗ |
| REHA-ROB [51] | 2007 | 3D motion | 3 | Shoulder + elbow | Stroke | In 2007, 30 hemipareses, ≈1 h for 20 days [51] | ABB & comp.: Hungary, UK, Germany, and Bulgaria [52] | ✗ |
| ACT$^{3D}$ [22] | 2007 | Planar motion | 3 | Shoulder + elbow | Stroke | In 2009, N/A hemiparesis, 3 h/wk for 8 wks [53] | Neuro-imaging, Motor Control, Northwestern University [53] | ✗ |
| Amadeo [54] | 2010 | Hand Mobility | 5 | Hand + fingers | Stroke, CT | In 2010, 12 ischemic strokes, 3 h/wk for 8 wks [55] In 2023, 58 strokes, average 3 h/wk for 10 wks [56] | TyroS software Tyromotion GmbH [57] | ✓ |
| Braccio di Ferro [58] | 2011 | Planar motion | 2 | Shoulder + elbow | Stroke, MS | In 2010, 10 hemiplegias, 6 to 12 sessions [59] | Neurolab, University of Genova [60] | ✗ |
| Wristbot [61] | 2014 | 3D motion | 3 | Wrist | Stroke, dystonia | In 2021, 23 wrist injuries, 5 h/wk for 3 wks [62] | REACH Prog. University of Minnesota [63] | ✗ |
| Diego [64] | 2014 | Cable-driven motion | 3 | Shoulder + elbow | Stroke, CP | N/A | TyroS software Tyromotion GmbH [65] | ✓ |
| MOTORE [66] | 2016 | Mobile Planar motion | 3 | Shoulder + elbow + wrist | Stroke, MD | N/A | Humanware, Scuola Superiore Sant'Anna of Pisa [65] | ✓ |

Abbreviations for the diseases mentioned: CP: cerebral palsy, MS: multiple sclerosis, TBI: traumatic brain injury, CT: carpal tunnel, MD: musculoskeletal disorder, h: Hours, wk: week, N/A: not applicable.

**Table 2.** Main features of the frequently addressed upper limb exoskeleton robots.

| Exoskeletons | Year | DoF | Targeted Joints | Type of Disease | Clinical Testing | Commercial |
|---|---|---|---|---|---|---|
| RUPERT [25] | 2005 | 5 | Shoulder + humeral + elbow + forearm + wrist | Stroke | ✓ | ✗ |
| MAHI EXO-II [26] | 2006 | 5 | Elbow + forearm + wrist | Stroke, SCI | ✓ | ✗ |
| MyoPro [27] | 2006 | 4 | Elbow + wrist + hand | Stroke, BPI, BI, SCI | ✓ | ✓ |
| CADEN [29] | 2007 | 7 | Shoulder + elbow + forearm + wrist | Stroke, SCI | ✓ | ✗ |
| ARMin II, III [30,31] | 2007–2009 | 6 | Shoulder + elbow + lower arm + wrist | Stroke, SCI | ✓ | ✗ |
| SUEFUL [32] | 2009 | 7 | Shoulder + elbow + forearm + wrist | - | ✓ | ✗ |
| EXO-UL7 [33] | 2011 | 7 | Shoulder + elbow + forearm + wrist | Stroke | ✓ | ✗ |
| ARMEO Power [34] | 2011 | 6 | Shoulder + elbow + forearm + wrist | Stroke, CP | ✓ | ✓ |
| HAL-SJ [35] | 2015 | 1 | Single joint, e.g., elbow | Joint-specific injury | ✓ | ✓ |

Abbreviations for the diseases mentioned: SCI: spinal cord injury, BPI: brachial plexus injury, BI: brain injury, CP: cerebral palsy.

### 3.2.1. Clinical Requirements

Clinical requirements and guidelines are necessary for effective clinical practice to improve the patient's recovery process [67]. There are several organizations providing clinical guidelines on stroke management and rehabilitation such as the National Institute for Health and Care Excellence (NICE), the Intercollegiate Stroke Working Party (ISWP), the European Stroke Organization (ESO), and others [67]. ESO strongly recommends robotic rehabilitation as an adjunct therapy procedure to the conventional therapy.

On top of the clinical requirements stated is the desirable trajectory designed for the patient to follow at each time instant for a successful rehabilitation therapy. Several dynamic rehabilitation-based recovery trajectories are considered for diverse patients with different individual configuration, health condition, and recovery stage [68–70]. These trajectories are divided into task-specific training (TST) and repetitive task training (RTT). RTT is contemplated to be important alongside traditional exercises. It can be used in unilateral and bilateral upper-limb rehabilitation depending on the task and level of impairment [67]. It should be intensive, task-specific, adaptive based on progress, goal-oriented, and meaningful, such as the reaching and grasping tracks which are considered to be prime activities of daily living (ADL). Regarding the TST, one of the most considered upper and lower extremities' rehabilitation-based trajectories is the Proprioceptive Neuromuscular Facilitation (PNF) pattern [71]. PNF is a therapeutic method designed to promote the response of nerve impulses to recruit muscles through stimulation of the proprioceptors (e.g., muscle spindle and Golgi tendon organs) [71]. The PNF pattern is one of the approaches used for upper and lower extremities in both unilateral and bilateral rehabilitation patterns [72]. The PNF patterns are broken into first and second diagonal patterns (D1 and D2) [73]. Each diagonal pattern is represented by a sequence of flexion–extension, abduction–adduction, and internal–external rotation of the addressed joints for an effective rehabilitation process. Thus, it is crucial to define the suitable rehabilitation trajectory to fulfill the addressed patient's requirements taking into account his/her current condition and recovery stage.

Moreover, the acceptance and engagement of both the therapists and patients. As clinicians may fear their replacement by new robotic technologies in clinics. However, the ability to assess and plan the patient's individual needs is still dependent on the therapist's expertise and judgment. Robot systems are technologies that are developed to assist therapists in attaining optimal outcomes for the patients as stated in [16,74].

Patients' engagement is vital for their recovery process as not all patients can feel safe and comfortable while being manipulated by a robotic system. Thus, robots offer multi-modal feedback incorporating visual, auditory, and haptic interfaces which can be utilized by interactive games using a Graphical User Interface (GUI) or Virtual Reality (VR) to gain the patient's acceptance. The aforementioned organizations do not mention VR in the context of upper-limb therapy; however, they recommend the use of mirror therapy and tele-rehabilitation for patients' engagement.

Another clinical aspect considered is the therapeutic intensity for effective therapy. NICE, ISWP, and ESO suggest a minimum of three hours on at least five days per week [67]. It is worth mentioning that there is no specific minimum or maximum therapy duration or frequency to guarantee upper-limb rehabilitation [67]. Based on the authors' point of view, the ultimate clinical goal is to restore the patient's ability to perform activities of daily living (ADL). Robots must facilitate movements to assist humans in achieving these tasks effectively. Thus, it is crucial to consider the control algorithm and structure used for rehabilitation robots.

#### 3.2.2. Functional Requirements

Furthermore, the functional requirements of the robotic systems are important to address. The degrees of freedom (DoF) and range of motion (RoM) of the robots should be contemplated to allow more natural full limb motion for a proximal or distal joint or for the end-effector coordination of patients. Moreover, the system should be adjustable and customizable to fit different patients' configuration and physical status including size, links lengths, and affected joints [74,75]. Robots should ideally be portable or easy to transport, especially if home-based rehabilitation is intended [76]. In addition, robots have to be robust and durable to withstand repetitive clinical tasks [75,76]. This includes having reliable actuators, sensors, and easy-to-maintain components. The robot's sensory feedback is required to monitor the human joint angles, forces, muscle activity, and tracked trajectory, providing real-time data for therapists to adjust the patient's treatment plan [76].

Added to that, robot control system should be adaptable to the patient's movements, adjusting assistance levels, force application, and trajectory based on the patient's performance and feedback in a real-time manner [74,77]. This ensures that the patient is neither over-assisted nor under-supported, promoting patient's participation. The robot should be capable of generating a suitable amount of force to move the patient's limb. In addition, it should take into account the back-drivability of the robot, by which the human should be able to feel the weight of the robotic system [74].

Another crucial functional consideration is the safety of the full process. The robot must prevent the application of excessive forces or incorrect movements that could lead to injuries. This requires safe and stable robotic system control methods which should be examined in multiple clinical trials on diverse subjects, taking into account various conditions to guarantee patient safety before treatment. This encourages the system's adaptability to adjust the robot's assistance based on the patient's abilities and robustness to handle various conditions.

#### 3.2.3. General Requirements

Another important consideration regarding the use of robots in rehabilitation and physical therapies is the cost of the treatment [16]. This includes the robotic system purchase and maintenance cost which can be relatively expensive for any clinical facility. In addition to the training cost for therapists and aides to be able to set up the robots, understand their hardware and software modules, interact with the robotic systems, and obtain the required data analyses of each patient, the cost of the treatment for the patient should be considered, which can also be expensive based on the patient's recovery status.

As this study focuses on end-effector upper-limb rehabilitation robots, Table 3 highlights the clinical and functional requirements for each end-effector robot mentioned previously in this section [78,79].

The table presents the most common requirements, such as the trajectory performed, the intensity of the therapy, the control algorithm developed, the sensory feedback used, the portability, and the possible interaction with the user through interactive games or other virtual reality demonstrations.

**Table 3.** Clinical and functional requirements of upper-limb end-effector robots.

| EE Robot | Trajectory | DoF | Therapy Intensity | Control | Feedback | Potability | Interactive Games |
|---|---|---|---|---|---|---|---|
| MIT Manus [15] | RTT planar motion | 2 | 3 h/wk for 12 wks [15] | Impedance control [60,80,81] | Handle torque and position, joint position, velocity, and torque | ✗ | ✓ InMotion |
| ARM-Guide [17] | Reaching motion, linear motion | 1 | 3 h/wk for 8 wks [39] | PD control [81] | Forearm position and torque | ✗ | N/A |
| NeReBot [21] | Cable-driven motion | 2 | ≈5 h/wk for 4 wks [42] | PID control [42] | Motor positions | ✗ | N/A |
| MIME [18] | Bi-manual Motion | 6 | 3 h/wk for 8 wks [43] | PID control [81] | Forearm pose and torque | ✗ | N/A |
| Bi-Manu-Track [19] | Bi-manual motion | 2 | 6 h/wk for 3 wks [45] | Position/force control [82] | Visual and force | ✗ | ✓ |
| GENTLE-/s [20] | 3D motion | 3 | 3 h/wk for 9 wks [47] | Admittance control [83] | End-point torque, position, and velocity | ✗ | ✓ |
| HAPTIC MASTER [49] | 3D motion | 3 | 4 h/wk for 8 wks [50] | Admittance control [83] | End-point torque, position, and velocity | ✗ | ✓ |
| REHA-ROB [51] | 3D motion | 3 | ≈1 h for 20 days [51] | Indirect Force control [84] | End-point torques | ✗ | N/A |
| ACT$^{3D}$ [22] | Reaching motion, planar motion | 3 | 3 h/wk for 8 wks [53] | *3D* Force control [85] | End-point torque, position, and velocity | ✗ | N/A |
| Amadeo [54] | Hand mobility | 5 | 3 h/wk for 10 wks [56] | Position control [86] | End-point position and force | ✓ | ✓ |
| Braccio di Ferro [58] | Planar motion | 2 | 6–12 sessions [59] | Impedance control [60,80,81] | Joint angles and end-point force | ✗ | ✓ |
| Wristbot [61] | 3D motion | 3 | 5 h/wk for 3 wks [62] | Impedance control [87] | Handle force and position and motor torque | ✓ | ✓ |
| Diego [64] | Cable-driven motion | 3 | 3–5 h/wk | N/A | Forearm pose | ✗ | ✓ |
| MOTORE [66] | Mobile planar motion | 3 | 3–5 h/wk | N/A | N/A | ✓ | ✓ |

Abbreviations mentioned: h: Hours, wk: Week, N/A: not applicable.

As shown, most of the end-effector robots presented perform repetitive 3*D* or planar movements to assist patients. The average therapeutic intensity is 3–5 h/wk for 8 wks. Several control algorithms are used for robots to assist the patient in various modes. The control modes and algorithms are studied in depth in the upcoming sections.The feedback elements are crucial to investigate for end-effector upper-limb rehabilitation robots due to their importance in the robotic system control architecture [88]. For most of the aforementioned end-effector systems, the control feedback is based on position and force of either the robot's joints and end-effector or the human's limb. The sensory feedback elements used to obtain the angular position and velocity of the robot joints are usually joint encoders or potentiometers. However, to obtain the robot's end-effector's position, the kinematic configuration of the robot is considered based on mathematical derivations or visual sensory feedback. Moreover, to obtain the human's joint configuration and wrist position, various approaches can be utilized, such as inertia measurement unit (IMU) sensors attached to the human body for direct measurement or visual sensory feedback depending on external depth cameras.

Regarding forces and torques, the robot's motor torques are measured by torque sensors attached to each joint. Moreover, the applied forces from the human to the robot can be measured using force/torque sensors attached to the robot's handle. In addition, human muscle strength and activity can be measured using Electromyography (EMG) sensors which can help in computing the human applied forces [10,37,88]. Most of the robots are not portable, as they are stationary robots used for clinical purposes and not designed for home use. Several robots utilize interactive games and virtual reality systems for patients' engagement.

## 4. Robotic Rehabilitation Training Modes and Control Challenges

After highlighting the common clinical and functional requirements for end-effector robot rehabilitation, it is worth mentioning the robotic rehabilitation training modes and challenges, which are addressed through this section.

The upper-limb rehabilitation process is divided mainly into two training modes: passive and active [7,11,37]. These training modes directly reveal the patient's recovery stage and are determined according to the control procedure. The passive training mode is considered to be a common mode in early stages of post-stroke therapy. During this mode, the patient has a significant difficulty in moving his/her affected limb [11]. Thus, the rehabilitation robotic system is used to control the human's limb motion rigidly along the desirable reference trajectory by utilizing a position controller with relatively high corrective gains. Moreover, the feedback controller gains have to be tuned carefully to avoid harming the human while tracking the trajectory. Thus, minimal compliance should be available to indicate muscle contractions, spasticity, and other synergies [37]. As a result, the human–robot interaction model indicating the compliance level should be considered mechanically or as part of the control algorithm.

Once the patient gains a minimal amount of muscle strength, the active training mode takes place, allowing for shared control of the movements between the human and the robot [37]. During the active training mode, the robotic control system can be used to assist the patient's motion to complete the training exercise. The patient in this phase starts to provide a sort of force which can be either assistive to track the desirable trajectory, or resistive to resist the robot's motion. In case of assistive force, an active-assistive training mode is activated, which encourages and promotes human engagement. In this regards, several assist-as-needed control methods have been examined in the literature to assist the patient's motion [7]. When the patient enters the final recovery stages, another active training mode is considered, the "active-resistive training mode", where the human subject can resist the motion of the robot by applying a resistive force in a direction opposing the specified track indicating a considerable muscle strength. In this case, the robot can be stiff towards the human limb's motion and push the subjected limb to gain more strength [7].

The passive and active training modes take into account the human–robot interaction model to be able to provide the adequate optimal force and position control signals necessary to achieve a safe and effective interaction during the rehabilitation process [11]. One of the common human–robot interaction models is a mass–spring–damper system by which the stiffness, damping, and mass parameters are changeable and optimized based on the current training mode, considering the patient's recovery stage, current position, and applied forces [7,11,89,90]. To achieve the desirable control objectives of the aforementioned training modes, there are several control challenges mentioned in the literature that should be examined and discussed.

### *Control Challenges in Rehabilitation Robotics*

The control methods used for upper-limb rehabilitation using end-effector robots have numerous challenges to handle [11]. One of the major challenges is the system's uncertainties including the unmodeled dynamics, the parametric uncertainties, and the system's nonlinearities that are not fully accounted in the robot's model [12]. Moreover, focusing on human's upper extremities, arm dynamics is complex, having multiple variables to consider.

One of these variables is the time-varying limb parameters that are function in the muscle strength, motor impairments, fatigue levels, and recovery progress. Thus, the process of modeling or estimating the human arm's parameters is challenging. Estimating or measuring the human arm's joints' motion is a vital challenge especially for end-effector robots, as end-effector robots can only provide movement measurements for the human limb's segment attached to the robot, e.g., the human wrist, and not for all arm segments and joints [12]. As a result, additive sensors such as off-board depth cameras or on-board Inertial Measurement Units (IMUs) or Electromyography (EMG) sensors attached to the human body are used to estimate the joint angles, velocities, muscle activity, and forces of the patient's arm. These sensors are considered to have noisy signals and transmission delays, which can result in inaccurate human states' estimation or measurement. The communication delays and loss of information transmitted through the control loop can affect the system's stability [11]. In addition, the potential stability loss may happen due to the uncertain human–robot interaction, as patients may perform sudden involuntary motion which can resist the robot's movement. In this regard, the robot's control system must detect and compensate for these variations to ensure a smooth and effective therapy without overshooting that can lead to instability. This can be performed by adding a motion intention prediction block in the system's control loop to predict the human arm's motion, by examining the interactive forces and joint parameters estimates to produce stable control with smooth human–robot interaction.

In order to deal with the aforementioned uncertainties and dynamically change human muscle activity based on the recovery status and unpredictable movements, adaptive control methods are considered. Most of the previous literature reviews considered the exoskeleton robots' control schemes, whether traditional, adaptive, learning-based, or others, to manipulate the human upper extremity in an effective and efficient way [11,37,91]. Thus, end-effector rehabilitation robots are considered in this review paper for their simplicity, adaptability, and effectiveness in delivering complex position and force patterns based on the patient's recovery status [10,12]. In this regard, various control methods, adaptation algorithms, interaction principles, and feedback elements for the upper-limb end-effector rehabilitation robots are discussed in the upcoming sections.

## 5. Upper-Limb Rehabilitation Robotic End-Effector Control Methods

The main objective of rehabilitation robotic system control approaches is to provide the optimal required position and force control to achieve safe and efficient passive and active patient training modes [11]. The performance of the control methods applied to the upper-limb rehabilitation process is evaluated based on several criteria. The main evaluation criteria are the accuracy of tracking the defined therapy's trajectory, the minimum force applied on the human, and the human's muscle activity, maximum overshoot, rise time, and settling time of the system's variables. Various control methods have been developed to achieve the aforementioned objective.

### *5.1. Proportional–Integral–Derivative (PID) Control*

One of the most popular model-based controllers usually used for position control purposes is the Proportional–Integral–Derivative (PID) controller. PID control is a simple linear model-free control method used mainly during the passive training mode, by which the patient is completely passive and the robot has full control over the patient arm's motion. PID control is used then for trajectory tracking purposes without considering the applied forces from and on the patient's arm [92]. The PID block diagram is shown in Figure 3, and its control law is given by:

$$u(t) = K_P e(t) + K_I \int_0^t e(\tau) d\tau + K_D \dot{e}(t) \tag{1}$$

where $e(t)$ is the difference between the desirable and actual robot's joint position, $\dot{e}(t)$ is its time derivative, and $u(t)$ is the control input, which can be the robot's computed torques.

Proportional, integral, and derivative gains are defined as $K_P$, $K_I$, and $K_D$, respectively.

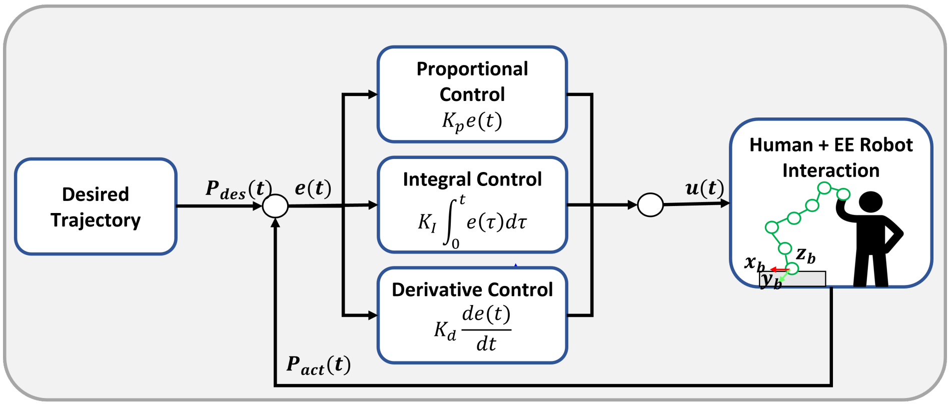



**Figure 3.** PID control structure for upper-limb robotic rehabilitation.

Despite its simple structure and implementation, PID control has several drawbacks. One of these drawbacks is tuning the gains, which is believed to be hard and time consuming, as customized gains for each patient are desirable based on his/her structure and recovery stage. In addition, there are a possible error accumulation and high-frequency oscillations that can result in system instability [92]. Thus, PID control is suggested to be combined with other advanced control methods such as intelligent, robust, or adaptive control. ARM-Guide and MIME robots are controlled using a PD and PID, respectively [81].

### *5.2. Impedance Control*

As the affected arm gains more strength, the human starts to apply a certain force on the robot which can be either assistive or resistive forces, activating the active training mode. These interactive forces ought to be regulated by the control approach through compliance or resistance. One of the main model-based controllers used to establish a dynamic relationship between the system's motion and the human–robot interactive forces is impedance control [7,11,89,90]. This relationship is defined by a mass–spring–damper system represented by:

$$\tau_{ext}(t) = M_d \ddot{e}(t) + B_d \dot{e}(t) + K_d e(t) \tag{2}$$

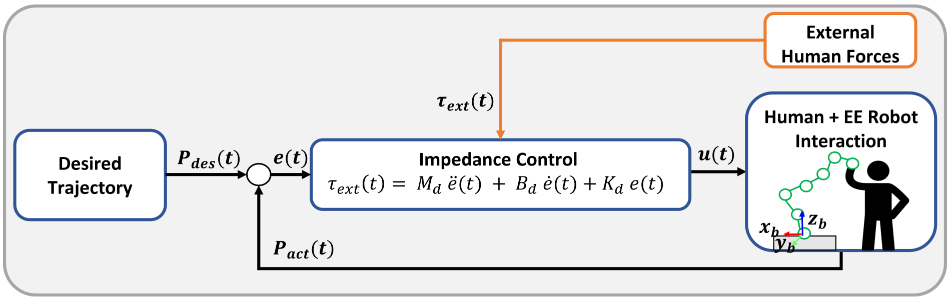
where $\tau_{ext}(t)$ is the joint external torque vector, $e(t)$ is the error between the actual measured joint angle $q$ and the desired $q_{des}$ considered without applying an external torque, and $\dot{e}(t)$ and $\ddot{e}(t)$ are the first and second derivatives of the error, respectively. The parameters $M_d$, $B_d$ and $K_d$ are the desired mass–spring–damper gains, respectively.

The impedance control has as input the joint angles $q$ indicating the system's motion state and as output the torques $\tau$ as shown in Figure 4a. Impedance control does not only consider the possible errors during motion tracking but also considers the human interaction forces. Thus, this control method is proven to have stable interaction. However, it does not compensate system uncertainties such as unmodeled dynamics. In addition, The utilization of a high impedance can lead to system instability. MIT-Manus and Braccio di Ferro employ impedance control [60,80,81].

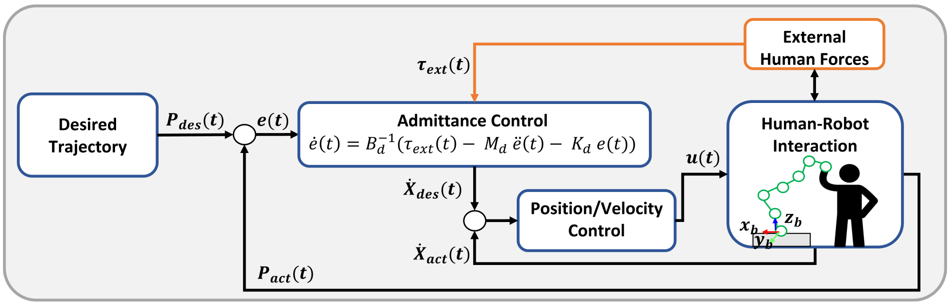
### *5.3. Admittance Control*

The admittance controller is similar to the impedance controller. However, the input of the admittance control structure is the system torques $\tau$, while the output is the desired joint angles $q_{des}$. The desired angles are then inputted into a joint controller to regulate the position error and output the governed system torques [93], as shown in Figure 4b. The accuracy and performance of the admittance control are critically dependent on the force sensor's accuracy [60]. It is suitable for stiff robots. Similarly to the impedance control, a high admittance can lead to system instability [11].

One of the commercial Tyromotion robots, Haptic Master, and GENTLE/s utilize an admittance control algorithm [83].




(**a**) Impedance control block diagram




(**b**) Admittance control block diagram

**Figure 4.** General impedance and admittance control structures for upper-limb robotic rehabilitation.

## *5.4. Robust Control*

One of the robust nonlinear model-based controllers used for upper-limb end-effector robotic rehabilitation is Sliding Mode Control (SMC). SMC is used to handle external disturbances and parametric uncertainties. It is designed to force the system states to converge on a sliding surface in finite time. With the help of a Lyapunov-based stability analysis, the SMC control output is designed to cancel the positive nonlinear terms and guarantee a negative definite or semi-definite rate of change in the designed Lyapunov function to ensure system stability [92,94]. The SMC structure is presented in Figure 5. The drawback of the SMC is the chattering effect, which can result in an undesirable switching behavior in the control action, which can damage the system mechanically. However, this issue can be solved by adding mathematical smoothing functions [11].

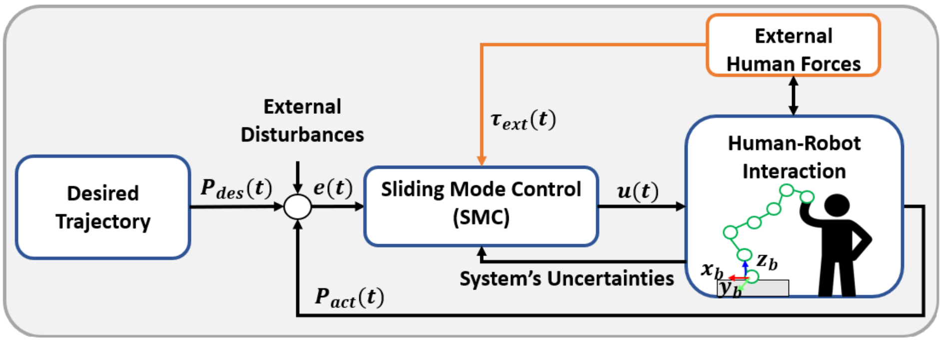



**Figure 5.** Sliding Mode Control (SMC) structure.

## *5.5. Adaptive Control*

One of the major drawbacks of the aforementioned control methods is a lack of time-varying adjustable control parameters, that should depend on the patient's involuntary movements, recovery stage, and cognitive level [11].

Thus, adaptive control is worthwhile implementing, as it adjusts the unknown system parameters in an online manner based on the ongoing operation's conditions. Figure 6 shows the general block diagram representation of an adaptive controller. There exist various adaptive control methods applied to the upper-limb rehabilitation process utilizing an end-effector manipulator. These methods can be categorized as adaptive impedance/admittance control, fuzzy-based adaptive control, machine learning-based adaptive control, adaptive Sliding Mode Control, Model Reference Adaptive Control (MRAC), adaptive backstepping control, and others. Each of these has its own features, advantages, and drawbacks which are discussed through the upcoming sub-sections.

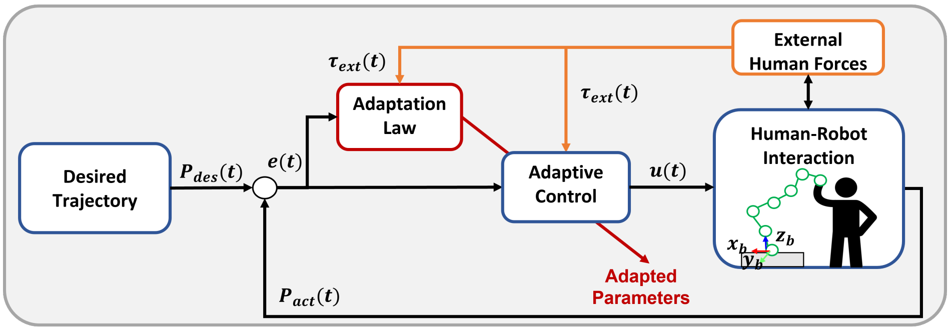



**Figure 6.** Abstracted block diagram of adaptive controllers for upper-limb manipulation.

#### 5.5.1. Adaptive Impedance/Admittance Control

Adaptive impedance/admittance controllers are considered to be the most commonly used controllers for the end-effector upper-limb rehabilitation process. This is due to their ability to adjust the robot's performance based on the patient's interaction forces, accommodating varying strength and engagement levels during rehabilitation exercises.

Wang et al. [95] proposed a hybrid impedance control (HIC) for a three-DoF upper limb robotic manipulator to perform planar rehabilitation motion, needed for the whole-joint coordination of the shoulder, elbow, and wrist. The controller was designed to switch between position and force control based on a selection matrix to track the desired position trajectory and follow the trajectory forces simultaneously. The proposed HIC performance was compared to an impedance controller through multiple simulation tests. It was observed that the HIC outperformed the impedance controller in terms of effective tracking of both position and force trajectories, taking into account the joints' limits. One of the shortcomings of the study was the absence of stability analysis, which is crucial in rehabilitation problems, as well as the possible inability to handle parametric uncertainties and external disturbances, which can affect the stability and performance of the system. Finally, the tests were performed in simulations only with no experimental clinical applications.

Moreover, Papaleo et al. [96] proposed a patient-tailored adaptive impedance controller utilizing a seven-DoF robotic arm for patients to perform planar and 3D point-to-point movements. The Cartesian stiffness matrix and the task duration were adapted based on the patient's bio-mechanical data and performance during the rehabilitation process. Lower stiffness values and shorter task completion time were associated with better performance in the presence of patient's active-assistive forces. While higher stiffness values and longer task duration were used to assist a struggling patient who was incapable of performing the task smoothly. The study observed that the system was capable of correctly evaluating the subject's behavior online. In addition, the system had the ability to adapt the control behavior depending on the human's bio-mechanical features, driving the human towards the target with a tuned assistance level depending on his/her motor abilities.

Zhang et al. [97] presented an adaptive impedance controller designed to regulate the interaction force between the robot and the patient, by adjusting the robot's mechanical impedance in response to the patient's exerted forces. It was performed by allowing automatic smooth transitions between three modes based on the patient's capabilities and requirements. These modes were human-dominant, robot-dominant, and safety stop modes.

That method demonstrated effective trajectory tracking with minimized steady-state errors. In addition, the safety stop mode was designed to prevent potential injuries when conflicting HRIs were detected, ensuring safety and effectiveness.

Luo et al. [98] proposed an adaptive impedance control used to estimate the stiffness and damping using a least-squares method, taking into account the end-effector's position and velocity and the patient's forces. The simulation results indicated that the patient's stiffness varied from 50 N/m to 100 N/m, for which the impedance parameters were adjusted accordingly, highlighting the controller ability to adapt based on the patient's conditions. The study showed that the more assistance provided by the robot, the less tracking error. However, excessive assistance might lead to negative patient efforts, as the patient might overly rely on the robot rather than engaging actively in the rehabilitation process.

A novel adaptive impedance control was proposed by Li et al. [99] to adaptively manage robot dynamics while ensuring stability in presence of parametric uncertainties. To stabilize the system, a backstepping method was applied to design a stable input for the adaptive impedance controller. The controller was able to switch between two modes in a smooth manner, which were the desired-impedance mode and the safety-stop mode. The stability of the system was guaranteed and proven using a Lyapunov-based stability method. The performance was also validated experimentally.

In 2020, Zhang et al. [100] proposed an impedance-based assist-as-needed (AAN) control by constructing a virtual channel around the predefined rehabilitation training trajectory, enabling the patient's arm to have spatial freedom. Thus, the patient's arm could move freely within the allowed virtual channel, while the robot provided assistance when deviating from the channel. In addition, a large deviation from the desired path was avoided by constructing a virtual stiffness gradient field around the channel. The controller was experimentally validated on a seven-DoF Kuka robot performing straight-line and circular training trajectories. Results showed effective AAN control and improved patient's performance. However, it was suggested to examine the controller in more complex trajectories on elderly volunteers and patients with upper-limb motor dysfunctions to help in providing more valid realistic results. Moreover, in 2023, Zhang et al. [101] proposed a self-switching adaptive impedance control based on the tracking error, dividing the virtual channel control stages into three modes. These modes were a Zero Interaction Force (ZIF) mode, where the robot was used to offer a fixed assistance in case of slacking human; an assist-as-needed (AAN) mode, where the robot would offer a variable level of assistance force by adjusting the controller stiffness coefficient; finally, a Restriction Interaction Region (RIR) mode, where the training task was considered to be hard for the subject, showing the difficulty to decrease the tracking error. It was observed that the performance-based assistance controller performed satisfactorily. However, no consideration for the interaction forces exerted by the human on the robot was examined. The control was only based on tracking-error convergence. Furthermore, the stability and safety of the switching mode system were not guaranteed.

Guatibonza et al. [102] proposed a control approach combining hybrid impedance control (HIC) and nonlinear adaptive control into a single structure for a seven-DoF upper-limb rehabilitation system. The controller was utilized to switch between position-based and force-based control schemes depending on a switching matrix. It was stated that the stability of the system could not be guaranteed during the transition between the control schemes using only HIC, thus its combination with a nonlinear controller was crucial to ensure stability. The nonlinear controller used was the backstepping control, which ensured stability and adaptability in the presence of system uncertainties and dynamic changes as mentioned previously [99]. Results showed effective control with a minimum error of 2% in trajectory tracking. Stability was proven using Lyapunov-based stability method. Stable response was achieved, as the response was stabilized within 0.9 s in absence of overshoots. The shortcomings were the absence of real-world experimentation and the integration of therapist which requires excessive healthcare training.

Another study that includes adaptive HIC was introduced by Sidek et al. [103], as the adaptive control framework was initiated to allow switching between position and force controllers utilizing a novel hybrid automata. The hybrid automata was composed of 7 states, the transition process between states was established based on the level of impairment classified by modified ashworth scale (MAS) for muscle assessment criteria. The automata was used to obtain the force control selection value depending on a recursive polynomial model estimator used to estimate the mechanical impedance parameters of the patient's limb. The controller was decomposed of inner loop handled by nonlinear feedback linearization and inverse dynamics control and an outer HIC loop. Results indicated safe HRI and effective task tracking. However, the stability of the system was not analyzed to ensure stability within the transitions.

In addition, Arantes et al. [104] investigated a novel adaptive impedance control which integrated real-time physiological measures; especially from EMG sensors to provide a customized robotic rehabilitation process. In this method, the participant's EMG signals were evaluated continuously during the rehabilitation task, to determine when should the robot provide assistance or resistance. Results indicated enhancements in performance metrics as in the average distance error and root-mean-square error (RMSE) between the robot handle and the target. From the results, an EMG sensor was considered to be the central feature of the controller to decide its future and also a way to quantify neural drive.

Jeyabalan et al. [105] developed an impedance-based controller that facilitated two modes of operation for robotic rehabilitation: Unassisted Mode (UAM) and Adaptive Weight Support Mode (WSM). UAM allowed subjects to perform voluntary active movements with no physical robotic assistance and minimal interaction forces from the robot's mechanical structure. While in WSM, the robot and user worked cooperatively to complete the task. While the user voluntarily moved his/her arm, the robot provided the amount of weight support needed to compensate for the weakness in the arm. This support was either fixed or adaptive based on the user's training type. This novel approach was demonstrated on an Arm Rehabilitation Robot (AREBO) designed as self-aligning end-effector robot capable of providing single-joint or multi-joint assistance. In case of adaptation, the algorithm utilized forgetting and learning factors to dynamically modify the level of assistance. Results indicated significance reduction in interaction forces and success rate of around 70% of the movements performed by the addressed subjects with increased range of motion. The controller was found to be stable during implementation. However, the stability was not proven mathematically due to the system's complexity. Only single-joint movement was considered, neglecting multi-joints movements that should be addressed.

Apart from impedance control, Lai et al. [106] implemented an adaptive admittance controller to personalize the control gains, in order to enhance the user comfort and improve the overall rehabilitation experience. Thus, the study adopted the damped least-squares method to calculate the robot's joint velocities and adjust the control parameters dynamically, depending on the patient–robot interaction and the subject's comfort. The study indicated that adapting the control parameters highly affected the patient's comfort and could improve the user experience dynamically.

A study that incorporated adaptive admittance control was introduced by Mashayekhi et al. [107], where a self-adapting admittance control was presented depending on the muscle fatigue level estimated by EMG signals. The detection and estimation processes of the fatigue level were performed utilizing Neural Network (NN) approaches. When fatigue was detected, the admittance control damping parameter was reduced, decreasing the motion difficulty for the patient by constructing a simple linear equation. The Self-Adapting Admittance Control (SAAC) was compared to a Non-Adapting Adaptive Control (NAAC). Results showed the effective fatigue detection and the improved movement performance of SAAC compared to NAAC. EMG sensor noise was a major drawback in the study which could affect the detection and system performance. In addition, specific training patterns were considered by limiting the exploration of fatigue patterns.

Cai et al. [108] developed a real-time robotic-assisted approach to reduce trunk compensation. This approach was based on an admittance control scheme implemented on a six-DoF Universal Robots robot to assist the three-DoF human shoulder, plus a customized two-DoF exoskeleton to control the human elbow and wrist joints. The human interaction forces were measured to estimate the user's intentions, which were then used to provide appropriate assistance composed of virtual shoulder and hand assistive forces to correct compensatory movements. The controller was tested in different modes: Reference-Free (RF) motion, Compensation with No robot Assistance (CNA), and Compensation with Robot Assistance (CRA). It was observed that the proposed strategy managed to reduce the compensation angle by adjusting the robot's assistance. Robustness was also guaranteed in different rehabilitation tasks, stating lower deviations between the desired and actual positions in CRA compared to CNA.

#### 5.5.2. Fuzzy-Based Adaptive Control

Other than the previously mentioned adaptive impedance/admittance controllers, fuzzy-based adaptive control methods have been utilized in various studies. These control methods adjust their parameters based on fuzzy-logic principles and are considered model-free intelligent systems.

In 2010, Xu et al. [109] proposed an adaptive impedance control based on a Dynamic Recurrent Fuzzy Neural Network (DRFNN). The algorithm adjusted the control parameters dynamically based on changing patient conditions. The controller was compared to traditional impedance control and Fuzzy Neural Networks (FNNs). It was shown through simulations that the DRFNN outperformed the other controllers in terms of performance, with reduced tracking errors and overshoot, stability, and smoothness. By integrating the dynamic feedback neurons into the control, the DRFNN could handle the nonlinearities and the dynamics' uncertainty. Despite the improvement in performance, the DRFNN was still affected by small overshoot and tracking errors. Moreover, in 2011, Xu et al. [110] improved the previously investigated method to incorporate an Evolutionary Dynamic Recurrent Fuzzy Neural Network (EDRFNN) algorithm which included a Genetic Algorithm (GA), Hybrid Evolutionary Programming (HEP), and Dynamic Back-Propagation (BP) learning. The GA and HEP were used offline to optimize the parameters of the DRFNN followed by online estimation using dynamic BP. Force and position tracking in constrained directions were compared for the EDRFNN, DRFNN, FNN, and traditional impedance control. The EDRFNN adaptive impedance control whose desired impedance parameters were tuned based on the combination of the DRFNN, GA, HEP, and dynamic BP algorithm had the best robust and dynamic performance in sharp changes exhibited by impaired limbs. In the same year, Xu et al. [111] proposed a fuzzy-based PD position control for passive training integrated with an impedance force controller. It was applied on a four-DoF robot for shoulder, elbow, and wrist joints' motion to achieve horizontal and vertical flexion/extension exercises. It was shown that the fuzzy-based PD controller outperformed the standard PD control in terms of joint position accuracy and trajectory tracking performance. The main drawback of any of these approaches is that they depend heavily on the fuzzy parameters which should be set by field experts.

A novel adaptive impedance control incorporating a backstepping method for robustness and fuzzy logic for parameter adaptation was proposed by Bai et al. [112]. The control parameters were adjusted using fuzzy rules in real time, based on the patient's interaction forces applied to the robot. Due to the presence of the backstepping control, the system responded effectively to uncertainties and variations in patients' conditions.

Wang et al. [113] presented a novel subject-adaptive AAN control which used the Recursive Least Squares (RLS) algorithm to identify the human arm's impedance parameters and obtain an optimal reference trajectory to align with the patient's motion intentions with minimum jerk. A fuzzy-logic controller was developed to tune the robot assistance level based on the patient's limb impedance and trajectory errors. The controller was designed to compensate for the unknown disturbances and maximize the active patient's participation.

A performance-based hybrid controller was developed by Li et al. [114] for personalized training utilizing a three-DoF cable-driven robot for shoulder, elbow, and wrist movements performing a planar circular trajectory. The algorithm examined three modes, resistance, assistance, and restriction modes, which were adjusted based on the tracking error that reflected the motor strength of the patient. Fuzzy logic was adopted to adapt the stiffness coefficient and damping forces of the controller based on the tracking error. The controller was tested on 10 healthy subjects to perform a circular trajectory on a horizontal plane. Results indicated that in resistance mode, the damping force provided was used to avoid slacking, while in the assistance mode, the stiffness was adjusted to assist the human, and in the restriction mode, a damping force was applied to limit the human's motion and ensure stability. These results indicated that the robot could effectively respond to the needs of the patient.

Hu et al. [115] used a fuzzy adaptive passive control strategy by which an Artificial Potential Field (APF) was used to generate the robot's assistive force. The fuzzy logic outputted the adapted stiffness coefficient of the potential field as higher potential indicated greater assistance. In addition, the stability of the system was proven using the Lyapunov-based stability method. The algorithm was tested experimentally on eight healthy volunteers performing a circular XY plane path utilizing a three-DoF bilateral robotic arm, one for the healthy arm and the other to assist the affected limb. The stability of the system was compared to that of the conventional impedance controller. It was proven that if the robot stopped suddenly, a huge force would be exerted by the conventional impedance controller, while the Fuzzy Artificial Potential (FAP) controlled the force generated, as it was dependent on the system's current position, avoiding any possible harm.

The aforementioned fuzzy-based adaptive methods have various advantages related to system performance, robustness, uncertainty compensation, and stability. However, the main drawback of using fuzzy-based adaptation is the complete dependence on the fuzzy parameters such as membership function, fuzzy rules, and defuzzification method which should be handled by experts in the field or tuned for reliable performance.

#### 5.5.3. Machine Learning-Based Adaptive Control

One of the most recent data-driven methods is the integration of machine learning approaches that can be used when building a control system. Several machine learning approaches have been used to adapt the control parameters for upper-limb rehabilitation utilizing end-effector robots.

One of these approaches was proposed by Wu et al. [116] combining adaptive admittance control with a Neural Network (NN)-based Disturbance Observer (AACNDO) to compensate for external uncertainties and dynamic errors. The disturbance observer designed was based on a Radial Basis Function (RBF). A position-error-based adaptation law was used to adjust the controller interaction compliance based on the patient's motion intention and recovery stage, facilitating both passive and cooperative training. Three experiments were used to evaluate the effectiveness of the AACNDO strategy including a sinusoidal track, circular track with admittance adjustment, and intention-based resistive training. Results showed that AACNDO guaranteed the position control accuracy of passive training. In addition, the feasibility of AACNDO in adjusting the compliance and interaction forces was ensured for better performance of cooperative training. Moreover, the controller's stability was proven by employing the Lyapunov-based stability method.

Another method was introduced by Ting et al. combining iterative learning motion control and adaptive iterative learning impedance control for an anthropomorphic arm's rehabilitation [117]. The iterative learning control was examined to ensure the robot's accurate trajectory tracking, while the adaptive iterative learning-based impedance control was used to adjust the control forces between the human and the robot, allowing compliance with variable dynamics. Results indicated effective tracking performance, improved compliance, robustness to disturbances, and stability of the system.

Miao et al. [118] combined the benefits of fuzzy logic and machine learning to adapt an admittance-based controller for upper-limb rehabilitation. The adaptation method used involved a piecewise learning rate-based iterative law to adapt the control gains for subject-specific training. The adaptation law took into account the Fugl-Meyer Assessment (FMA) regression model that was used to indicate the subject's motor performance. The fuzzy-logic method was used to refine the control parameters based on real-life dynamic feedback from the subject. Results indicated that the fuzzy-logic model was more robust in maintaining the stable performance of the system. In addition, the method was considered to be adaptive to possible perturbations and improved the evaluation reliability.

Shoaib et al. [119] examined various adaptive control approaches on various cable-driven robotic systems. One of these controllers was an iterative learning controller applied to a four-DoF cable-driven end-effector robot for upper-limb manipulation. The controller compensated model uncertainties and handled external disturbances which improved the system performance. Three different modes were examined, the patient-in-charge, robot-in-charge, and hybrid support modes. Results demonstrated improved performance over iterations, adaptability to patient's needs, and reduced the control effort. However, it was noted that the performance of the system could be sensitive to the assigned learning rate and initial conditions. In addition, the time complexity of the controller, especially considering online adaptation, was huge.

Ai et al. [14] provided a focused review on machine learning-based methods in intention recognition and human–robot interactive control. Focusing on the control part, two different categories were inspected: NN-based adaptive interaction control, including the adaptive impedance/admittance, RBF-NN, robust iterative learning, and others, in addition to reinforcement learning (RL)-based interactive control, including the actor–critic controllers, impedance/admittance with model-based RL, and others. The NN-based adaptive control was observed to suffer from inevitable reconstruction errors limiting the control trajectory to a bounded stability. In addition, its performance relied heavily on sufficient training data. It could be time consuming to implement in real time in the presence of dynamically changing patient's interactions. Moreover, the RL-based interactive control might suffer from sub-optimal performance resulting from exploration or exploitation. It might struggle with convergence as it depends on the reward function. It also had a high computational cost.

#### 5.5.4. Adaptive Sliding Mode Control

When considering adaptive robust controllers examined for upper-limb rehabilitation, Sliding Mode Control (SMC) would be one of the highly regarded controllers. Hashemi et al. [120] designed an SMC approach for end-effector rehabilitation robot incorporating a GA for automatic weight adjustment. SMC was applied to a two-DOF, four-linkage, fully actuated planar parallelogram manipulator for a planar motion focusing on the shoulder and elbow joints. SMC was used to manage the system nonlinearities and disturbances effectively. The GA was used to adapt the SMC parameters by minimizing the cost function including the end-effector position error, robot input and rate, and the human's torque. The adaptation was performed offline. Results showed that the tracking error had an RMSE of 10.2 mm and 10.3 mm/s for the velocity. The stability and feasibility indicating the control effort (torque) bounds were guaranteed. In that study, human model dynamics were oversimplified; in order to apply the controller on experimental bases, a more realistic model should be taken into account.

Wu et al. [121] developed an adaptive neural cooperative control based on human motion intention recognition. The human intentions were estimated based on the interaction forces and the human muscle forces estimated from sEMG sensors with a Kalman filter, which acted as inputs to a Gaussian Radial Basis Function Network (RBFN) to obtain the appropriate incremental motion of the upper limb. Additionally, robust adaptive SMC was integrated into the cooperative control scheme to ensure the accuracy and stability of the inner-position control loop with uncertainties.

It was applied to follow a triangular referenced trajectory through a point-to-point motion task for a two-DoF robot. The controller results were found to be accurate in terms of trajectory tracking with an average RMSE of 7.23 mm and a Mean Tracking Error (MTE) of 20.84 mm in high-interaction compliance conditions, and an RMSE of 3.24 mm and an MTE of 7.78 mm in low-interaction compliance conditions. The controller was guaranteed to be stable and robust towards external disturbances and uncertainties.

#### 5.5.5. Adaptive Backstepping Control

Another controller classified as robust is the backstepping control approach. Adaptive backstepping control was utilized for upper-limb rehabilitation by Abbas et al. [122,123]. Two adaptation methods for the adaptive backstepping controller were defined in [122] to estimate the unknown dynamics and to maintain the system's stability. It was applied on a five-DoF Scorbot-ER Plus to perform a rectangular trajectory. It was observed to surpass the adaptive computed torque and PID controllers in terms of performance and bandwidth usage. In [123], an admittance controller was added in the outer control loop to maintain the compliant interaction, while an event-triggered adaptive backstepping controller was placed in the outer control loop to handle the uncertainties. Results indicated a faster response and lower tracking error compared to PID and adaptive SMC with smooth joint torques compared to adaptive SMC, which had a chattering effect in the control effort.

#### 5.5.6. Model Reference Adaptive Control (MRAC)

A Model Reference Adaptive Impedance Control (MRAIC) was proposed by Sharifi et al. [124,125]. The adaptation law was used to adjust the control parameters online to compensate for model uncertainties. It ensured that the control loop dynamics of the robot mimicked the designed reference model for effective tracking. Thus, it was considered as a model-based control method. The controller was firstly tested in simulations on a MIT-MANUS rehabilitation robot model [124]; afterwards, it was tested experimentally on a five-DoF robot equipped with a six-axis force/torque sensor performing the yaw motion of a tool rod and linear insertion motion [125]. This approach was considered to be highly sensitive to reference model inaccuracies and external disturbances.

Recently, another implementation of MRAIC was proposed by Omrani et al. [126] through a time delay estimation-based MRAIC used to estimate the unknown dynamics and uncertainties and ensure the system stability of a three-DoF robot when performing a circular trajectory. The controller was compared to a Time-Delay Control (TDC) and the proposed controller outperformed the TDC in terms of precise and accurate tracking, robustness, and ability to prevent the effects of unknown dynamics and uncertainties in the presence of varying external forces.

#### 5.5.7. Discussion

After presenting various end-effector controllers for human upper-limb manipulation in a rehabilitation process, it is worth mentioning the advantages and drawbacks addressed in previous studies for each control approach, which are highlighted in this section.

PID controllers have been widely implemented and commercialized in several products [88]. The main advantage of the PID controller is its design simplicity. Acceptable performance can be achieved when operating in normal conditions and moderate system frequencies with minimal external disturbances. Thus, the literature presented earlier shows that a number of successful rehabilitation robotic systems have adopted PID controllers to perform simple rehabilitation motion with minimal user intervention. However, a standalone PID controller is not enough to produce advanced rehabilitation performance with dynamically changing conditions, as sudden changes and high-frequency dynamics can cause delays or system instability. PID control lacks the ability to detect and handle abnormalities. It is also considered to handle predefined trajectories, which is not desirable in dynamic rehabilitation. As a result, adaption methods are required to find the best tuning parameters of the PID control [88].

Moreover, impedance and admittance controllers are the most common controllers developed and examined for upper-limb rehabilitation end-effector robots. Conventional impedance and admittance controllers allow the robotic manipulator to track changing target positions or forces within a certain range of trajectory tracking errors [115]. However, external disturbances, such as sudden spasticity of the patient's arm, can result in an abrupt halt of the robotic system during the rehabilitation training process. This occurrence may cause the impedance controller to generate excessive force that could lead to the instability of the system and result in secondary injury [127].

As the rehabilitation robotic systems are directly connected to the human body, a small perturbation or wrong movement can cause critical injuries and affect the patient adversely. Therefore, to ensure better performance and to achieve advanced abilities to reject disturbances, other classes of controllers are adopted in rehabilitative robots, such as robust and adaptive controllers [88]. The robust control theory focuses on dealing explicitly with system's uncertainties and disturbances that are within a predefined boundary [88]. It can operate at high frequencies. It is desirable for handling dynamically changing rehabilitation trajectories in a smooth manner. As presented, robust controllers are capable of achieving stable performance in the presence of bounded errors proven by Lyapunov-based stability analysis methods. The robust controllers examined in the review are the SMC and the backstepping controller. In the literature, several robust controllers have been compared directly with conventional PID control methods for upper-limb rehabilitation scenarios. Robust controllers are said to be able to control a robotic system with an advanced robustness level and higher abilities to resist uncertainties, parameter changes, and disturbances applying to the system, such as a patient's hand tremor [88,127].

On the other hand, there are several drawbacks in the addressed robust control methods. For SMC, a possible chattering effect in its control effort is its main drawback that can decrease its chance to be used in experimental and clinical applications. The chattering control effort may result in instability and system damage. The backstepping controller may suffer from a slow response compared to others, which can affect the rehabilitation process negatively, especially in active training methods.

Fixed parameter control approaches are considered to be simple, yet these controllers lack adaptability, which is one of the prime aspects needed to be considered in upper-limb end-effector rehabilitation robotic systems. One of the model-based adaptive controllers that depends heavily on model equations is the impedance/admittance control. It is considered to have the ability to adjust the human–robot interaction forces by taking into account the patient's recovery mode and engagement level. Compared to PID control, which is the benchmark of all control methods, an adaptive controller shares with PID control its simple structure, However, it can reject the disturbances and uncertainties affecting the system. It can operate at high frequencies. However, apart from the impedance/admittance adaptive control advantages, the method of adaptation utilized can affect the system's complexity, as it may be undesirable for large dimensional systems [88].

Another model-based adaptive controller is MRAC, which is suitable for dynamically adapting to system changes in real time based on model discrepancies. Its main drawback is its dependency on the reference model; thus, there should exist a model which accurately defines the human–robot interaction behavior [124,125].

Apart from the model-based controllers, there exist other control methods which can be classified as data-driven systems and can be utilized for control system adaptation. One of these methods is the fuzzy-logic method. Fuzzy logic can be utilized to serve as an adaptive control method, such as fuzzy-based adaptation controllers, which are considered to be intelligent approaches that do not depend on the system's model, thus not subjected to model inaccuracies and uncertainties. Thus, it is desirable for handling dynamically changing rehabilitation trajectories in a smooth manner. However, the response of the system depends heavily on the choice of the fuzzy membership functions and rules, which should be continuously tuned based on the patient's interaction and condition [88,115].

Another data-driven adaptation method is the machine learning-based control method, that can be defined as a customizable, flexible method by which the network used can be trained to handle specific patient needs. Machine learning-based adaptive controllers can handle nonlinearities and uncertainties present in a human model and predict the human and robot's models. Thus, it is desirable in predicting dynamically changing rehabilitation trajectories, human configuration, and engagement levels. However, they are considered to be time consuming and hard to implement in real time, as a result of their dependence on the data used for training. These methods require a large volume of training data to perform satisfactorily. In addition, they can suffer from overfitting problems [88].

Table 4 highlights the mentioned difference between the examined control methods.

**Table 4.** Control methods' classification, advantages, and disadvantages.

| Controller | Class | Advantages | Disadvantages |
|---|---|---|---|
| PID [81,92] | Model-based | - Simple | - Needs parameters tuning<br>- Suffers from noise amplification<br>- Nonoptimal and can be unstable |
| Impedance admittance [7,11,89,90,93] [60,80,81,83] | Model-based | - Tracks target position/force<br>- Considers human interactive forces | - Sensitive to sudden changes<br>- Unstable at high impedance |
| SMC [11,92,94] | Model-based | - Robust to uncertainties, nonlinearities, and disturbances<br>- Stable | - Chattering effect |
| Adaptive impedance/admittance [95–99,99–108] | Model-based | - Adaptive performance<br>- Tracks target position/force<br>- Considers human interactive forces | - Not practical for large dimension systems |
| Fuzzy-based adaptive control [109–115] | Model-free | - Adaptive performance<br>- Model independent<br>- Robust to uncertainties and nonlinearities | - Highly dependent on the choice of fuzzy sets and rules<br>- Adaptation for sets and rules is desirable |
| Machine learning-based adaptive control [14,116–119] | Data-driven | - Adaptive performance<br>- Model independent<br>- Handles uncertainties and nonlinearities<br>- Predicts models | - Needs to be trained<br>- Needs a large dataset<br>- High computations<br>- Overfitting problem |
| Robust adaptive control [120–123] | Model-based | - Robust to uncertainties, nonlinearities, and disturbances<br>- Stable | - Chattering effect (SMC)<br>- Slow response (backstepping) |
| MRAC [124–126] | Model-based | - Adaptive performance<br>- Tracks the reference model<br>- Considers human interactive forces | - Depends on reference model |

## 6. Conclusions

This article presented an overview of upper-limb robotic end-effector and exoskeletons' structure mentioning their features, advantages, and limitations. The study focused on the upper-limb robotic end-effector structures due to their simple configuration and ability to handle the rehabilitation motion of diverse patients with different postural configurations and health conditions. The clinical and functional requirements for these upper-limb end-effectors were discussed. The control modes and methods for end-effector upper-limb rehabilitation were presented in a comprehensive review concerning several conventional, robust, and adaptive controllers. There exist several adaptive techniques that can be used to handle the upper-limb rehabilitation problem, each of which has its own advantages and drawbacks to consider. It is hard to mention a suitable adaption method that can be used for all possible conditions.

Thus, it is desirable to investigate and implement various adaptive control methods and hybridize these methods to obtain suitable results applicable to different subjects with diverse conditions for possible future clinical applications.

**Author Contributions:** D.M.M. gathered the presented literature's information related to end-effector upper-limb rehabilitation features and control systems. The literature structure and organization was performed by D.M.M. and F.A. The draft of the paper was written by D.M.M. and O.M.S., while F.A. and E.I.M. analyzed and reviewed the paper. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research received funding from Project $COM^3$ CUP H53D23000610006 funded by EU in NextGenerationEU plan through the Italian "Bando Prin 2022—D.D. 104 del 02-02-2022" by MUR.

**Data Availability Statement:** All the data gathered for the study are available from D.M.M. on reasonable request.

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

## Abbreviations

The following abbreviations are used in this manuscript:

| | |
|---|---|
| AACNDO | Adaptive Admittance Control Neural Network-based Disturbance Observer |
| AAN | Assist-as-needed |
| ACT | Arm Coordination Training |
| ADL | Activities of daily living |
| APF | Artificial Potential Field |
| AREBO | Arm Rehabilitation Robot |
| ARM | Assisted Rehabilitation and Measurement |
| BP | Back-Propagation |
| CADEN | Cable-Actuated Dexterous Exoskeleton for Neuro-rehabilitation |
| CNA | Compensation with No robot Assistance |
| CRA | Compensation with Robot Assistance |
| D | Dimensional |
| DoF | Degree of Freedom |
| DRFNN | Dynamic Recurrent Fuzzy Neural Network |
| EDRFNN | Evolutionary Dynamic Recurrent Fuzzy Neural Network |
| EMG | Electromyography |
| FAP | Fuzzy Adaptive Potential |
| FMA | Fugl-Meyer Assessment |
| FNN | Fuzzy Neural Network |
| GA | Genetic Algorithm |
| GUI | Graphical User Interface |
| HEP | Hybrid Evolutionary Programming |
| IHME | Institute of Health Metrics and Evaluation |
| MAS | Modified Ashworth Scale |
| MIME | Mirror-Image Movement Enabler |
| MRAC | Model Reference Adaptive Control |
| MRAIC | Model Reference Adaptive Impedance Control |
| MSD | Musculoskeletal disorders |
| MTE | Mean Tracking Error |
| NAAC | Non-Adapting Admittance Control |
| NN | Neural Network |
| PD | Proportional–Derivative |
| PID | Proportional–Integral–Derivative |
| PNF | Proprioceptive Neuromuscular Facilitation |
| RBF | Radial Basis Function |
| RBFN | Radial Basis Function Network |
| RF | Reference Free |
| RIR | Restriction Interaction Region |

| | |
|---|---|
| RL | Reinforcement learning |
| RLS | Recursive Least Squares |
| RMSE | Root-mean-square error |
| RUPERT | Robotic Upper Extremity Repetitive Trainer |
| SAAC | Self-Adapting Admittance Control |
| sEMG | Surface Electromyography |
| SMC | Sliding Mode Control |
| TDC | Time-Delay Control |
| UAM | Unassisted Mode |
| WHO | World Health Organization |
| WSM | Weight Support Mode |
| ZIF | Zero Interaction Force |

## References


1. World Health Organization. *Global Oral Health Status Report: Towards Universal Health Coverage for Oral Health by 2030*; World Health Organization: Geneva, Switzerland, 2022.
2. Sebbag, E.; Felten, R.; Sagez, F.; Sibilia, J.; Devilliers, H.; Arnaud, L. The world-wide burden of musculoskeletal diseases: A systematic analysis of the World Health Organization Burden of Diseases Database. *Ann. Rheum. Dis.* **2019**, *78*, 844–848. [CrossRef]
3. Belluzzi, E.; Pozzuoli, A.; Ruggieri, P. Musculoskeletal Diseases: From Molecular Basis to Therapy. *Biomedicines* **2023**, *12*, 32. [CrossRef]
4. World Health Organization. *Neurological Disorders: Public Health Challenges*; World Health Organization: Geneva, Switzerland, 2006.
5. Feigin, V.L.; Brainin, M.; Norrving, B.; Martins, S.; Sacco, R.L.; Hacke, W.; Fisher, M.; Pandian, J.; Lindsay, P. World Stroke Organization (WSO): Global stroke fact sheet 2022. *Int. J. Stroke* **2022**, *17*, 18–29. [CrossRef] [PubMed]
6. Gimigliano, F.; Negrini, S. The World Health Organization "rehabilitation 2030: A call for action". *Eur. J. Phys. Rehabil. Med.* **2017**, *53*, 155–168. [CrossRef] [PubMed]
7. Zhang, L.; Guo, S.; Sun, Q. An assist-as-needed controller for passive, assistant, active, and resistive robot-aided rehabilitation training of the upper extremity. *Appl. Sci.* **2020**, *11*, 340. [CrossRef]
8. Sheng, B.; Zhang, Y.; Meng, W.; Deng, C.; Xie, S. Bilateral robots for upper-limb stroke rehabilitation: State of the art and future prospects. *Med. Eng. Phys.* **2016**, *38*, 587–606. [CrossRef]
9. Molteni, F.; Gasperini, G.; Cannaviello, G.; Guanziroli, E. Exoskeleton and end-effector robots for upper and lower limbs rehabilitation: Narrative review. *PM&R* **2018**, *10*, S174–S188.
10. Iandolo, R.; Marini, F.; Semprini, M.; Laffranchi, M.; Mugnosso, M.; Cherif, A.; De Michieli, L.; Chiappalone, M.; Zenzeri, J. Perspectives and challenges in robotic neurorehabilitation. *Appl. Sci.* **2019**, *9*, 3183. [CrossRef]
11. Proietti, T.; Ambrosini, E.; Pedrocchi, A.; Micera, S. Wearable robotics for impaired upper-limb assistance and rehabilitation: State of the art and future perspectives. *IEEE Access* **2022**, *10*, 106117–106134. [CrossRef]
12. Bhujel, S.; Hasan, S. A comparative study of end-effector and exoskeleton type rehabilitation robots in human upper extremity rehabilitation. *Hum.-Intell. Syst. Integr.* **2023**, *5*, 11–42. [CrossRef]
13. Qassim, H.M.; Wan Hasan, W. A review on upper limb rehabilitation robots. *Appl. Sci.* **2020**, *10*, 6976. [CrossRef]
14. Ai, Q.; Liu, Z.; Meng, W.; Liu, Q.; Xie, S.Q. Machine learning in robot assisted upper limb rehabilitation: A focused review. *IEEE Trans. Cogn. Dev. Syst.* **2021**, *15*, 2053–2063. [CrossRef]
15. Krebs, H.I.; Ferraro, M.; Buerger, S.P.; Newbery, M.J.; Makiyama, A.; Sandmann, M.; Lynch, D.; Volpe, B.T.; Hogan, N. Rehabilitation robotics: Pilot trial of a spatial extension for MIT-Manus. *J. Neuroeng. Rehabil.* **2004**, *1*, 5. [CrossRef]
16. Hidler, J.; Nichols, D.; Pelliccio, M.; Brady, K. Advances in the understanding and treatment of stroke impairment using robotic devices. *Top. Stroke Rehabil.* **2005**, *12*, 22–35. [CrossRef] [PubMed]
17. Nef, T.; Riener, R. ARMin-design of a novel arm rehabilitation robot. In Proceedings of the 9th International Conference on Rehabilitation Robotics, ICORR 2005, Chicago, IL, USA, 28 June–1 July 2005; pp. 57–60.
18. Lum, P.S.; Burgar, C.G.; Van der Loos, M.; Shor, P.C.; Majmundar, M.; Yap, R. The MIME robotic system for upper-limb neuro-rehabilitation: Results from a clinical trial in subacute stroke. In Proceedings of the 9th International Conference on Rehabilitation Robotics, ICORR 2005, Chicago, IL, USA, 28 June–1 July 2005; pp. 511–514.
19. Hesse, S.; Schulte-Tigges, G.; Konrad, M.; Bardeleben, A.; Werner, C. Robot-assisted arm trainer for the passive and active practice of bilateral forearm and wrist movements in hemiparetic subjects. *Arch. Phys. Med. Rehabil.* **2003**, *84*, 915–920. [CrossRef] [PubMed]
20. Loureiro, R.; Amirabdollahian, F.; Harwin, W. 22 A Gentle/S Approach to Robot Assisted Neuro-Rehabilitation. In *Advances in Rehabilitation Robotics: Human-Friendly Technologies on Movement Assistance and Restoration for People with Disabilities*; Springer: Berlin/Heidelberg, Germany, 2004; pp. 347–363.
21. Stefano, M.; Patrizia, P.; Mario, A.; Ferlini, G.; Rizzello, R.; Rosati, G. Robotic upper limb rehabilitation after acute stroke by NeReBot: Evaluation of treatment costs. *BioMed Res. Int.* **2014**, *2014*, 265634. [CrossRef] [PubMed]

22. Ellis, M.D.; Sukal, T.; DeMott, T.; Dewald, J.P. ACT 3D exercise targets gravity-induced discoordination and improves reaching work area in individuals with stroke. In Proceedings of the 2007 IEEE 10th International Conference on Rehabilitation Robotics, Noordwijk, The Netherlands, 12–15 June 2007; pp. 890–895.
23. Stienen, A.H.; McPherson, J.G.; Schouten, A.C.; Dewald, J.P. The ACT-4D: A novel rehabilitation robot for the quantification of upper limb motor impairments following brain injury. In Proceedings of the 2011 IEEE International Conference on Rehabilitation Robotics, Zurich, Switzerland, 29 June–1 July 2011; pp. 1–6.
24. Singh, H.; Unger, J.; Zariffa, J.; Pakosh, M.; Jaglal, S.; Craven, B.C.; Musselman, K.E. Robot-assisted upper extremity rehabilitation for cervical spinal cord injuries: A systematic scoping review. *Disabil. Rehabil. Assist. Technol.* **2018**, *13*, 704–715. [CrossRef]
25. Balasubramanian, S.; Wei, R.; Perez, M.; Shepard, B.; Koeneman, E.; Koeneman, J.; He, J. RUPERT: An exoskeleton robot for assisting rehabilitation of arm functions. In Proceedings of the 2008 Virtual Rehabilitation, Vancouver, BC, Canada, 25–27 August 2008; pp. 163–167.
26. Fitle, K.D.; Pehlivan, A.U.; O'malley, M.K. A robotic exoskeleton for rehabilitation and assessment of the upper limb following incomplete spinal cord injury. In Proceedings of the 2015 IEEE International Conference on Robotics and Automation (ICRA), Seattle, WA, USA, 26–30 May 2015; pp. 4960–4966.
27. Chang, S.R.; Hofland, N.; Chen, Z.; Tatsuoka, C.; Richards, L.G.; Bruestle, M.; Kovelman, H.; Naft, J. Myoelectric arm orthosis assists functional activities: A 3-month home use outcome report. *Arch. Rehabil. Res. Clin. Transl.* **2023**, *5*, 100279. [CrossRef] [PubMed]
28. Garcia, D.A.; Arredondo, R.; Morris, M.; Tosunoglu, S. A review of rehabilitation strategies for stroke recovery. In Proceedings of the ASME Early Career Technical Conference, Atlanta, GA, USA, 30 July–1 August 2012; pp. 2–3.
29. Perry, J.C.; Rosen, J.; Burns, S. Upper-limb powered exoskeleton design. *IEEE/ASME Trans. Mechatron.* **2007**, *12*, 408–417. [CrossRef]
30. Nef, T.; Mihelj, M.; Kiefer, G.; Perndl, C.; Muller, R.; Riener, R. ARMin-Exoskeleton for arm therapy in stroke patients. In Proceedings of the 2007 IEEE 10th International Conference on Rehabilitation Robotics, Noordwijk, The Netherlands, 12–15 June 2007; pp. 68–74.
31. Nef, T.; Guidali, M.; Klamroth-Marganska, V.; Riener, R. ARMin-exoskeleton robot for stroke rehabilitation. In *Proceedings of the World Congress on Medical Physics and Biomedical Engineering, Munich, Germany, 7–12 September 2009: Vol. 25/9 Neuroengineering, Neural Systems, Rehabilitation and Prosthetics*; Springer: Berlin/Heidelberg, Germany, 2009; pp. 127–130.
32. Gopura, R.A.R.C.; Kiguchi, K.; Li, Y. SUEFUL-7: A 7DOF upper-limb exoskeleton robot with muscle-model-oriented EMG-based control. In Proceedings of the 2009 IEEE/RSJ International Conference on Intelligent Robots and Systems, St. Louis, MO, USA, 11–15 October 2009; pp. 1126–1131.
33. Perry, J.C.; Powell, J.M.; Rosen, J. Isotropy of an upper limb exoskeleton and the kinematics and dynamics of the human arm. *Appl. Bionics Biomech.* **2009**, *6*, 175–191. [CrossRef]
34. El-Shamy, S.M. Efficacy of Armeo® robotic therapy versus conventional therapy on upper limb function in children with hemiplegic cerebral palsy. *Am. J. Phys. Med. Rehabil.* **2018**, *97*, 164–169. [CrossRef] [PubMed]
35. Hyakutake, K.; Morishita, T.; Saita, K.; Fukuda, H.; Shiota, E.; Higaki, Y.; Inoue, T.; Uehara, Y. Effects of Home-Based Robotic Therapy Involving the Single-Joint Hybrid Assistive Limb Robotic Suit in the Chronic Phase of Stroke: A Pilot Study. *BioMed Res. Int.* **2019**, *2019*, 5462694. [CrossRef]
36. van Delden, A.E.; Peper, C.E.; Kwakkel, G.; Beek, P.J. A systematic review of bilateral upper limb training devices for poststroke rehabilitation. *Stroke Res. Treat.* **2012**, *2012*, 972069. [CrossRef] [PubMed]
37. Proietti, T.; Crocher, V.; Roby-Brami, A.; Jarrasse, N. Upper-limb robotic exoskeletons for neurorehabilitation: A review on control strategies. *IEEE Rev. Biomed. Eng.* **2016**, *9*, 4–14. [CrossRef] [PubMed]
38. Krebs, H.I.; Edwards, D.J.; Volpe, B.T. Forging mens et manus: The mit experience in upper extremity robotic therapy. In *Neurorehabilitation Technology*; Springer: Cham, Switzerland, 2022; pp. 597–621.
39. Reinkensmeyer, D.J.; Kahn, L.E.; Averbuch, M.; McKenna-Cole, A.; Schmit, B.D.; Rymer, W.Z. Understanding and treating arm movement impairment after chronic brain injury: Progress with the ARM guide. *J. Rehabil. Res. Dev.* **2000**, *37*, 653–662. [PubMed]
40. Sadeghnejad, S.; Abadi, V.S.E.; Jafari, B. Rehabilitation robotics: History, applications, and recent advances. In *Medical and Healthcare Robotics*; Academic Press: Cambridge, MA, USA, 2023; pp. 63–85.
41. Rosati, G.; Gallina, P.; Masiero, S. Design, implementation and clinical tests of a wire-based robot for neurorehabilitation. *IEEE Trans. Neural Syst. Rehabil. Eng.* **2007**, *15*, 560–569. [CrossRef]
42. Rosati, G.; Gallina, P.; Masiero, S.; Rossi, A. Design of a new 5 dof wire-based robot for rehabilitation. In Proceedings of the 9th International Conference on Rehabilitation RoboticsICORR 2005, Chicago, IL, USA, 28 June–1 July 2005; pp. 430–433.
43. Lum, P.S.; Burgar, C.G.; Shor, P.C. Evidence for improved muscle activation patterns after retraining of reaching movements with the MIME robotic system in subjects with post-stroke hemiparesis. *IEEE Trans. Neural Syst. Rehabil. Eng.* **2004**, *12*, 186–194. [CrossRef] [PubMed]
44. Burgar, C.G.; Scremin, A.E.; Garber, S.L.; Van der Loos, H.M.; Deborah Kenney, O.T.R. Robot-assisted upper-limb therapy in acute rehabilitation setting following stroke: Department of Veterans Affairs multisite clinical trial. *J. Rehabil. Res. Dev.* **2011**, *48*, 445. [CrossRef] [PubMed]

45. Hsieh, Y.W.; Liing, R.J.; Lin, K.C.; Wu, C.Y.; Liou, T.H.; Lin, J.C.; Hung, J.W. Sequencing bilateral robot-assisted arm therapy and constraint-induced therapy improves reach to press and trunk kinematics in patients with stroke. *J. Neuroeng. Rehabil.* **2016**. [CrossRef]
46. Wu, C.Y.; Yang, C.L.; Chen, M.D.; Lin, K.C.; Wu, L.L. Unilateral versus bilateral robot-assisted rehabilitation on arm-trunk control and functions post stroke: A randomized controlled trial. *J. Neuroeng. Rehabil.* **2013**, *10*, 35. [CrossRef] [PubMed]
47. Amirabdollahian, F.; Loureiro, R.; Gradwell, E.; Collin, C.; Harwin, W.; Johnson, G. Multivariate analysis of the Fugl-Meyer outcome measures assessing the effectiveness of GENTLE/S robot-mediated stroke therapy. *J. Neuroeng. Rehabil.* **2007**, *4*, 4. [CrossRef] [PubMed]
48. van der Linde, R.Q.; Lammertse, P. HapticMaster–a generic force controlled robot for human interaction. *Ind. Robot. Int. J.* **2003**, *30*, 515–524. [CrossRef]
49. Van der Linde, R.Q.; Lammertse, P.; Frederiksen, E.; Ruiter, B. The HapticMaster, a new high-performance haptic interface. In *Proc. Eurohaptics*; Edinburgh University: Edinburgh, UK, 2002; pp. 1–5.
50. Timmermans, A.A.; Lemmens, R.J.; Monfrance, M.; Geers, R.P.; Bakx, W.; Smeets, R.J.; Seelen, H.A. Effects of task-oriented robot training on arm function, activity, and quality of life in chronic stroke patients: A randomized controlled trial. *J. Neuroeng. Rehabil.* **2014**, *11*, 45. [CrossRef]
51. Fazekas, G.; Horvath, M.; Troznai, T.; Toth, A. Robot-mediated upper limb physiotherapy for patients with spastic hemiparesis: A preliminary study. *J. Rehabil. Med.* **2007**, *39*, 580–582. [CrossRef]
52. Bratanov, D.; Vitliemov, P. The experience behind the reharob project–a new robotic system for simultaneous rehabilitation of upper and lower human limbs. In Proceedings of the 2020 International Conference on Assistive and Rehabilitation Technologies (iCareTech), Gaza, Palestine, 28–29 August 2020; pp. 19–23.
53. Ellis, M.D.; Dewald, J.P. Application of the ACT 3D Robot in the Evaluation of Functional Reaching Performance and the Administration of Experimental Interventions. In *Proceedings of the World Congress on Medical Physics and Biomedical Engineering, Munich, Germany, 7–12 September 2009: Vol. 25/9 Neuroengineering, Neural Systems, Rehabilitation and Prosthetics*; Springer: Berlin/Heidelberg, Germany, 2009; pp. 374–376.
54. Serrano-Lopez-Terradas, P.A.; Seco-Rubio, R. Effectiveness of robotic therapy in the proximal and distal rehabilitation of the upper limb in patients after stroke using the Amadeo® and Armeo® devices: A systematic review of randomized clinical trials (Efectividad de la terapia robótica en la rehabilitación proximal y distal del miembro superior en personas tras un ictus con los dispositivos Amadeo® y Armeo®: Una revisión sistemática de ensayos clínicos aleatorizados). *Stud. Psychol.* **2022**, *43*, 132–178.
55. Helbok, R.; Schoenherr, G.; Spiegel, M.; Sojer, M.; Brenneis, C. *Robot-Assisted Hand Training (Amadeo) Compared with Conventional Physiotherapy Techniques in Chronic Ischemic Stroke Patients: A Pilot Study*; DGNR: Bremen, Germany, 2010.
56. Serrano-López Terradas, P.A.; Criado Ferrer, T.; Jakob, I.; Calvo-Arenillas, J.I. Quo Vadis, Amadeo Hand Robot? A Randomized Study with a Hand Recovery Predictive Model in Subacute Stroke. *Int. J. Environ. Res. Public Health* **2022**, *20*, 690. [CrossRef] [PubMed]
57. López-Terradas, P.A.S.; Rosendo, D.M.; Lago, M.R. Hand Functional Recovery in Sub-acute Brain Injury Stage Patients using AMADEO® Robotic-assisted Therapy-A Pilot Clinical Study with Apraxic and Neglect Patients. In *Special Session on Virtual and Augmented Reality Systems for Upper Limbs Rehabilitation*; Scitepress: Setúbal, Portugal, 2013; Volume 1.
58. Colombo, R.; Sterpi, I.; Mazzone, A.; Delconte, C.; Pisano, F. Taking a lesson from patients' recovery strategies to optimize training during robot-aided rehabilitation. *IEEE Trans. Neural Syst. Rehabil. Eng.* **2012**, *20*, 276–285. [CrossRef] [PubMed]
59. Vergaro, E.; Casadio, M.; Squeri, V.; Giannoni, P.; Morasso, P.; Sanguineti, V. Self-adaptive robot training of stroke survivors for continuous tracking movements. *J. Neuroeng. Rehabil.* **2010**, *7*, 13. [CrossRef]
60. Casadio, M.; Sanguineti, V.; Morasso, P.G.; Arrichiello, V. Braccio di Ferro: A new haptic workstation for neuromotor rehabilitation. *Technol. Health Care* **2006**, *14*, 123–142. [CrossRef]
61. Elangovan, N.; Yeh, I.L.; Holst-Wolf, J.; Konczak, J. A robot-assisted sensorimotor training program can improve proprioception and motor function in stroke survivors. In Proceedings of the 2019 IEEE 16th International Conference on Rehabilitation Robotics (ICORR), Toronto, ON, Canada, 24–28 June 2019; pp. 660–664.
62. Albanese, G.A.; Taglione, E.; Gasparini, C.; Grandi, S.; Pettinelli, F.; Sardelli, C.; Catitti, P.; Sandini, G.; Masia, L.; Zenzeri, J. Efficacy of wrist robot-aided orthopedic rehabilitation: A randomized controlled trial. *J. Neuroeng. Rehabil.* **2021**, *18*, 130. [CrossRef] [PubMed]
63. Konczak, J. WristBot: A Robotic System for the Diagnosis and Physical Rehabilitation of Sensory and Motor Dysfunction of the Wrist and Hand. 2024. Available online: https://news.cehd.umn.edu/konczak-receives-grant-to-advance-robotic-rehabilitation-technology/ (accessed on 24 November 2024).
64. Passon, A.; Schauer, T.; Seel, T. Inertial-robotic motion tracking in end-effector-based rehabilitation robots. *Front. Robot. AI* **2020**, *7*, 554639. [CrossRef]
65. MOTIONrehab. Robot-Assisted Arm Rehabilitation with DIEGO. 2024. Available online: https://www.motionrehab.co.uk/intensive-neurological-rehabilitation-centre/diego/ (accessed on 27 November 2024).
66. Saracino, L.; Avizzano, C.A.; Ruffaldi, E.; Cappiello, G.; Curto, Z.; Scoglio, A. MOTORE++ a portable haptic device for domestic rehabilitation. In Proceedings of the IECON 2016-42nd Annual Conference of the IEEE Industrial Electronics Society, Florence, Italy, 24–27 October 2016; pp. 728–734.

67. O'Flaherty, D.; Ali, K. Recommendations for upper limb motor recovery: An overview of the UK and European rehabilitation after stroke guidelines (2023). *Healthcare* **2024**, *12*, 1433. [CrossRef]
68. Irgens, E.L.; Henriksen, N.; Moe, S. Variations in physiotherapy practice in neurological rehabilitation trajectories–an explorative interview and observational study. *Physiother. Theory Pract.* **2020**, *36*, 95–107. [CrossRef]
69. Harmelink, K.; Dandis, R.; der Van der Wees Pj, P.; Zeegers, A.; der Sanden, M.N.V.; Staal, J. Recovery trajectories over six weeks in patients selected for a high-intensity physiotherapy program after Total knee Arthroplasty: A latent class analysis. *BMC Musculoskelet. Disord.* **2021**, *22*, 179. [CrossRef]
70. Coratti, G.; Pera, M.C.; Montes, J.; Pasternak, A.; Scoto, M.; Baranello, G.; Messina, S.; Dunaway Young, S.; Glanzman, A.M.; Duong, T.; et al. Different trajectories in upper limb and gross motor function in spinal muscular atrophy. *Muscle Nerve* **2021**, *64*, 552–559. [CrossRef]
71. de Assis, I.S.A.; Luvizutto, G.J.; Bruno, A.C.M.; de Souza, L.A.P.S. The proprioceptive neuromuscular facilitation concept in parkinson disease: A systematic review and meta-analysis. *J. Chiropr. Med.* **2020**, *19*, 181–187. [CrossRef] [PubMed]
72. Adler, S.S.; Beckers, D.; Buck, M. *PNF in Practice: An Illustrated Guide*; Springer: Berlin/Heidelberg, Germany, 2007.
73. Chaturvedi, P.; Singh, A.K.; Kulshreshtha, D.; Thacker, A.K. PNF in acute stroke. *MOJ Anat. Physiol.* **2018**, *5*, 391–399. [CrossRef]
74. Babaiasl, M.; Mahdioun, S.H.; Jaryani, P.; Yazdani, M. A review of technological and clinical aspects of robot-aided rehabilitation of upper-extremity after stroke. *Disabil. Rehabil. Assist. Technol.* **2016**, *11*, 263–280. [CrossRef]
75. Le Danseur, M. Stroke rehabilitation. *Crit. Care Nurs. Clin.* **2020**, *32*, 97–108. [CrossRef] [PubMed]
76. Li, L.; Fu, Q.; Tyson, S.; Preston, N.; Weightman, A. A scoping review of design requirements for a home-based upper limb rehabilitation robot for stroke. *Top. Stroke Rehabil.* **2022**, *29*, 449–463. [CrossRef] [PubMed]
77. Casals, A. Adaptive control in neurorehabilitation. In *Converging Clinical and Engineering Research on Neurorehabilitation*; Springer: Berlin/ Heidelberg, Germany, 2013; pp. 123–127.
78. Maciejasz, P.; Eschweiler, J.; Gerlach-Hahn, K.; Jansen-Troy, A.; Leonhardt, S. A survey on robotic devices for upper limb rehabilitation. *J. Neuroeng. Rehabil.* **2014**, *11*, 3. [CrossRef] [PubMed]
79. Yeh, T.N.; Chou, L.W. Clinical Demands of Designs for Rehabilitation Robots in Taiwan. *Innovation* **2022**, *1*, 42–47. [CrossRef]
80. Richardson, R.; Brown, M.; Bhakta, B.; Levesley, M. Design and control of a three degree of freedom pneumatic physiotherapy robot. *Robotica* **2003**, *21*, 589–604. [CrossRef]
81. Akdoğan, E.; Aktan, M.E.; Koru, A.T.; Arslan, M.S.; Atlıhan, M.; Kuran, B. Hybrid impedance control of a robot manipulator for wrist and forearm rehabilitation: Performance analysis and clinical results. *Mechatronics* **2018**, *49*, 77–91. [CrossRef]
82. Hesse, S.; Schmidt, H.; Werner, C. Machines to support motor rehabilitation after stroke: 10 years of experience in Berlin. *J. Rehabil. Res. Dev.* **2006**, *43*, 671. [CrossRef]
83. Loureiro, R.C.; Harwin, W.S. Reach & grasp therapy: Design and control of a 9-DOF robotic neuro-rehabilitation system. In Proceedings of the 2007 IEEE 10th International Conference on Rehabilitation Robotics, Noordwijk, The Netherlands, 13–15 June 2007; pp. 757–763.
84. Tóth, A.; Arz, G.; Fazekas, G.; Bratanov, D.; Zlatov, N. 25 Post stroke shoulder-elbow physiotherapy with industrial robots. In *Advances in Rehabilitation Robotics: Human-Friendly Technologies on Movement Assistance and Restoration for People with Disabilities*; Springer: Berlin/Heidelberg, Germany, 2004; pp. 391–411.
85. Yao, J.; Sheaff, C.; Dewald, J.P. Usage of the ACT 3D Robot in a Brain Machine Interface for Hand Opening and Closing in Stroke Survivors. In Proceedings of the 2007 IEEE 10th International Conference on Rehabilitation Robotics, Noordwijk, The Netherlands, 12–15 June 2007; pp. 938–942.
86. Huang, X.; Naghdy, F.; Du, H.; Naghdy, G.; Todd, C. Temporal difference (TD) based critic-actor adaptive control for a fine hand motion rehabilitation robot. In *Mechatronics and Machine Vision in Practice 3*; Springer: Cham, Switzerland, 2018; pp. 195–207.
87. Pippo, I.; Albanese, G.A.; Zenzeri, J.; Torazza, D.; Berselli, G. Understanding human–robot interaction forces: A new mechanical solution. *Int. J. Interact. Des. Manuf. (IJIDeM)* **2024**, *18*, 4765–4774. [CrossRef]
88. Fareh, R.; Elsabe, A.; Baziyad, M.; Kawser, T.; Brahmi, B.; Rahman, M.H. Will your next therapist be a robot?—A review of the advancements in robotic upper extremity rehabilitation. *Sensors* **2023**, *23*, 5054. [CrossRef] [PubMed]
89. Li, M.; Zhang, J.; Zuo, G.; Feng, G.; Zhang, X. Assist-as-needed control strategy of bilateral upper limb rehabilitation robot based on GMM. *Machines* **2022**, *10*, 76. [CrossRef]
90. Guatibonza, A.; Solaque, L.; Velasco, A.; Peñuela, L. Assistive Robotics for Upper Limb Physical Rehabilitation: A Systematic Review and Future Prospects. *Chin. J. Mech. Eng.* **2024**, *37*, 69. [CrossRef]
91. Bauer, G.; Pan, Y.J. Review of control methods for upper limb telerehabilitation with robotic exoskeletons. *IEEE Access* **2020**, *8*, 203382–203397. [CrossRef]
92. Li, L.; Han, J.; Li, X.; Guo, B.; Wang, X.; Du, G. A novel end-effector upper limb rehabilitation robot: Kinematics modeling based on dual quaternion and low-speed spiral motion tracking control. *Int. J. Adv. Robot. Syst.* **2022**, *19*, 17298806221118855. [CrossRef]
93. Maithani, H.; Ramon, J.A.C.; Mezouar, Y. Predicting human intent for cooperative physical human-robot interaction tasks. In Proceedings of the 2019 IEEE 15th International Conference on Control and Automation (ICCA), Edinburgh, UK, 16–19 July 2019; pp. 1523–1528.
94. Khan, M.M.R.; Swapnil, A.A.Z.; Ahmed, T.; Rahman, M.M.; Islam, M.R.; Brahmi, B.; Fareh, R.; Rahman, M.H. Development of an end-effector type therapeutic robot with sliding mode control for upper-limb rehabilitation. *Robotics* **2022**, *11*, 98. [CrossRef]

95. Wang, J.; Li, Y. Hybrid impedance control of a 3-DOF robotic arm used for rehabilitation treatment. In Proceedings of the 2010 IEEE International Conference on Automation Science and Engineering, Toronto, ON, Canada, 21–24 August 2010; pp. 768–773.
96. Papaleo, E.; Zollo, L.; Spedaliere, L.; Guglielmelli, E. Patient-tailored adaptive robotic system for upper-limb rehabilitation. In Proceedings of the 2013 IEEE International Conference on Robotics and Automation, Karlsruhe, Germany, 6–10 May 2013; pp. 3860–3865.
97. Zhang, J.; Cheah, C.C. Passivity and stability of human–robot interaction control for upper-limb rehabilitation robots. *IEEE Trans. Robot.* **2015**, *31*, 233–245. [CrossRef]
98. Luo, L.; Peng, L.; Hou, Z.; Wang, W. An adaptive impedance controller for upper limb rehabilitation based on estimation of patients' stiffness. In Proceedings of the 2017 IEEE International Conference on Robotics and Biomimetics (ROBIO), Macau, China, 5–8 December 2017; pp. 532–537.
99. Li, X.; Liu, Y.H.; Yu, H. Adaptive impedance control for compliantly actuated robots with a unified safety measure. In Proceedings of the 2018 13th World Congress on Intelligent Control and Automation (WCICA), Changsha, China, 4–8 July 2018; pp. 444–449.
100. Zhang, L.; Guo, S.; Sun, Q. Development and assist-as-needed control of an end-effector upper limb rehabilitation robot. *Appl. Sci.* **2020**, *10*, 6684. [CrossRef]
101. Zhang, L.; Guo, S.; Xi, F. Performance-based assistance control for robot-mediated upper-limbs rehabilitation. *Mechatronics* **2023**, *89*, 102919. [CrossRef]
102. Guatibonza, A.; Solaque, L.; Velasco, A.; Penuela, L. Hybrid Impedance and Nonlinear Adaptive Control for a 7-DoF Upper Limb Rehabilitation Robot: Formulation and Stability Analysis. In Proceedings of the ICINCO, Paris, France, 6–8 July 2021; pp. 685–692.
103. Sidek, S.N.; Fatai, S. Design and Control of a 3D Robot-Assisted Rehabilitation Device for Post-Stroke. In *Control Engineering in Robotics and Industrial Automation: Malaysian Society for Automatic Control Engineers (MACE) Technical Series 2018*; Springer: Cham, Switzerland, 2022; pp. 5–18.
104. Arantes, A.P.; Bressan, N.; Borges, L.R.; McGibbon, C.A. Evaluation of a novel real-time adaptive assist-as-needed controller for robot-assisted upper extremity rehabilitation following stroke. *PLoS ONE* **2023**, *18*, e0292627. [CrossRef]
105. Mathavan Jeyabalan, P.K.; Nehrujee, A.; Elias, S.; Magesh Kumar, M.; Sujatha, S.; Balasubramanian, S. Design and Characterization of a Self-Aligning End-Effector Robot for Single-Joint Arm Movement Rehabilitation. *Robotics* **2023**, *12*, 149. [CrossRef]
106. Lai, Y.; Sutjipto, S.; Clout, M.D.; Carmichael, M.G.; Paul, G. GAVRe 2: Towards data-driven upper-limb rehabilitation with adaptive-feedback gamification. In Proceedings of the 2018 IEEE International Conference on Robotics and Biomimetics (ROBIO), Kuala Lumpur, Malaysia, 12–15 December 2018; pp. 164–169.
107. Mashayekhi, M.; Moghaddam, M.M. EMG-driven fatigue-based self-adapting admittance control of a hand rehabilitation robot. *J. Biomech.* **2022**, *138*, 111104. [CrossRef]
108. Cai, S.; Xie, P.; Li, G.; Xie, L. Compensation-corrective adaptive control strategy for upper-limb rehabilitation robots. *Robot. Auton. Syst.* **2024**, *177*, 104701. [CrossRef]
109. Xu, G.; Song, A. Adaptive impedance control based on dynamic recurrent fuzzy neural network for upper-limb rehabilitation robot. In Proceedings of the 2009 IEEE International Conference on Control and Automation, Christchurch, New Zealand, 9–11 December 2009; pp. 1376–1381.
110. Xu, G.; Song, A.; Li, H. Adaptive impedance control for upper-limb rehabilitation robot using evolutionary dynamic recurrent fuzzy neural network. *J. Intell. Robot. Syst.* **2011**, *62*, 501–525. [CrossRef]
111. Xu, G.; Song, A.; Li, H. Control system design for an upper-limb rehabilitation robot. *Adv. Robot.* **2011**, *25*, 229–251. [CrossRef]
112. Bai, J.; Song, A.; Wang, T.; Li, H. A novel backstepping adaptive impedance control for an upper limb rehabilitation robot. *Comput. Electr. Eng.* **2019**, *80*, 106465. [CrossRef]
113. Wang, C.; Peng, L.; Hou, Z.G.; Wang, W.; Su, T. A novel assist-as-needed controller based on fuzzy-logic inference and human impedance identification for upper-limb rehabilitation. In Proceedings of the 2019 IEEE Symposium Series on Computational Intelligence (SSCI), Xiamen, China, 6–9 December 2019; pp. 1133–1139.
114. Li, X.; Yang, Q.; Song, R. Performance-based hybrid control of a cable-driven upper-limb rehabilitation robot. *IEEE Trans. Biomed. Eng.* **2020**, *68*, 1351–1359. [CrossRef]
115. Hu, Y.; Meng, J.; Li, G.; Zhao, D.; Feng, G.; Zuo, G.; Liu, Y.; Zhang, J.; Shi, C. Fuzzy Adaptive Passive Control Strategy Design for Upper-Limb End-Effector Rehabilitation Robot. *Sensors* **2023**, *23*, 4042. [CrossRef] [PubMed]
116. Wu, Q.; Chen, B.; Wu, H. Adaptive admittance control of an upper extremity rehabilitation robot with neural-network-based disturbance observer. *IEEE Access* **2019**, *7*, 123807–123819. [CrossRef]
117. Ting, W.; Aiguo, S. An adaptive iterative learning based impedance control for robot-aided upper-limb passive rehabilitation. *Front. Robot. AI* **2019**, *6*, 41. [CrossRef]
118. Miao, Q.; Li, Z.; Chu, K.; Liu, Y.; Peng, Y.; Xie, S.; Zhang, M. Performance-based iterative learning control for task-oriented rehabilitation: A pilot study in robot-assisted bilateral training. *IEEE Trans. Cogn. Dev. Syst.* **2021**, *15*, 2031–2040. [CrossRef]
119. Shoaib, M.; Asadi, E.; Cheong, J.; Bab-Hadiashar, A. Cable driven rehabilitation robots: Comparison of applications and control strategies. *IEEE Access* **2021**, *9*, 110396–110420. [CrossRef]
120. Hashemi, A.; McPhee, J. Assistive sliding mode control of a rehabilitation robot with automatic weight adjustment. In Proceedings of the 2021 43rd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC), Virtual, 1–5 November 2021; pp. 4891–4896.

121. Wu, Q.; Chen, Y. Development of an intention-based adaptive neural cooperative control strategy for upper-limb robotic rehabilitation. *IEEE Robot. Autom. Lett.* **2020**, *6*, 335–342. [CrossRef]
122. Abbas, M.; Narayan, J.; Dwivedy, S.K. Event-triggered adaptive control for upper-limb robot-assisted passive rehabilitation exercises with input delay. *Proc. Inst. Mech. Eng. Part I J. Syst. Control Eng.* **2022**, *236*, 832–845. [CrossRef]
123. Abbas, M.; Narayan, J.; Dwivedy, S.K. Event-triggered adaptive control for upper-extremity therapeutic robot in active-assist mode: A simulation study. *Proc. Inst. Mech. Eng. Part C J. Mech. Eng. Sci.* **2024**, *238*, 4628–4643. [CrossRef]
124. Sharifi, M.; Behzadipour, S.; Vossoughi, G. Model reference adaptive impedance control of rehabilitation robots in operational space. In Proceedings of the 2012 4th IEEE RAS & EMBS International Conference on Biomedical Robotics and Biomechatronics (BioRob), Rome, Italy, 24–27 June 2012; pp. 1698–1703.
125. Sharifi, M.; Behzadipour, S.; Vossoughi, G. Model reference adaptive impedance control in Cartesian coordinates for physical human–robot interaction. *Adv. Robot.* **2014**, *28*, 1277–1290. [CrossRef]
126. Omrani, J.; Moghaddam, M.M. Nonlinear time delay estimation based model reference adaptive impedance control for an upper-limb human-robot interaction. *Proc. Inst. Mech. Eng. Part H J. Eng. Med.* **2022**, *236*, 385–398. [CrossRef] [PubMed]
127. Islam, M.R.; Spiewak, C.; Rahman, M.H.; Fareh, R. A brief review on robotic exoskeletons for upper extremity rehabilitation to find the gap between research porotype and commercial type. *Adv. Robot. Autom.* **2017**, *6*, 10-4172. [CrossRef]