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# Wearable Assistive Rehabilitation Robotic Devices—A Comprehensive Review

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**Abstract:** This article details the existing wearable assistive devices that could mimic a human's active range of motion and aid individuals in recovering from stroke. The survey has identified several risk factors associated with musculoskeletal pain, including physical factors such as engaging in high-intensity exercises, experiencing trauma, aging, dizziness, accidents, and damage from the regular wear and tear of daily activities. These physical risk factors impact vital body parts such as the cervical spine, spinal cord, ankle, elbow, and others, leading to dysfunction, a decrease in the range of motion, and diminished coordination ability, and also influencing the ability to perform the activities of daily living (ADL), such as speaking, breathing and other neurological responses. An individual with these musculoskeletal disorders requires therapies to regain and restore the natural movement. These therapies require an experienced physician to treat the patient, which makes the process expensive and unreliable because the physician might not repeat the same procedure accurately due to fatigue. These reasons motivated researchers to develop and control robotics-based wearable assistive devices for various musculoskeletal disorders, with economical and accessible solutions to aid, mimic, and reinstate the natural active range of motion. Recently, advancements in wearable sensor technologies have been explored in healthcare by integrating machine-learning (ML) and artificial intelligence (AI) techniques to analyze the data and predict the required setting for the user. This review provides a comprehensive discussion on the importance of personalized wearable devices in pre- and post-clinical settings and aids in the recovery process.

**Keywords:** artificial neural networks; exoskeletons; machine learning; rehabilitation robots; wearable assistive devices

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## 1. Introduction

Rehabilitation or physical therapy is a systematic approach aimed at improving the capabilities of individuals dealing with disabilities. It plays a crucial role in minimizing the physical impediments hindering daily activities and facilitates the restoration of mobility. Prescribed for those recovering from accidents, undergoing surgery, facing musculoskeletal disorders (MSDs), and for the elderly, rehabilitation focuses on enhancing overall mobility. The benefits of physical therapy are that it can enhance physical capacity, reduce pain, strengthen muscles, and improve gait, posture, coordination, flexibility, and joint mobility [1,2].

Physical therapy is suggested for individuals dealing with musculoskeletal disorders (MSDs), which often arise from abrupt or excessive strain on the muscles. This strain can occur when lifting or carrying heavy loads over an extended period, leading to muscle weakness and subsequent pain.

In the human body, MSDs can be observed in the joints, muscles, limbs, neck, and spinal cord [3–7]. Physical therapy manipulation is conducted in rehabilitation centers to address individuals with musculoskeletal disorders. This clinical setting necessitates extended and intensive therapy sessions for patients. These physical therapies are specialized exercises and stretches designed to alleviate pain, restore strength, and enhance controlled movements. Generally, such therapies are recommended for individuals dealing with musculoskeletal injuries or disorders like strokes, sprains, spinal cord-related injuries, and post-surgical rehabilitation.

In many instances, physical therapy involves the collaboration of one or more physicians for effective patient treatment. Physicians require years of practice, making it a costly process.

This process involves prolonged hours of therapy sessions, leading to fatigue for the physician and compromising the reliability of the therapy. Due to the increase in the demand for physical therapy, the training sessions are generally shorter than the required duration, which might not meet an individual's requirements [8–12].

Robotic-assisted rehabilitation is a contemporary strategy aimed at addressing the limitations observed in clinical rehabilitation. The incorporation of robotics into the rehabilitation field and assistive devices has the potential to enhance the number of training sessions through consistent repetition, ultimately leading to a reduction in therapy costs. In recent years, there has been increasing interest in closed-loop manipulators in the area of rehabilitation. The closed-loop Stewart platform parallel manipulators provide a better load-to-weight ratio, load distribution, high-precision positioning, and better rigidity [13–15].

The adoption of parallel manipulators (PMs) in the medical field has surged owing to their precision and high stiffness. This has led to the demand for specialized robotic manipulators in complex surgical procedures such as brain tumor removal, cervical spine interventions, and orthoscopic knee surgeries, where precise positioning is paramount. Consequently, the development of devices with high-precision and user-friendly mechanical systems is underway to assist both healthcare professionals and patients effectively. Parallel manipulators also find applications in brain-scanning operations. Previous research on these manipulators highlights their attributes, including the high load-carrying capacity, effective dynamic performance, and precise positioning, affirming their significance in medical procedures [16,17]. Most of the parallel manipulators considered for the study are six degrees of freedom (6-DoF) manipulators, which are inherited from the Stewart–Gough platform [18,19].

Wearable powered exoskeletons offer a potential solution to traditional rehabilitation challenges. Rigid exoskeletons have been shown to be safe and beneficial for stroke survivors, improving strength and postural control. Patients and physiotherapists have concerns about the safety of rigid exoskeletons, such as falls, despite limited evidence of such incidents. Rigid exoskeletons may force patients into unnatural movement patterns or detect and force incorrect movements. The limitations of current exoskeletons identified by physiotherapists and patients include safety concerns, a one-size-fits-all approach, ease of use, weight, placement of the device, cost, and appearance. Potential solutions to these limitations include the use of compliant actuators, sensors, suit attachments fitting to the user's body, and the implementation of control algorithms [20,21].

To address the limitations of rigid exoskeletons, soft actuator-enabled exoskeletons, i.e., soft exoskeletons, are currently the subject of research interest. Soft robots are wearable devices characterized by their lightweight and flexible structure. While they are primarily designed to be worn and used for supporting and assisting with the activities of daily living (ADLs), they have also shown promise as tools for rehabilitation purposes. Soft exoskeletons can utilize soft robotic actuators, body attachments, sensing systems, and control

algorithms. Soft robotics technology enables the development of medical assistive devices for purposes like rehabilitation and addresses issues like safety, compliance, freedom of motion, biocompatibility, and ease of use. Currently, various technologies like dielectric elastomer actuators (DEAs), fluid-based actuators, twisted string actuators (TSAs), etc., have been developed to mimic the motion of living beings. Soft actuators offer improved compliance and interaction safety in medical assistive devices. Incorporating soft and flexible materials allows for better adaptation to anatomical structures. Advanced sensing and feedback systems enable the precise and coordinated movements of soft actuators [22,23].

Significant advances in material science and engineering have led to the development of smart actuators for modern robotic systems. These systems utilize intelligent materials such as ionic polymer metal composites (IPMCs), dielectric elastomers (DEAs), piezoelectric polymers (PEPs), and shape-memory alloys (SMAs) to create compact and lightweight designs. SMAs are particularly attractive due to their excellent properties, such as the ability to revert to their original shape or size upon heating. They are favored over traditional electric, pneumatic, and hydraulic actuators because of their many advantages, including the low volume, high energy density, low weight, high force, flexibility, noiseless operation, simple structure, very compact design, and ease of integration into new systems. As a result, SMAs are used in biomedical, automotive, aeronautical, and robotics applications [24].

SMAs are intelligent materials that return to their original shape after being heated to a specific phase transformation temperature. SMA actuators offer a high power-to-weight ratio, a simple actuation mechanism, and a long fatigue life, making them highly attractive for practical use. However, several challenges remain before SMA actuators can be widely adopted. These include the high energy consumption, the low cooling rates, and the need for improved control techniques to enhance accuracy and reliability. Additionally, increasing the output stroke and ensuring a rapid response is essential for future applications [25].

This review article aims to present the current research on robotic wearable assistive devices to aid the rehabilitation method. The existing devices are classified according to the number of degrees of freedom and mechanisms, movements, type of actuation methods, control system, and the presence of artificial intelligence (AI). This review article is structured into three main sections. The first section provides insights into the causes of musculoskeletal disorders, emphasizes the importance of manual physical therapy, and discusses the need for robotic-assisted wearable devices to replicate human motions. Furthermore, section two discusses in detail the recent developments and research in active rehabilitation wearable assistive devices and their mechanisms for various parts of the human body, such as the head/neck, hand, fingers, ankle, and also artificial intelligence, machine- and deep-learning approaches implemented in assisting the wearable assistive devices. Finally, section three provides an extensive discussion on possible areas of research and development for wearable assistive devices.

## 2. Literature Survey

### *2.1. Head/Neck Mechanisms for Wearable Assistive Devices*

The neck serves as the juncture connecting the head and torso, with the cervical spine playing a crucial role in facilitating head movements. In addition to the spine, the neck is a conduit for nerves, ligaments, glands, digestive tracts, and veins. The nerves and ligaments in the neck play a supportive role by bearing the weight of the head and providing stability. The arrangement of nerves in the neck appears to be linearly parallel, ensuring the equal distribution of load on the nerves, aided by the structure of the cervical spine ($C_1$ to $C_7$), as shown in Figure 1.

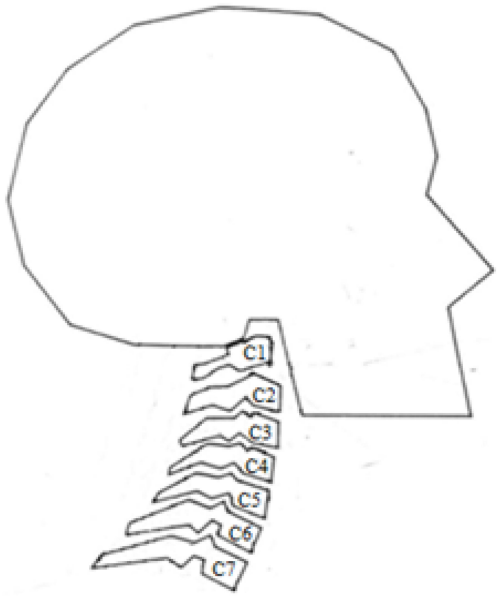


**Figure 1.** Human cervical spine [26]. Copyright © 2019 Lingampally P.K. et al.

Among the seven vertebrae, the first vertebrae, the atlas (C1), and the axis vertebrae (C2) help with head rotation. The total DoF of the neck are typically considered 6-DoF. Figure 2 shows the active range of motion (AROM) of the head/neck movement, i.e., extension (E), flexion (F), axial rotation (left and right), and lateral flexion (right and left), and also shows the natural angular tilt/ROM for an adult's head/neck motions [27,28].

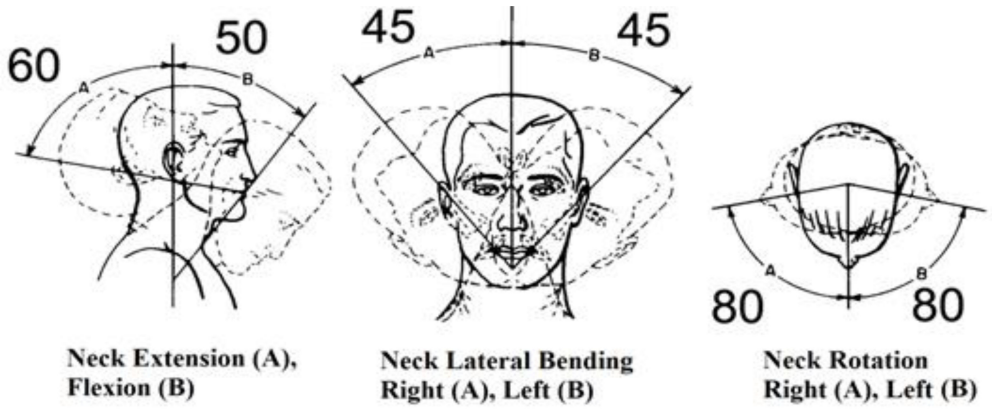


**Figure 2.** Human head/neck range of motion (ROM) [29]. Copyright © 2019 Lingampally P.K et al.

Cervical spine immobilization is a pre-hospital setting commonly recommended in the case of cervical spinal cord injuries (SCIs) during a traumatic incident. The non-surgical immobilization of the cervical spine is accomplished through the application of cervical collars. These collars, also known as orthoses, serve the purpose of treating neck injuries or providing immobilization post-surgical procedures [30]. However, it is essential to note that cervical collars, in general, lack the flexibility to accommodate variations in head and neck dimensions. The use of improperly sized collars may result in over-extension and the potential for creating separation among the cervical vertebrae. Despite this, cervical collars are widely employed globally to address trauma cases in emergency conditions. These collars stabilize and constraint head/neck motions to a single configuration, but users experience a great deal of discomfort as the head/neck is constrained to a single configuration for a longer period, which also creates problems like immeasurable pain near the shoulders and pressure on the lower jaw [31–34].

Current cervical collars are primarily designed and developed to restrict motion, highlighting a requirement for dynamic cervical collars capable of stabilizing the neck, maintaining posture, enhancing cervical proprioception, facilitating exercises, and reducing stress on the neck muscles. Research on dynamic braces, rehabilitation, and assistive devices is constrained, primarily due to the limited space available and the inherent challenges associated with integrating a mechanism between the head and the shoulders. However, a few studies have been conducted to mimic the head/neck motions, which are discussed below.

Beira et al. (2006) designed a robot head for the Robot-Cub (iCub) project. The specifications for the humanoid neck included dimensions of 7 cm in width and 9 cm in length, and three unique neck mechanisms, spring neck, parallel neck, and serial neck, were developed to mimic the head/neck motions. A 3-DoF (degrees of freedom) serial neck, equipped with DC micro-motors featuring planetary gearheads, was implemented. To enhance the robustness, especially during abrupt falls akin to those experienced by a child, an overload clutch system was incorporated into the robot. This arrangement with the serial neck has more advantages when compared to the other delicate neck mechanisms [35]. Brouwer et al. (2009) designed a fast 4 degrees of freedom (4-DoF) serial humanoid neck mechanism, choosing it over the parallel mechanism because parallel mechanisms often depend on prismatic joints, necessitating the use of linear motors or spindles. However, the power density of linear motors is relatively low, prompting the preference for a serial mechanism in this particular design. A differential drive system was used for building the mechanism and the achievement of head/neck motions. The system is capable of achieving pitch ($\pm 36^\circ$), roll ($\pm 102^\circ$), and yaw ($\pm 49^\circ$). The main disadvantage of this mechanism lie in its complexity in terms of the serial setup using differential drives [36].

Gao et al. (2013) have carried out workspace analysis for a 3-DoF cable-driven flexible parallel mechanism. This design consists of a moving platform connected to the fixed base using cables, each separated by $120^\circ$ from the other, where a compression spring serves as a cervical spine between the two platforms and is driven by motors located at the fixed platform [37]. Gao et al. (2014) designed a 2-DoF lateral-bending spring spine using a cable-driven parallel mechanism. This mechanism can generate pitch and roll movements. A spring is realized as a cervical spine in this mechanism. This mechanism generated a relatively small lateral-bending angle [38]. Setiawan et al. (2015) designed a 7-DoF (degrees of freedom) mechanism for the FLoW humanoid. This mechanism comprises three integral parts: an eye mechanism utilizing the Helmholtz mechanism to support two cameras and facilitate pan and tilt movements, a head incorporating the Agile eye, and a neck employing a three-legged Gough–Stewart platform, where two legs are dynamic and the other is a fixed leg. Specifically, the neck in this mechanism features 2-DoF. The workspace for the mechanism is determined through the application of forward kinematics equations. This mechanism helped in obtaining motions of the head such as tilt ($35^\circ$), swing ($14^\circ$), and pan ($30^\circ$) [39]. Wu et al. (2016) have proposed and developed a 6-3 UPS exoskeleton for head/neck motion and surface electromyography (sEMG) with signals offered as input to a feedforward neural network to acquire the necessary force and torque to actuate the exoskeleton. This exoskeleton can be used for rehabilitation applications or a helmet mount display support for virtual reality applications [40].

Ke et al. (2015) have developed a humanoid robot based on facial expressions. This humanoid consists of the eyebrow, eyeball, lid, jaws, and neck mechanisms. This facial robot has 19-DoF, out of which the eyebrows have 3-DoF, 4-DoF for the eyeball, 4-DoF for the lid, 3-DoF for the neck, 2-DoF for the eyelids, and 3-DoF for the jaw. The neck mechanism is built using an RSSR parallel configuration and driven by two motors. Experimental studies show facial expression robots with head/neck coordination to produce various vivid expressions [41]. Nori et al. (2007) have developed a 3-DoF tendon-driven neck mechanism, where the neck bone is realized with a steel spring surrounded by three steel tendons separated $120^\circ$ apart. The length of each tendon is adjusted with the help of three motors positioned at the base, and the motors are controlled using PID to move the head

along the roll and pitch axes [42]. Mahmood et al. (2021) have introduced a passive neck orthosis designed for individuals afflicted with progressive muscular diseases such as ALS. This orthosis enabled the patient to attain 10° flexion, 40° extension, and up to 40° of left and right rotation of the head movements. This brace could not provide lateral bending for the patient, and no study was conducted to measure the mechanical losses [43].

Shoaib et al. (2019) [44] developed an innovative dynamic rehabilitation neck brace, i.e., Car-Neck, by employing a cable-driven system specifically designed for individuals with dropped head syndrome (DHS). This design incorporates two on-links and one hybrid cable-driven joint, facilitating the patient in achieving 3-DoF. Despite the proximity of the cables, the brace is designed to offer enhanced stability and accuracy, providing flexion/extension motions to aid DHS patients.

In addition to this, kinematic, static, and cable tension analysis is performed for the device [44]. Kim et al. (2017) developed a posture correction device designed for individuals with forward head posture (FHP). FHP is a common issue observed in individuals who spend prolonged periods using computers and smartphones. The device incorporates flex sensors, a rigid chin rest made of plastic, a scissor linkage, and a pneumatic artificial muscle (PAM). The study demonstrated the device's capability to exert a strong force, particularly when utilizing bellow-type actuators and a PAM, in comparison to pneumatic actuators and traditional linkages. These passive systems allow the individual to maintain the head in an upright position but would not restore the dynamic head/neck movements [45]. Uyama and Hanaki (2015) have designed and developed a neck-positioning system for disabled children, with a support system integrated into the wheelchair. The system incorporates a rigid link, a revolute, and a spherical joint. This arrangement aids users in stabilizing their head position while the wheelchair is in motion, allowing for a tilt of 30°. The system addresses issues related to respiration function, contributing to enhanced comfort and support for the user. The limitation of this system is the lower flexibility, and it also becomes damaged if any external weight is added to the neck-positioning system other than the user's head weight [46].

Dai Yue et al. (2022) have proposed and developed a 6-SPS/CS parallel manipulator-based cervical exoskeleton. The mechanism's inverse kinematic solutions were derived using space coordinate transformation and the closed-loop vector method. An ADAMS simulation study was carried out to determine the actuator length, speed, and acceleration for the dynamic neck brace. This innovative cervical exoskeleton represents a significant development in the field of assistive devices for neck support and rehabilitation. Experimental studies were conducted for the dynamic exoskeleton, and it was found that the exoskeleton could mimic head/neck motion and produced $\pm 15°$ for flexion/extension motion, $\pm 20°$ for lateral bending motion, and $\pm 15°$ for rotation motion [47]. Mostafa Ibrahim et al. (2021) have designed and simulated a 3-RPS dynamic neck brace for patients to reduce neck pain. This design successfully achieved $\pm 7°$ lateral bending and $\pm 8°$ flexion/extension motion. The forward and inverse equations for the brace were solved using MATLAB, and an operable workspace was determined. This innovative dynamic neck brace offers promising potential for addressing neck pain and promoting mobility in patients. This design helps patients to position the neck in either symmetric or asymmetric positions [48]. Alejandro L. et al. (2022) have developed a 4-DoF active robotic neck orthosis based on the Stewart platform. The first sliding mode controller with a state-dependent gain control strategy was implemented to control the neck orthosis, and it was found that this control system is eight times more efficient and robust when compared to the PD control system [49].

Table 1 summarizes the various robotic active head/neck mechanisms, highlighting their degrees of freedom (DoF), range of motion (ROM), control methods, and applications. This comparison underscores the diversity and specificity of designs aimed at addressing different aspects of head/neck movement and support, from rehabilitation to research and posture correction. The development of dynamic and adaptable neck braces and mechanisms represents a significant advancement in wearable assistive devices, providing enhanced comfort, flexibility, and functionality for users with various needs. Traditional

cervical collars offer essential support but often lack adaptability and comfort. In contrast, innovative designs for dynamic neck braces and robotic mechanisms significantly improve rehabilitation, posture correction, and user-specific movements.

**Table 1.** Active head/neck mechanisms.

| Source | DoF | Mechanism/Type of Operation | Range of Motion (ROM) | Control Method | Application |
|---|---|---|---|---|---|
| • Dai Yue et al. [47] | 6 | • Parallel mechanism. | • Flexion/extension ± 15°, Lateral bending motion ± 20°, Rotation motion ± 15°. | • Not provided | • Research and rehabilitation |
| • J.L. Rueda-Arreguín et al. [50]. | 6 | • Force-based spring mechanism. | • Maximum pitch of 18°, and roll angle of 10°. | • Force and IMU sensor control | • Rehabilitation |
| • A. Raffin et al. [51]. | 6 | • Tendon-driven mechanism. | • Flexion/extension—±20°, lateral bending—±50°, and rotation ± 5°. | • Tendon-tension controller and external camera-marker pose tracking. | • Rehabilitation |
| • K. Berns and T. Braum [52]. | 4 | • DC motor-based neck mechanism. | • Flexion/extension—±30°, lateral bending—±40°. | • Inertia-based servo control using DSP (Motorola 56F803) connected with CPLD (complex programmable logic device) (Altera EPM 70 128) | • Rehabilitation |
| • Brouwer et al. [36] | 4 | • Serial humanoid neck mechanism. | • Pitch (±36°), roll (±102°), yaw (±49°). | • Differential drive control using magnetic encoders. | • Research |
| • Beira et al. [35,53]. | 3 | • DC micro-motors featuring planetary gearheads. | • Pan, swing, and tilt. | • Motor controlled with optical encoders. | • Robotic research |
| • Nori and et al. [42]. | 3 | • Tendon-driven. | • Roll and Pitch movements. | • PID Controller | • Robotic research |
| • Shoaib et al. [44]. | 3 | • Two on-links and one hybrid cable-driven joint. | • Flexion+/extension −57° to 51°, lateral bending ± 35°, axial rotation ± 70°. | • Not provided | • Research and rehabilitation |
| • Mostafa Ibrahim et al. [48]. | 3 | • Parallel mechanism. | • Lateral bending ± 7° and flexion/extension motion ± 8°. | • Not provided | • Research |
| • J. Liu et al. [54]. | 3 | • RXS, X-shaped compliant joint-based parallel mechanism. | • Flexion/extension—±22°, right/left bending—±20°, right/left torsion—±28°. | • Not provided | • Research |
| • P. Boyraz et al. [55]. | 3 | • Cable-driven neck mechanism. | • Pitch and roll—±60°. | • PWM and PID control. | • Robotic research platform. |

**Table 1.** *Cont.*

| Source | DoF | Mechanism/Type of Operation | Range of Motion (ROM) | Control Method | Application |
|---|---|---|---|---|---|
| • S. Barker et al. [56]. | 3 | • McKibben pneumatic actuator muscles (PAMs). | • Pitch—±30°, roll—±25°, and yaw—±27°. | • PWM-based microcontroller. | • Robotic research platform. |
| • Y. Tadesse et al. [57]. | 2 | • Serial chain four-bar mechanism. | • Maximum nodding of 70°, and roll angle of 10°. | • PD controller. | • Robotic research platform. |
| • M. Penčić et al. [58]. | 2 | • Bevel gear-based differential mechanism. | • Flexion/extension—±100°, rotation—±90°. | • Proportional with magnetic encoders. | • Robotic research platform. |

The advancement in head/neck mechanisms for wearable assistive devices shows significant progress in enhancing user comfort, flexibility, and functionality. The comparative analysis underscores the diversity of the approaches and technologies, each addressing specific needs and applications, from robust robotic systems to rehabilitation-focused exoskeletons. Continued research and innovation in this field are essential for further improving the quality of life of individuals requiring neck support and rehabilitation.

### *2.2. Wearable Assistive Mechanisms for Ankle Rehabilitation Devices*

The ankle joint is important for a human to produce locomotion while walking, as this joint can produce motions like plantarflexion (PL), dorsiflexion (DO), inversion (IN), eversion (EV), abduction (AB), and adduction (AD). The ankle joint should sustain the entire weight of the body during movements such as walking, running, sitting, and standing [59].

As this joint bears a huge amount of load, it is often reported that this joint produces sprain on the muscle due to sudden falls or fractures because of accidents. Due to this, the patient might not be in a position to walk or produce a normal human gait. This could also lead to an increase in body weight if the patient is bedridden for a longer period. To recover from the ankle injury, motion assistance is necessary to regain normal gait, which requires physiotherapist assistance. This conventional method has drawbacks such as inconsistency in treatment, fatigue (patient and therapists), and slow recovery. To address these alternative therapeutic methods or approaches, robot-based rehabilitation devices are being researched to minimize human intervention to assist patients in recovering and recovering from injuries. Ankle rehabilitation robots are grouped into exoskeletons (wearable devices) and platform robots. Exoskeletons are used to correct and improve the gait pattern while carrying heavy loads, whereas platform robots are used to provide exercise and manipulate the ankle motions. A few recent trends in the ankle rehabilitation devices are discussed below.

Mustafa S. et al. (2016) have developed and evaluated a 2-DoF redundant parallel ankle rehabilitation device, controlled by implementing a fuzzy-based adaptive admittance approach. The ankle robot was designed using 3-UPS (Universal–Prismatic–Spherical) joints and a central strut was provided to have high stiffness and a singularity-free workspace. A fuzzy logic controller (FLC) was incorporated into the mechanism to improve the trajectory of the robot. This controller was tuned using the cuckoo search algorithm. A comparison study was conducted for the ankle robot with the proposed controller and the conventional PID controller. It was observed that the proposed algorithm reduced the steady-state tracking errors by 50% when compared to the PID controller [60]. A. Saglia and et al. (2009) presented a 2-DoF ankle rehabilitation device using a redundantly actuated parallel mechanism. This mechanism consists of three identical active limbs with UPS joints and a passive central strut. The top end of the strut is attached to a universal joint. The stroke length of the prismatic actuator considered is 10 cm to meet the force requirement. An incremental encoder is equipped in each actuator to measure and track the position of the actuator. In

addition, a load cell is equipped on the top of the actuator to accurately measure the force exerted. The designed system is capable of achieving ± 25° of angular tilt at a constant speed of 500 °/s and a maximum torque of 28 Nm [61].

Prashant K. and et al. (2014) developed an adaptive 3-DoF wearable ankle device to treat ankle sprain using parallel architecture and actuated by compliant PMAs. This ankle robot achieved a maximum ROM of 46° in dorsiflexion and plantarflexion at a moment capacity of 120 Nm, while for inversion/eversion the device achieved 26°, 52° for adduction/abduction motions at 96 Nm, and 68 Nm maximum moment capacity, respectively. As the PMAs are difficult to model, a closed-loop adaptive fuzzy-logic controller with a Fuzzy-Based Disturbance Observer (FBDO) approach was implemented to control the device. It was observed that the FBDO was able to reduce the nonlinearity of PMAs and other disturbances [62]. Shipling Zuo et al. (2020) designed and evaluated the performance of a parallel mechanism-based wearable ankle assistive device for patients with ankle disabilities. A 2-UPS/RRR parallel kinematic configuration was implemented for designing the robot, and double linear guide rails with a slider mechanism were provided to support and adjust according to the patient's thigh. Simulation studies were conducted to evaluate the performance of the device. Based on the studies, it was observed that the proposed mechanism produced enough motion isotropy while attaining maximum force and torque [63].

Matteo Russo and Marco Ceccarelli (2020) proposed a lightweight wearable assistive device for ankle motion using an S-4SPS cable-driven parallel mechanism. An analytical approach was implemented to analyze the proposed design. Simulation studies were conducted for the proposed design, and it was observed that the ankle device achieved 10° ROM for inversion/eversion and adduction/abduction motions with a load-carrying capacity under 30 N. This device used a portable 10,000 mAh batteries to power the motors and may provide 2 h of continuous ankle motions for the patient [64]. Hiroshi T. et al. (2012) designed and developed a 6-DoF active ankle–foot rehabilitation device by using the Stewart platform. By implementing a parallel mechanism, this device achieved a maximum ROM of ±20° in dorsi/plantar flexion and also in eversion/inversion, and ±50° in rotation. An I-PD controller was engaged to control the position of the double-acting pneumatic cylinders [65].

Junghan K. et al. (2019) have designed and developed a soft wearable ankle–foot orthosis to assist in gait rehabilitation for post-stroke patients. Bi-directional cable-driven actuators are used to achieve dorsi/plantar flexion motions. This device is also equipped with gait sensors to track the leg trajectory while using the device, and 3-D gait analysis is conducted using an optical motion capture system by placing 15 reflective markers to evaluate the kinematic data. This device achieved a maximum ROM of 20° in dorsiflexion and plantarflexion [66]. Ishak N.Z. et al. (2017) have developed an ankle–foot orthosis (AFO) for disabled children using a pneumatic artificial muscle (PAM) for gait rehabilitation application. Simulation studies are conducted for the proposed design using Autodesk Inventor. Based on the simulation study, it is observed that at a pressure of 343.233 N, which is considered to be the average weight of the child, and for the design, the von-mises stress value is 283.86 MPa for a displacement of 7.89 mm. The AFO is fabricated using 3D printing materials (thermoplastic elastomer and polylactic acid) [67].

R. Jimenez-Fabian et al. (2017) designed an adjustable actuator-based mechanical ankle–foot prosthesis for obtaining controlled equilibrium positioning while walking. In this design, a parallel spring was incorporated to equal the positioning of the ankle and also this arrangement reduced the torque load [68]. D.J. Hyun et al. (2019) developed a wearable exoskeleton for paraplegics. This device consisted of a two-DoF ankle joint actuated using a spring-loaded passive cam mechanism. This arrangement allowed the patient to achieve ±15° ROM for plantar/dorsiflexion motions. Gait synthesis was performed using Beizer curves for ascending and descending stairs [69].

Recent developments in exoskeletons and wearable technologies in the military, automotive, and material-handling industries are shown in Figure 3a,b [70–72], and Table 2 provides the various robotic active ankle configurations and their range of motions.



(**a**) (**b**)

**Figure 3.** Wearable sitting exoskeleton in (**a**) the manufacturing industry [71] and (**b**) material handling operations [72].

**Table 2.** Active ankle mechanisms.

| Source | DoF | Configuration | Range of Motion (ROM) | Control Method | Application |
|---|---|---|---|---|---|
| • Hiroshi T et al. [65] | 6 | • SPS. | • Dorsi/plantar flexion ± 20°, eversion/inversion ± 20°, and rotation ± 50°. | • I-PD controller | • Ankle rehabilitation exercise platform |
| • M. Girone et al. [73] | 6 | • SPS. | • Dorsi/plantar flexion—±45°, inversion/eversion—±40°, adduction/abduction—±80°. | • Computer-controlled haptic interface integrated with virtual environment | • Ankle rehabilitation exercise platform |
| • J. Yoon and J. Ryu [74] | 4 | • PSPP. | • Dorsi/plantar flexion—±50°, inversion/eversion—±55°. | • Electro-pneumatic controller | • Ankle rehabilitation exercise platform |
| • Matteo Russo and Marco Ceccarelli [64] | 4 | • SPS cable-driven parallel mechanism. | • 10° ROM for inversion/eversion and adduction/abduction motions. | • Simulation study | • Research |
| • Mustafa S et al. [60] | 3 | • UPS. | • Dorsiflexion, plantar flexion passive position inversion, eversion. | • Fuzzy logic controller (FLC) and tuned using the cuckoo search algorithm. | • Ankle rehabilitation exercise platform |

**Table 2.** *Cont.*

| Source | DoF | Configuration | Range of Motion (ROM) | Control Method | Application |
|---|---|---|---|---|---|
| • Prashant K et.al. [62] | 3 | • Parallel architecture and actuated by compliant PMAs. | • Dorsiflexion and plantarflexion ± 46°, inversion/eversion ± 26°, adduction/abduction ± 52°. | • Closed-loop adaptive fuzzy-logic controller with FBDO (Fuzzy-Based Disturbance Observer). | • Ankle rehabilitation exercise platform |
| • G. Liu et al. [75] | 3 | • RSS/S. | • Dorsi/plantar flexion—±42°, inversion/eversion—±43°, adduction/abduction—±54°. | • Multi-axis control card incorporated with three amplifiers, 3-photoelectric encoders, and a 6-DoF force sensor | • Ankle rehabilitation exercise platform |
| • C. Wang et al. [76] | 3 | • RUS/RRR. | • Dorsi/plantar flexion—±60°, inversion/eversion—±37°, adduction/abduction—±92°. | • Not provided | • Research |
| • M. Vallés et al. [77] | 3 | • PRS. | • Dorsi/plantar flexion—±50°, inversion/eversion—±50°. | • ROS (robot operating system) integrated with Orocos (Open Robot Control Software, 2017) along with force and torque sensors | • Active-assistive Exercise Platform |
| • M. Dong et al. [78] | 3 | • UPS/RRR. | • Dorsi/plantar flexion—±40°, inversion/eversion—±16°, adduction/abduction—±33°. | • Encoder-based linear actuator control | • Isokinetic muscle strength rehabilitation platform |
| • Y. Zou et al. [79] | 3 | • RRS. | • Dorsi/plantar flexion—±30°, adduction/abduction—±20°. | • Position-speed double closed-loop control strategy | • Ankle rehabilitation exercise platform |
| • A. Saglia et.al. [61] | 2 | • UPS. | • Angular tilt of ±25°. | • Capstan drive-based motor control | • Ankle rehabilitation exercise platform |
| • E.M. Ficanha et al. [80] | 2 | • Cable-driven mechanism. | • Dorsi/plantar flexion—±20°, inversion/eversion—±14°. | • PD controller | • Ankle rehabilitation exercise platform |

P—Prismatic joint; R—Revolute joint, S—Spherical joint, U—Universal joint, PD—Proportional–Derivative, I-PD – Integral Proportional and Derivative.

Table 2 serves as a comprehensive guide to robotic ankle mechanisms, offering insights into their configurations and range of motions for ankle rehabilitation. This resource aids researchers, engineers, and practitioners in understanding the diverse array of designs available, facilitating informed decision-making and comparative analysis. Each mechanism's degrees of freedom, configurations, control methods, and applications are systematically presented, showcasing the versatility and adaptability of current technologies. From simple 2-DoF mechanisms to complex systems incorporating fuzzy logic controllers, these innovations improve rehabilitation outcomes and patient mobility. By surpassing the limitations of traditional physiotherapy methods, robot-based devices offer consistent, targeted assistance, thereby enhancing patient care and quality of life. Continued research and development are vital for further refining these devices, making them more accessible, user-friendly, and effective in addressing the diverse needs of individuals undergoing ankle rehabilitation.

### *2.3. Wearable Assistive Mechanisms for Upper-Limb Rehabilitation Devices*

Each upper limb of the human body consists of the shoulder (three bones and a ball-and-socket joint), elbow (three bones and two joints), and hand. The shoulder has a total of three rotational motions (yaw, roll, and pitch), the elbow has 2-DoF (flexion/extension and pronation/supination), and the hand or wrist joint has 2-DoF (flexion/extension and rotation), as shown in Figure 4. Upper-limb dysfunction is the most common musculoskeletal disorder that can be found in elderly people due to weak muscles due to aging factors, while stroke and accidents are also considered the reasons for upper-limb dysfunction. This musculoskeletal disorder affects the patient in performing the ADLs, such as eating and grasping activities. This disability leads the patient to depend on caretakers for food and water. The upper-limb rehabilitation robots are widely studied and researched because they are similar to the end-effector robots that are widely used in industries for picking and grasping applications [40–42,81–86].

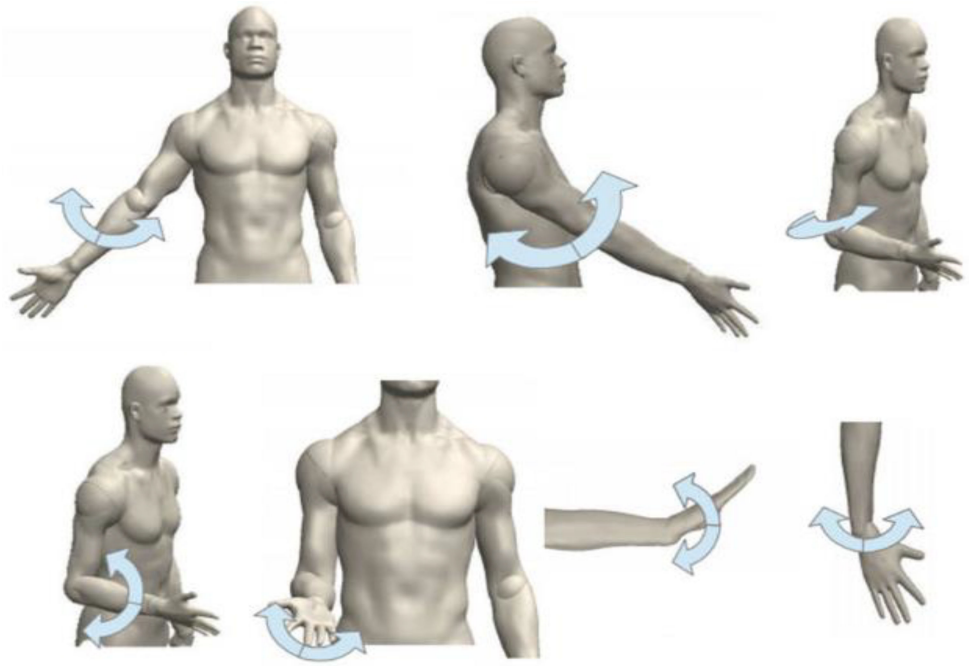

**Figure 4.** Human hand, elbow and wrist motions [83].

Yudai K. et al. (2018) have proposed and developed a parallel mechanism-based training device for the wrist joints. This device can produce 3-DoF of rotation and translation motion in the wrist. Linear DC servomotors are used and controlled using a PID controller to actuate the length of the linear motors. This device's mimicking of the ROM for palmar/dorsiflexion is $\pm 60^{\circ}$, radial/ulnar deviation is $\pm 45^{\circ}$, and pronation and supination is $\pm 45^{\circ}$ motions. Experimental studies are conducted on the test subjects. It is observed that the device produces a posture difference of a minimum of $-0.8^{\circ}$ and a maximum value of $6.5^{\circ}$, and position error minimum of $-2.2$ mm and a maximum of 8.2 mm [87].

Young-min K. et al. (2009) have developed a 3-DoF parallel mechanism-based upper-limb rehabilitation device for stroke patients. The proposed design was simulated, and based on the studies, it was found that the device achieved $90^{\circ}$ ROM for flexion [88].

Xinbo C. et al. (2022) have developed a soft wearable upper limb rehabilitation device using sot pneumatic actuators. This device was fabricated using medical-grade silicon rubber consisting of multi-layered TP composite bladders to form a high-strength fiber for the outer surface. A thin film sensor was placed in the device to sense the deflection in the actuators when actuated. Motion analysis of the proposed device was performed using the Pythagorean theorem. Experimental studies were conducted to measure the force generated by the system by using a dynamometer and a digital scale. Based on the study,

it was found that for a maximum expansion height of 40 mm, a force of 400 N force is generated [89].

Zaixiang P. et al. (2021) have designed and analyzed shoulder rehabilitation mechanisms using gear and rack transmission. This mechanism could mimic 2-DoF of shoulder motion (flexion/extension and abduction/adduction). The mechanism consists of harmonic reduction motors to actuate the transmission mechanism. Kinematic analysis is performed using the DH coordinate system, and dynamic analysis is performed using Lagrange equations. The PD iterative learning control strategy is implemented to track the trajectory of the shoulder movement. Simulation studies are conducted using MATLAB and ADAMS, and based on the simulations, it is observed that the rehabilitation device has enhanced control of the system and produced the desired trajectory [90].

Wu Qingcong et al. (2013) designed an upper limb exoskeleton using Bowden cable actuators for stroke patients. The proposed design allows the patient to compensate for gravity and achieve uniform motion of the arm with the help of springs [91]. B.K. Dinh et al. (2017) developed a Bowden cable transmission using a gear and rack mechanism for shoulder rehabilitation patients. Due to friction and backlash effects in the Bowden cable transmission, accurate control of the mechanism was not achieved. To overcome these challenges, a backlash compensation strategy was implemented, which helped the adaptive controller to enhance the position accuracy [92].

Y. Park et al. (2018) developed a cable-driven hand exoskeleton for virtual reality applications. This system measures the motion and force applied by the fingers while holding the objects and a force feedback control system along with potentiometers are used to measure the finger movement [93].

J. Yang et al. (2016) designed jointless tendon-driven human fingers. This research also addressed the drawbacks of traditional tendon-drive hand exoskeleton systems, such as the asymmetrical finger bending sequence. The uniform bending of the proposed system is achieved by having tendon-driven cables on both sides of the finger (top and bottom). This exoskeleton achieved 100° of flexion for 37% of the cable input tension force [94].

Erkin G. et al. (2016) designed a 1-DoF Watt II 6-bar rehabilitation finger structure for stroke patients. The IR reflector-based motion capturing system allowed the obtaining of trajectory data of the finger and further used it for performing kinematic synthesis. This mechanical arrangement limits the fingers to producing over-extension/flexion while performing human motions [95]. N. Robson et al. (2016) proposed a 1-DoF planar 8-bar linkage mechanism for mimicking human finger motion. A sensor-glove with a tri-axis accelerometer and optical markers are used for obtaining the finger position, velocity, and acceleration. A geometric approach is implemented to obtain the optimal link lengths and necessary joints for the fingers [96].

N. Conti et al. (2016) developed a low-cost DoF finger mechanism using rotary actuators. A motion capture (MoCap-Kinovea) system was implemented for obtaining the finger geometrical and trajectory data. A PID control system was used to achieve better performance in terms of the stiffness and force while mimicking the opening and closing gestures of the fingers [97].

E. Peña-Pitarch et al. (2016) developed a spring and ratchet wheel mechanism for active and de-active mechanisms while holding round and oval-shaped objects. This exoskeleton achieved 3 mm of finger compression and generated a maximum force of 15 N for each finger, and collectively the fingers generated 60 N while holding objects [98].

H.D. Lee et al. (2014) proposed a three-DoF electric actuator-based upper-limb exoskeleton for human–robot cooperation (HRC). An external load compensation is provided to enhance the lifting capability of the human while using the exoskeleton. Damped least squares (DLS) was implemented to eliminate the singularity position. A comparative study was conducted between the DLS and pseudo-inverse method controller, and it was observed that the DLS method achieved better control stability at the singular position and the pseudo-inverse controller had joint vibrations at the singular position [99]. A surface electromyography (sEMG) controller system-based PAM-driven exoskeleton was devel-

oped for human–robot cooperation. A support vector machine approach was implemented to avoid shaking at the joints of the exoskeleton. The developed system achieved better performance, but due to the complicated controller, the computational time increased. The sEMG data acquisition and calculation of joint torque was also complex, and the force model required calibration for every test subject [100].

L. Zhang et al. (2020) developed a hand and wrist rehabilitation device to provide exercise for stroke patients. A 2-SPU/RR configuration parallel mechanism was developed to mimic wrist flexion/extension and radial/ulnar motions. A VICON system and eight infrared cameras were used to record and measure the angular motion of the wrist at a sampling frequency of 1000 FPS [101].

W. Jackson et al. (2021) developed a hand-wearable tremor suppression device for stroke patients suffering from essential tremor (ET) and Parkinson's disease (PD) using a fiber-reinforced bending pneumatic artificial muscle (BPAM). It was designed to be compact and fit along the back of the human fingers. The actuator was capable of producing 40° peak-to-peak amplitudes in the required frequency range of 4–8 Hz. From the experimental studies, it was found that the device could potentially aid in reducing the hand tremor in human fingers [102].

A rehabilitation device requires a mechanism or external source to make a passive device into an active device. As discussed in the previous section and shown in Tables 1 and 2, it is observed that the majority of the rehabilitation devices employ mechanisms such as pneumatic (PAM), mechanism, cable-driven, linkage, and gear-motor-based actuation.

Pneumatic actuation offers significant torque and control for rehabilitation purposes, with a key advantage being its favorable weight-to-torque ratio. However, the main drawback of pneumatic devices is the amount of space they require. Pneumatic systems rely on multiple components, such as compressors, separate chambers, pumps, and additional power sources. While low-weight options are available, pneumatic devices can hinder exoskeleton design and precise control. Additionally, although compressed air functions efficiently in a closed loop, the actuation performed by these devices often has a slow response time. Increasing the rotational speed necessitates higher-cost solutions to achieve better torque and control.

Linkage-based actuation is a popular choice for remote rehabilitation. By using links that are either 3D printed or machined, powered actuation is achieved through linear actuators and various motors. This type of actuation is versatile and can be implemented with a variety of control methods, unlike pneumatic actuation, which is restricted to pneumatic controllers. Combining actuators with a rigid exoskeleton allows for flexion and extension motions. However, linkage-based actuation has a drawback: the motors and the necessary translational linkages can add weight to the system, despite the simplicity of the motion. To achieve a compact design, more expensive actuators might be used, but this comes at the expense of other sensing components that could be crucial for the patient's rehabilitation. Additionally, the inclusion of linkages complicates the kinematics of the exoskeleton. Unlike other actuation mechanisms, the kinematics of linkage-based systems are significantly affected by changes in the dimensions. For example, with pneumatic actuation, the kinematics remain constant, but in linkage-based systems, the mass, inertia, and center of gravity of each link can alter the kinematics.

Cable-driven exoskeletons use servo or rotary motors to generate sufficient torque for hand rehabilitation. One of the key benefits of cable-driven systems is the incorporation of soft exoskeletons to frame the device. This design allows for adaptability to different shapes and sizes, offering a customizable fit for each patient. However, a significant drawback of cable-driven systems is the loss of control and efficiency. The reliance on cables for actuation leads to transmission losses during exercises. Additionally, cable-driven systems are susceptible to friction losses because the cable relies on a spool to release and retract. Consequently, maintaining precise control becomes challenging. These exoskeletons can become bulky due to the complexity of the mechanisms needed for complete actuation and

control. The variable positioning of the cable in adjustable designs necessitates multiple control methods beyond simple position control.

Gear-motor actuation mechanisms involve the translation of power and motion using gear motors or gear trains. However, this approach tends to be costly and challenging to implement. Actuating with gear motors requires multiple gears and gear trains, which significantly increases the expense. Additionally, gear-motor actuation faces similar weight challenges as linkage-based actuation, with both requiring heavy components to ensure safety and security comparable to that provided by pneumatic actuation.

In summary, the wearable assistive mechanisms for upper-limb rehabilitation devices offer diverse solutions for enhancing patient recovery. Pneumatic actuators provide significant torque, while linkage-based mechanisms offer versatility. Cable-driven systems provide customizable fits, and gear-motor actuation ensures precise control. Each mechanism presents unique advantages and challenges, catering to specific rehabilitation needs. By understanding these differences, researchers and practitioners can make informed decisions to optimize patient outcomes and improve rehabilitation effectiveness. Continued advancements in these technologies hold promise for enhancing the quality of life of individuals with upper-limb dysfunctions.

### *2.4. Intelligent Systems in Sensor-Integrated Wearable Rehabilitation Assistive Devices*

Sensor-integrated wearable rehabilitation assistive devices generate enormous and crucial data on the patient's movement characteristics. The examiner needs to understand the sensor data for different human motions or activities. As the data are huge and complex, analyzing or interpreting the data is an impossible task, which requires an intelligent system to compute the data. The use of intelligent systems such as back propagation (BP) neural networks [103], convolution neural networks (CNNs), artificial neural networks (ANNs) [104], machine-learning algorithms (MLAs), and deep-learning algorithms (DLAs) are recognized as the best techniques to assess the patient's performance. The ANNs and other learning algorithms consist of input and output layers along with multiple hidden layers, and the layers have multiple neurons associated with weights. This method minimizes the errors and generates accurate predictions by undergoing numerous iterations and adjusted by training algorithm [105–109].

Qingcong Wu et al. (2019) proposed a neural network-enhanced torque estimation controller (NNETEC) for a wearable elbow exoskeleton. Feedback signals from the sensors are fused with the neural networks to enhance the accuracy of the joint torques for the proposed exoskeleton. The proposed neural network has five layers. The sEMG sensor raw data are provided as an input for the initial layer, the three hidden layers are weight derivatives of the nodes with respect to time, and the fifth is an output layer. For the sigmoid and mean square loss function, the updated weight of the neurons is performed using the gradient descent optimization strategy and the backpropagation algorithm is implemented in the neural network [110].

M. Iosa et al. (2021) proposed and implemented a feedforward neural network (FFNN) based on multiple layer perceptrons (MLPs). Using this ANN procedure, gait data produced by the stroke patients with the wearable device are analyzed. In this method, 17 Inertial Measurement Unit (IMU) sensor data are entered as an input, and two layers with 5 elements are considered for the network module for analyzing the IMU data. The proposed FFNN is compared with the forward stepwise logistic regression (FSLR) and it is found that the FFNN accuracy for the ROM is 99.6%, whereas in the case of the FSLR for the same data, it is found to be 75.8% [111].

Zaroug et al. (2020) studied and investigated the kinematics of the lower-limb trajectory for walking motion using long short-term memory (LSTM) neural networks. A total of 2665 strides from 6 participants are collected and the strides of 5 participants are compared with the sixth participant's walking stride data. The 3D position and force data are collected using Visual 3D using a low-pass digital filter to avoid repeated data. A recurrent neural network (RNN) along with MLPs and feedforward hidden layers are implemented in this

method. As the data are initially processed through the RNNs, the data are processed again in the LSTM. Each LSTM cell consists of three gates (input, forget, and output), where the forget gate chooses which information needs to be processed or omitted from the cell for further processing. Based on the prediction, it is found that this approach achieved a 0.98 correlation coefficient [112]. S.Y. Tang et al. conducted similar research using LSTM, RNNs, and the feedforward technique. Based on the study, it is observed that the neural network achieved above 80% accuracy for the walking patterns in Parkinson's disease patients [113].

G. Yang et al. (2017) developed an IoT-based wearable smart armband for hand stroke patients. The smart armband consists of sEMG sensors to record the hand motion data of the patient. The sensor data are analyzed using MLAs for different hand motions (nine hand gestures). Based on the experimental study, it is found that the algorithm successfully predicts the patient hand gestures and achieves 96.2% accuracy [114]. S. Mekruksavanich and A. Jitpattanakul focused on identifying human activity based on the exercise performed by the patient. A smart wearable armband (MYO) was used to record and collect exercise data of the patient, and the collected data were evaluated using the Waikato Environment for Knowledge Analysis (WEKA) machine-learning tool along with decision tree (DT) and MLP classifiers to process the data. A comparison study was conducted between these classifiers and it was found that the MLP achieved 99.97% accuracy for the provided gait input, whereas DT achieved 99.0% accuracy [115].

E. Kańtoch's (2017) research focused on classifying gait activities such as the sitting, standing, walking, and exercise squatting positions of the user. An ML neural network classification technique was implemented to process the sensor data. A sixth-order Butterworth filter was used for filtering the data. Based on the experimental study, it was found that the proposed technique classified the various gait activities at an accuracy level of 82% [116]. H.C. Siu et al. (2021) proposed a neural network method to estimate or predict the joint torque produced for various human lower-limb motions. The gait patterns were recorded using body markers and a Vicon Motion capture system. The sensor data were processed using fully connected feedforward, LSTM, and CNN neural networks to map the ankle position and orientation [117]. C. Lin et al. (2021) studied and predicted nine foot gestures using the CNN approach, and each CNN layer was connected to the ReLU non-linearity layer. The proposed technique recognized the foot gestures at an accuracy level of 93.98%, meaning that the obtained accuracy level was 11% higher than the standard methods [118]. H.M.C.M.B. Herath et al. (2021) controlled a 2-DoF upper-limb rehabilitation device using voice control. The MLA (LSTM) approach was implemented to recognize various voice commands. Based on the experimental study, a comparison was conducted with existing techniques and it was found that the proposed approach obtained 99.5% accuracy, whereas the support vector machine (SVM) and naïve Bayes approach obtained 98% and 94% accuracy, respectively [119].

H. Zhang et al. (2020) analyzed the gait for walking and running movements using a machine-learning approach. In this approach, there were two methods: (i) subject-specific (10-fold cross-validation) and (ii) generic (leave-one-out cross-validation), as implemented to predict the accuracy and precision of the user movements. For both methods, LASSO and support vector regression (SVR) models were used to train the data separately. Based on the study, it was found that the SVR models produced better accuracy irrespective of the type of data and approach [120].

A. Hua et al. (2020) monitored and analyzed the joint angles for upper-limb home-based exercise by the patient using wearable IMU sensors. A random forest classifier was implemented to predict the accuracy of the user exercise and it was found that the classifier obtained 98.6% accuracy when compared to the other classifiers. MLP obtained 95.7% and the K-nearest neighbor approach obtained 97.4% [121]. M. Panwar et al. (2019) presented a deep-learning approach based on a CNN for semi-natural and natural arm movements. Based on the study, it was found that the proposed framework achieved 97.89% accuracy for semi-natural and 88.87% accuracy for natural arm movements, whereas the accuracy of

the natural arm movement for the linear discriminant analysis (LDA) and SVM approaches achieved 26.17% and 19.57%, respectively [122].

C. Fang et al. (2020) collected and analyzed the ground reaction force with the help of EMG sensors. The sensor data were analyzed using a machine-learning technique, SVM. The proposed technique predicted the walking movements of 10 subjects with an accuracy of 96.38% [123]. Ibrahim et al. (2021) implemented a one-dimensional convolutional multilayer perceptron model (1D-CNN-MLP) to predict tremors in Parkinson's disease patients. The proposed model achieved an overall accuracy of 99.2% with a minimum processing time of 1.5 ms for 100 steps [124]. H. Ri et al. (2018) proposed a feedforward neural network (fast artificial neural network (FANN) library) and the neural network was trained using the resilient back propagation (RPROP) algorithm for predicting the muscle strength for various hand exercises with and without weights. Based on the experimental study, the proposed neural network approach achieved an overall accuracy of 78% [125]. P.F. Xu et al. (2021) studied hand kinematics using the CNN approach. The proposed neural network was developed based on Alexnet and a rectified linear unit (ReLU), and it obtained 98.79% accuracy [126]. H. De Cannière et al. (2020) studied and implemented a machine-learning approach t-distributed stochastic neighboring embedding (t-SNE) technique to monitor the wearable sensor data of cardiovascular disease patients [127].

The integration of intelligent systems such as neural networks and machine-learning algorithms in wearable rehabilitation assistive devices has revolutionized the analysis of patient movement data. These systems offer precise and accurate assessments of various human motions, enabling tailored rehabilitation programs for individuals with different needs. From enhancing torque estimation in elbow exoskeletons to predicting joint angles and recognizing hand gestures, the application of these technologies holds immense potential to improve patient outcomes. As research continues to evolve in this field, we can anticipate further advancements in wearable technology, ultimately leading to more effective and personalized rehabilitation strategies.

### *2.5. AR/VR in Wearable Assistive Rehabilitation Devices*

Robotic rehabilitation and virtual reality (VR) devices have gathered growing interest in the rehabilitation community due to their versatile applications in aiding patients' physical recovery processes. Robot-assisted rehabilitation has demonstrated promising outcomes, primarily attributed to its ability to offer intensive, repetitive, and task-oriented activities. These activities are instrumental in treating motor impairments stemming from a variety of neurological and musculoskeletal conditions.

Alberto Topini et al. (2022) integrated VR technology with the hand exoskeleton and developed a digital twin for mimicking the actual hand motions using the Webots framework. Two different control strategies (classical (C-AC) and variable (V-AC) admittance control) were implemented to analyze the VR environment and it was observed that the V-AC changed the model parameters according to the inputs from the user when compared to the C-AC model. This approach led to checking the overall consistency of the physical exoskeleton and the VR visual feedback over the therapy [128].

Similarly to robotics, virtual reality (VR) is recognized as an emerging tool in the field of rehabilitation, representing a trending and widely accessible technology for treating various medical conditions. VR can be described as a system based on computer-simulated 3D environments that allow users to navigate through and interact with them by integrating auditory, visual, and haptic feedback. Consequently, VR possesses three key characteristics: immersion, presence, and interactivity. Immersion refers to the extent to which VR can provide multisensory stimuli originating from the virtual environment (VE), along with a high degree of correspondence between the user's actions and the cues generated by the system. As a result, immersion in and interactivity with VEs significantly influence a patient's experience and perception, thereby affecting their sense of presence. Despite these distinctions, the incorporation of both robotics and VR into rehabilitation programs entails

higher costs compared to conventional treatments, rendering research in this area more expensive [129,130].

Based on a study conducted among subacute stroke patients, it is observed that VR demonstrates significant improvement in motor function among patients with subacute stroke compared to their pre-intervention state. However, in comparison to conventional therapy (CT), there is only mild to no significant enhancement in motor function observed. Consequently, VR can serve as a supplementary tool to CT in the rehabilitation process for restoring motor function in affected limbs [131].

The integration of augmented reality (AR) and virtual reality (VR) technologies into wearable assistive rehabilitation devices presents a promising frontier in rehabilitation. Through innovative approaches like digital twins and variable admittance control, researchers are enhancing the consistency and effectiveness of rehabilitation interventions. VR's immersive and interactive nature offers significant potential for improving motor function in stroke patients and other conditions. While cost remains a consideration, the benefits of AR/VR technologies as supplementary tools to conventional therapy are evident, pointing toward a future where these advancements play a vital role in optimizing rehabilitation outcomes.

## 3. Conclusions

This article provides a comprehensive review of existing research on wearable assistive devices for rehabilitation, focusing on various body parts, such as the head/neck, ankle, arm, elbow, and wrist. It emphasizes the need for practical implementation in clinical settings, highlighting the challenges and areas for improvement. Future research directions include exploring advanced control systems and algorithms for improved device performance, integrating artificial intelligence (AI) techniques for personalized rehabilitation, addressing challenges in terms of user acceptance, security, ethics, and data management, and reducing manufacturing costs to enhance device accessibility. These advancements aim to make wearable assistive technologies a preferred choice for rehabilitation, offering enhanced functionality and usability in both clinical and personal settings.

One major concern is the weight of wearable assistive devices, and this article suggests the use of compact electric linear actuators, shape memory alloy actuators (SMAs), and pneumatic artificial muscle actuators (PAMs) to create lightweight and portable mechanisms. This approach aims to enhance the comfort and safety of the devices, making them more suitable for prolonged use by patients.

Another challenge addressed is the prevalence of wired connections in current wearable devices, leading to potential issues in the case of defective wires. This article also suggests the integration of safe wireless technology to facilitate communication between the device and external systems. This not only improves the reliability of the devices but also allows patients to wear them more frequently and engage socially in public settings.

This article also highlights the importance of advanced intention detection and control systems. The current limitations of control systems and basic algorithms may hinder the performance of wearable assistive devices, particularly under load conditions. The proposal is to implement high-end control systems with sophisticated algorithms to process captured data efficiently, ensuring a prompt response from the system.

There is a growing belief that the integration of wearable technologies in healthcare could lead to enhanced patient care quality and reduced overall healthcare costs, particularly in areas like patient rehabilitation outside traditional hospital settings. The substantial amount of big data generated by these wearable devices presents both challenges and opportunities for researchers. Future endeavors may involve applying artificial intelligence (AI) techniques to analyze and derive insights from this wealth of data. Despite the promising potential, it is crucial to acknowledge that many wearable technologies are still in their prototype stages. Addressing issues such as user acceptance, security, ethics, and the effective management of big data remains imperative to improve the usability and functionality of these devices for practical healthcare applications.

Furthermore, this article acknowledges the limited adoption of wearable assistive technologies in clinical and personal settings, attributing this to the high manufacturing and assembling costs. It suggests that addressing these cost-related challenges could make wearable assistive devices a more attractive option for patients compared to conventional rehabilitation therapies.

In conclusion, by addressing the outlined challenges in developing wearable assistive devices, this article suggests that these devices could become a preferred choice for rehabilitation purposes. The incorporation of lightweight materials, wireless communication, advanced control systems, and cost-effective manufacturing may contribute to the increased adoption of wearable assistive technologies in both clinical and personal settings.

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