



Review

# A Survey of Robots in Healthcare

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**Abstract:** In recent years, with the current advancements in Robotics and Artificial Intelligence (AI), robots have the potential to support the field of healthcare. Robotic systems are often introduced in the care of the elderly, children, and persons with disabilities, in hospitals, in rehabilitation and walking assistance, and other healthcare situations. In this survey paper, the recent advances in robotic technology applied in the healthcare domain are discussed. The paper provides detailed information about state-of-the-art research in care, hospital, assistive, rehabilitation, and walking assisting robots. The paper also discusses the open challenges healthcare robots face to be integrated into our society.

**Keywords:** healthcare; robotics; care robots; nursing robots; hospital robots; assistive robots; rehabilitation robots; walking assisting robots



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## 1. Introduction

An aging population presents a growing challenge in our society. Worldwide, it has been projected that 21.1% of the population will be above the age of 60 years by 2050 [1]. Sander et al. [1] summarized three main challenges of a rapidly aging population: “the biological challenge is to retain a high level of physical and mental capacity in late stages of life; the social challenge is to optimize the retirement age and the cultural challenge is to provide older individuals with the opportunity to live with purpose and dignity”. To address these challenges, the need for healthcare workers and caregivers is particularly important. However, there is a caregiver shortage in hospitals, nursing and rehabilitation centers, and assisted living communities [2]. This shortage does not influence only the elderly and their families but everyone who is in need of physical or mental care, and even influences the healthcare workers themselves. A study conducted on 53,846 nurses from six countries showed a relationship between nurse burnout and ratings of care quality [3]. Burnout is a widespread phenomenon described by a decrease in worker’s energy, emotional exhaustion, lack of motivation, and feelings of frustration, all of which can lead to a decrease in work efficacy and productivity. The physical and mental well-being of healthcare personnel is connected to safe and high-quality healthcare [4].

In recent years, with the advancements in Robotics and Artificial Intelligence (AI), robots have the potential to support and assist humans in a variety of environments, such as homes [5,6], workplaces [7,8], schools [9], and more. One application of robots is in healthcare and this is not a new concept. The first documented use of a robot-assisted surgical procedure occurred in 1985 when a robotic arm interfaced with a Computerized Tomography (CT) scanner was used for a CT-guided brain tumor biopsy [10]. Since then, technology has rapidly progressed impacting positively the capabilities of robots.

This survey paper provides an overview of nonsurgical robots used to support healthcare workers, such as nurses, caregivers, and therapists. This article has the following aims:

(i) present the recent state-of-the-art in this field and (ii) identify the open challenges and future research directions. In this paper, robots have been grouped into the following five categories; hospital, care, assistive, rehabilitation, and walking-assistant robots. For each category of robots, the most recent work is presented and analyzed, both for commercially available and research robots. The purpose of this review is to present the effectiveness of the available healthcare robots, to address the open challenges they face, and to discuss the future of robotic technology in healthcare. This article seeks to answer the following questions:

1. What research has been performed towards developing robotics for healthcare?
2. How commercially available robots are used in healthcare?
3. What are the challenges the robots are facing in the -world environments?

These questions guide us to identify the current technology readiness level of healthcare robots and to identify the potential future research and development needed to integrate robots into human-centric environments. The paper is organized as follows: Section 2 discusses care robots, Section 3 presents the recent advances in hospital robots, Section 4 discusses assistive robots, and Sections 5 and 6 describe the advances in rehabilitation and walking assisting robots, respectively. Section 7 discusses the open challenges for robots in healthcare and concludes the paper.

## 2. Methodology

The selection of the papers consisted of three steps: (i) initial search in digital libraries, (ii) filtering based on defined criteria, and (iii) the final selection of research papers. In the first step, a systematic search of IEEE Explore, ACM Digital Library, ScienceDirect, and Google Scholar were performed to identify research papers that discuss robotic systems in healthcare. These databases were selected as they include a collection of indexed publications, conference proceedings, and journals associated with robotics and they are accessible within the library of the University of Texas at Arlington (UTA). The search was restricted to publications in English between the years 2015 and 2020. These databases were searched using the following search terms: robot or robotic system combined in all possible ways with the words health, care, assistance, rehabilitation, or healthcare. Several robotic platforms were discussed in more than one paper. After removing duplicates, the initial list included 105 robotic platforms.

In the second step, this list of potentially relevant articles was reviewed by the authors based to the following criteria: (1) the robotic platform should not be a surgical robot, (2) the physical prototype of the robot exists, and (2) an evaluation with at least one human subject has been conducted. The final set of 30 robotic platforms were selected, which were categorized according to their application. Some robotic platforms were presented in more than one category. Moreover, the COVID-19 pandemic [11] accelerated research in hospital robotic platforms [12]. Therefore, online news were also searched to ensure the latest robotic systems are included in this survey. Eight robotic platforms were added to the final set. The final number of robotic platforms discussed in this paper is 38.

## 3. Care Robots

As is discussed by Wynsberghe [13], one cannot define exclusively the characteristics of a Care Robot, as a robot can be named as such only by the way it is used, i.e., for providing or assisting people in the process of patient care. Thus, this obscure definition can include a variety of robots in this category with different hardware specifications and capabilities. The vast majority of applications and surveys of Care Robots [14–21] are oriented towards monitoring and assisting older adults both mentally (reminding, supporting emotionally, motivating, etc.) and physically (handing over objects, delivering items or assisting in dining) or diagnosing and assisting in the education of children with mental disorders, such as autism.

Pepper [22] and Nao from Softbank Robotics (formerly Aldebaran Robotics) are social robots with a potential application in care [23]. Pepper in Figure 1 is a four-foot semi-

humanoid robot with a wheeled base (instead of legs) on which sonar, laser, and bumper sensors are mounted. There is a 10.1-inch touch display on its torso, and it has a total of twenty Degrees of Freedom (DOF), including six DOF for each hand, two each for the head and hips, one in the knees, and three in the base. The head hosts two RGB cameras, a depth camera, a microphone, and a tactile sensor to perceive the world, and two speakers where the ears would be on a human. A six-axis Inertial Measurement Unit (IMU) in the base and two tactile sensors on its hands conclude the sensors Pepper is equipped with. Pepper has been deployed successfully as a teaching assistant for children [24], as a companion for elderly people [25], and as a coach to guide elderly people with psychiatric disorders through rehabilitation recreational activities [26]. Recently, Carros et al. [27] employed Pepper in a group setting scenario in an institutional care facility with older adults for ten weeks and twenty sessions. The finding shows that the older adults enjoyed the robotic interaction and their engagement was high during the sessions. However, the study participants made it clear that they do not want robots to replace caregivers. Moreover, for all participants, it was not always easy to understand what the robot was doing. There were also some malfunctions of the robot, for example, robot applications did not load in the intended timeframe, or the touchscreen sensitivity was unsatisfactory.



Figure 1. Pepper robot [28].

Another interactive robotic system is PHAROS [21,29,30], which is designed to help the elderly by suggesting and monitoring their daily physical activities at home. It consists of a three-fold architectural arrangement that exploits the vision capabilities of Pepper using Deep Learning (DL) techniques. In particular, the robot records subjects while exercising and produces data that is afterward fed to a system that recognizes the type of exercise being performed and generates a sequence of exercises encapsulated in each user's daily schedule. Another characteristic of assistive importance is that PHAROS provides verbal commentary as well as visual demonstrations geared towards assisting the user to comprehend the proposed exercise. The overall performance of the PHAROS system still has to be strictly evaluated without the presence of a therapist/supervisor. Figure 2 shows a photo of the PHAROS robotic system being evaluated in a care home.



**Figure 2.** PHAROS robotic system in a pilot study in a care home [30].

Nao, shown in Figure 3, is a 22.8-inch humanoid robot and the latest version (6th generation) has twenty-five DOF, with eleven of them in the legs and pelvis and the rest in the upper body, similar to the upper body DOF of Pepper. Nao has two RGB cameras, nine tactile sensors on its head and in its hands, four microphones, a sonar range finder, two infrared emitters and receivers, one inertial board, and eight pressure sensors. Both robots use the NAOqi operating system, which is open-source and supports many programming languages, including Python and C++. There are numerous applications that these two robots have been used for and many scenarios in which their interactions with humans have been studied. Nao has been deployed as an assistant tutor for autistic children [31], a physiotherapeutic assistive trainer for the elderly [32], a cognitive trainer [33], and a healthcare assistant [34]. Recently, Qidwai et al. [35] employed NAO in a short study as a teaching assistant for children with autism. The robot was programmed for a number of teaching and therapeutic behaviors, such as singing, exercise, explaining, and playing with children. The participants of the study were fifteen children with autism (ages 7–11) in a school for children with special needs. The findings of the study were very encouraging and show the potential of robots to enhance the learning process for children with autism. One interesting observation from the study was that children who were afraid of the robot from the very beginning did not perform well. In contrast, those who were fascinated by the robot from the beginning performed the same activities easily and fluently. The authors did not discuss any technical issues that may encounter with the robot. However, they mention that the cost of the robot is an obstacle for its more frequent use by more children.



**Figure 3.** Nao robot [36].



Zorabots [37] provides a universal software, called ZBOS, that bridges commercially available robots with a platform-specific implementation for each robot. The range of robotic platforms they support is wide, varying between android, mascot, mechanical and non-humanoid robots [21]. Some of the robotic platforms that Zorabots supports are Pepper, Nao, JAMES (Figure 4), and others. Therefore, there are a plethora of different configurations and resulting DOF values, depending on the robotic platform that is under consideration. In [38] the use of Nao is considered a robotic platform for therapeutic and educational purposes for rehabilitation and special education in children with severe physical disabilities. After a series of intervention sessions using Zorabots' Nao (Zora Nao for short), its high contribution was observed in achieving patients' goals as set by professionals regarding their movement and communication skills, and there was evidence of positive impact in cognitive skills and attention. The value of Zora Nao was also confirmed in a two-year study in fourteen nursing care organizations [39], where the role of the care robot was to offer pleasure and entertainment or to stimulate the physical activities of clients in residential care. In the first year of the study, the goal was to monitor and evaluate how the Zora Nao robot is used daily. In the second year, the focus was on evaluating whether the use of Zora Nao robots by care professionals can be extended to other groups. For the evaluation of the robot, the authors collected data through interviews, questionnaires, and observations. Several care professionals experienced several barriers while using the robot. For example, long start-up time, software failures, short battery life, and misunderstanding in speech recognition were some of the barriers mentioned.



Figure 4. James Robot [40].

Care-O-Bot 4 [41] is a service robot from Fraunhofer that is capable of working in numerous scenarios and taking multiple roles, including serving as a mobile information center, an item collection and delivery tool, and a security or surveillance tool. It can also serve as a research platform due to its open-source software interfaces. It consists of an omnidirectional platform, a torso above which a sensor ring is placed, and a head that includes a touch screen, as shown in Figure 5. It has also the option to include zero to two arms with grippers. Each arm has seven DOF and each gripper has two, while the torso and the head can have either one or three DOF each, with the latter option providing 360 degrees of rotation. The most important feature of Care-O-Bot 4 is its hardware modularity and its agility, due to the spherical joints it utilizes. These features in combination with its facial expressions and speech, facial and gesture recognition, can potentially communicate different social moods to the users and thus forms a research platform for Human–Robot Interaction (HRI) scenarios. Care-O-Bot 4 has been used successfully as a human helper in a series of electronics retail stores and a museum in Germany [42,43] as a receptionist

that greets and directs customers, but to our knowledge, there is no evaluation study of its use as a caregiver. Its predecessor, Care-O-Bot 3 [44] was evaluated as a caregiver robot in two practical evaluations of one week each in a senior care facility [45]. Care-O-Bot 3 was used to bring water from a water cooler to the inhabitants and the inhabitants could play the game “memory” on the robot’s tray. The overall experience of the personnel and the inhabitants of the care facility towards the robot was very positive. However, the main challenge for the robot during the delivery of water was the identification of the person under poor lighting conditions and approaching them in a crowded sitting room with several obstacles, such as chairs and walkers.



Figure 5. Care-O-bot 4 [46].

Lio [47] is another Care Robot developed by F&P Robotics, that has been tested in nursing and retirement facilities, as well as for support at home. It consists of a four-wheeled mobile base, on which there is mounted a P-Rob 3 [48] collaborative robotic arm with six DOF and a payload weighing three to five kilograms. The base is equipped with two RGB-D cameras and a wide fish-eye camera, two LiDARs, ultrasonic distance sensors, and infrared sensors for floor detection. There are also different holders (for bottles, cups, etc.), a screen, and speakers and omnidirectional microphones on the base, as shown in Figure 6. Utilizing the aforementioned sensors in combination with state-of-the-art mapping, localization, and perception algorithms, Lio can navigate freely in any wheelchair-accessible room, recognize and greet people, identify objects, and receive voice commands. The default gripper on Lio’s arm has two DOF and a camera mounted on it, but more options are available, such as vacuum grippers or massage heads. Furthermore, this Care Robot has many features that enhance its safe use while interacting with humans. A compliant motion controller, fully covered in soft artificial leather material, collision detection, and limited speed and force capabilities are the most important of these features. In terms of privacy, Lio’s visual and navigation data are processed by integrated units onboard and the data is anonymized and encoded before being stored. All the above measures enable Lio to comply with ISO13482 standard safety requirements for personal care robots. The use of Lio has already been evaluated in seven different health care institutions in Germany and Switzerland. Lio took different roles throughout each day, varying between delivering items like mail or blood samples, entertaining and motivating patients, and reminding patients of important things by knocking on and opening their doors to access their rooms. In another case, Lio was used at home to support a paraplegic person with everyday tasks, e.g., opening and handing over bottles or assisting the person with taking off a jacket for several weeks. Its functionality was hybrid, with some tasks being carried out exclusively autonomously and other tasks with the control of the person.



Figure 6. Lio [49].

Hobbit [50] (Figure 7), another care robot system designed for older adults, sets as its main goals the detection and prevention of potential falls, as well as the proper handling of emergency situations. It consists of a robotic platform equipped with a five-DOF robotic arm and a gripper that can grasp objects of various shapes and structures. Regarding its vision scheme, it has two cameras, a floor-parallel depth camera, and an RGB-Depth camera (Microsoft Kinect), which facilitate the tasks of self-localization, obstacle detection (juxtaposed with the use of eight ultrasound distance sensors), grasping and human-robot interaction. Before executing any of its tasks, Hobbit's operation relies heavily on the success and precision of the following systems: Navigation, Human-Detection and Tracking, Gesture Recognition, Grasping, and Object Learning and Recognition. Subsequently, Hobbit is able to achieve an array of actions such as "Call Hobbit", cleaning the floor from objects, learn/bring new objects to the user, and recognize a user's instability. Having been tested in a controlled environment, Hobbit's functionality was characterized as understandable and straightforward by the primary users involved.



Figure 7. The Hobbit robot [21].

We will next cover the RAMCIP [51] robot (Robotic Assistant for patients with Mild Cognitive Impairment). RAMCIP [52] is a project intended to provide home assistance to the elderly. With regards to the hardware integrated, the system encompasses a two-DOF Mobile Platform, an elevation mechanism, a nine-DOF hand with a two-DOF wrist, and a

five-DOF arm manipulator, a two-DOF head with a mounted display, an Augmented Reality (AR) module, and finally a perception scheme of one RGB-Depth camera and two laser scanners. Furthermore, RAMCIP robot's main axes of operation are the following: (1) the development of cognitive functions based on each subject along with modeling and monitoring of his/her home environment while the robot is responsible for the type of assistance to be selected, (2) the formulation of human-robot communication interfaces, focused on empathic communication and AR displays, and (3) the need for ensuring safety and dexterity with respect to the manipulator's motion, since the robot interacts directly with the user. Hence, the robot is engaged in actions such as potential emergencies related to a user's fall, turning off electric appliances, etc., and improving the user's daily activities by aiding with delivering medication, picking up fallen objects, and so on. The robot was assessed in home environments, and although there were cases of uncertainty and skepticism by some users, it managed to accomplish all of its target tasks while successfully interacting with the subjects.

Kosecki et al. [53] describe the development of a telepresence robot system that assists the elderly in daily living activities and can support professional caregivers as well. The hardware incorporated is comprised of a mobile robot base, a main body equipped with a linear actuator and a robot manipulator, and a 10-inch tablet with an integrated camera, which serves as the robot's head. Specifically, the manipulator carries a two-DOF end-effector for grasping and holding a specially designed proprietary sensor that receives input from electroencephalogram (EEG) sensors, as well as temperature and respiration rate data. The architecture proposed acts in a shared control fashion. In particular, the operator (high-level) commands the robot (low-level) while simultaneously giving the latter the obligation to accomplish the task successfully. Hence, the robot receives orders in two ways; either by being given a general direction of movement or by following a series of ordered primitives such as "TakeVitalSignsSensor, WallFollowing, DoorPassing", etc. The study was performed in a senior care home with thirty-five participants, five of them being professional caregivers. They were instructed on how to operate the robot (motion, manipulation, grasping, etc.). Experiments conducted included procedures such as driving the robot, using the manipulator, and responding to the robot's reminders to take medication. Results showed that the participants considered the telepresence robot's performance as acceptable and highlighted their eagerness to use such systems for both social and medical purposes.

#### 4. Hospital Robots

Recently, the industry has shown a growing interest in developing robots to assist nurses in hospitals and clinics. The robotic nursing assistants are designed to function under the direct control of nurses. A robotic nursing assistant will act as a teammate, helping nurses by performing non-critical tasks, such as fetching supplies, giving nurses more time to focus on critical tasks, such as caring for patients. Moreover, the COVID-19 pandemic showed how vulnerable nurses are due to shortages of personal protective equipment [54]. Robots, on the other hand, are not vulnerable to viruses or other microorganisms and they can assist during pandemics.

In recent years, there are a variety of commercially available robots that are currently used in hospitals to help with transportation tasks. One example is Moxi [55] developed by Diligent Robotics, which retrieves and brings supplies to hospital rooms and nursing stations, delivers samples to laboratories, and removes soiled linen bags. Moxi, shown in Figure 8, consists of a mobile base, a seven-DOF robotic arm with a two-finger gripper, and sensors for environmental perception such as a camera and laser scanner. For the last several years, Moxi has been tested in several hospitals around the state of Texas in the USA [56]. Moxi manipulates objects known in advance, and the manipulation is very structured. When Moxi is deployed in a hospital in the beginning, the robot learns the locations of the supply rooms and the locations of where objects need to be delivered. Moxi is able to navigate fully autonomously and safely by avoiding static and dynamic obstacles.



The trials at the Texas hospitals showed that Moxi was accepted not only by the nurses and the clinical staff but also by the patients and their relatives [56]. However, Moxi did not have any physical interactions with patients.



**Figure 8.** The Moxi robot gathering supplies [55].

The robotics company ABB has demonstrated the concept of a dual-arm mobile laboratory robot called YuMi to work alongside medical staff and lab workers [57]. Each robotic arm of YuMi has seven DOF and it is equipped with a two-finger gripper. The Texas Medical Center (TMC) Innovation Institute in Houston evaluates the YuMi robot in a variety of logistic tasks, such as loading and unloading centrifuges, handling liquids, preparing medicines, and picking up and sorting test tubes. The mobile robot TUG [58] by Aethon helps with the delivery of medications, meals, supplies, tests, and waste. TUG does not have any robotic arm, and it relies on the medical staff to load and unload the objects it delivers. Similarly, the mobile robot Relay [59] by Swisslog Healthcare delivers medications, lab samples, and other critical items. TUG and Relay are able to navigate hallways autonomously and deliver objects from point A to point B while avoiding obstacles.

However, there are some nursing robots whose main tasks are to assist patients. In Japan, the RIKEN and Sumitomo Riko Company Limited have developed an experimental nursing robot, called ROBEAR [60], which is capable of lifting a patient from a bed into a wheelchair or helping a patient to stand up. Moreover, Veebot Systems developed a needle insertion robot [61]. The Veebot robot automates drawing blood and inserting Intravenous therapy (IV). The Veebot robot can correctly identify the best vein with an accuracy of 83 percent [61]. Furthermore, the social robot Pepper [62] by SoftBank Robotics has been used in several roles in healthcare, such as acting as receptionists in hospitals, conducting survey research on patient satisfaction, and supporting staff in health monitoring [23].

Das et al. [63] proposed a sitter robot in a hospital environment that can monitor patient vital signs, carry out conversational interactions with a patient, and inform the nurse if abnormal patient conditions are detected. The authors developed a mobile app to augment the verbal commands given to a robot through natural speech, camera, and other native interfaces. The app enables the robot to assist the patient with decision-making during pick and place tasks, monitor the patient's health over time, and communicate with the patient during sitting sessions. In the recent work of Das [64], an Adaptive Robotic Nursing Assistant (ARNA) is presented. ARNA is a multipurpose robot that helps nurses with day-to-day tasks, such as walking patients, fetching objects, and monitoring patients' health. ARNA was deployed and evaluated in a hospital environment at the School of Nursing at the University of Louisville in Kentucky. Healthcare professionals were involved in the evaluation of ARNA. Several metrics including completion time and rate and level of user satisfaction were collected, and the results indicate an overall positive response towards the use of a nursing robot. Moreover, ARNA was evaluated on

a cohort trial with 24 human subjects and results of this preliminary user study indicate good usefulness and ease of use of the essential user sitter and walker characteristics of the robot [65]. Recently, the Fraunhofer Institute for Manufacturing Engineering and Automation developed a prototype robot, called DeKonBot, which consists of a mobile base and a robotic arm. Its main task is to disinfect potentially contaminated surfaces, such as door handles or elevator buttons [66]. However, both research platforms are still in the development phase and have only been evaluated in laboratory settings.

## 5. Assistive Robots

People with paralysis have difficulties performing Activities of Daily Living (ADLs) or working. In 2013, nearly 5.4 million people in the U.S (1.7% of the U.S. population) were living with paralysis [67]. Stroke was the leading cause of paralysis, followed by Spinal Cord Injury (SCI), Multiple Sclerosis (MS), and Cerebral Palsy (CP) [67]. In recent years, with the advancements in robotics and Artificial Intelligence (AI), assistive robots have the potential to provide care and support ADLs at home or at the workplace. In this paper, we define assistive robots as robots that assist people with disabilities.

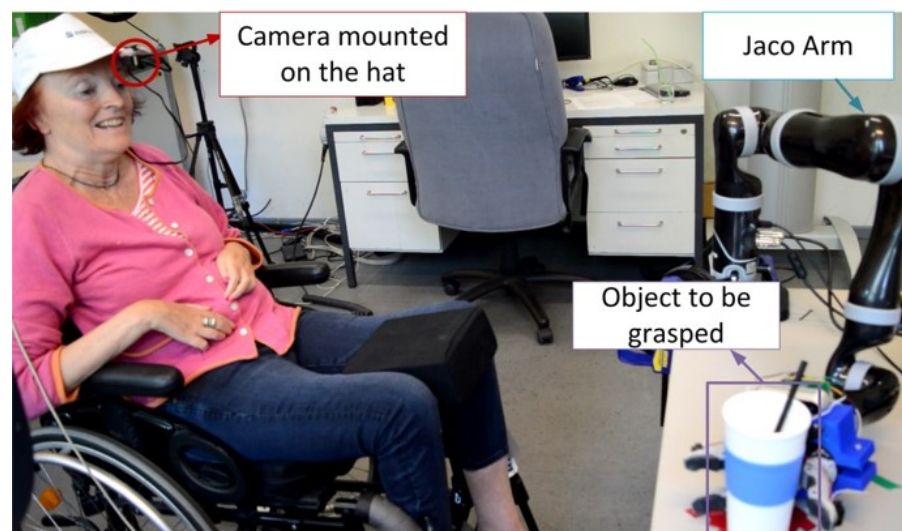
Various assistive robotic systems have been developed based on a Wheelchair Mounted Robotic Arm (WARM). One example of an assistive robotic system is the FRIEND system, which is an intelligent wheelchair-mounted manipulator [68,69]. The FRIEND has passed through four generations; the first generations were focused on assisting people with quadriplegia with ADLs, such as drinking and eating, while the fourth generation of FRIEND focused on supporting these individuals in real-world environments. The FRIEND IV [68] consists of a wheelchair platform, a seven-DOF robotic arm equipped with a two-finger gripper and a hand camera, a chin joystick and head control interface, a stereo-camera and a laser scanner. The FRIEND IV supported an individual with quadriplegia (end-user) while the individual was working as a librarian retrospectively cataloging collections of old books. The robotic system was responsible for autonomously recognizing and manipulating the books, placing them in a specially designed book holder. The cataloging of the books was done by the end-user using speech recognition. Moreover, whenever there was a failure of the autonomous book manipulation, the end-user was able to take control using an advanced Human-Machine Interface (HMI). With the end-user's intervention, a success rate of 95% was achieved.

However, most of the focus of assistive robots is to help people perform ADLs. Drinking and eating tasks are considered highly prioritized tasks according to a survey of potential end-users of robotic manipulators [70]. The Jaco 2 robotic arm from Kinova [71] is a commercially assistive robot, which can be used for manipulation tasks by end-users. It has two versions, one with six DOF and one with seven DOF, and it is equipped with a two- or three-finger gripper. The Jaco 2 is widely used in research for assisting with drinking and eating tasks as well as with manipulation tasks. Gordon et al. [72] developed an adaptive robot-assisted feeding system. The system consists of a six-DOF Jaco 2 robotic arm with a two-finger gripper. The gripper grabbed a fork equipped with a force-torque sensor using a 3D-printed custom-built fork holder. The system uses an RGB-Depth camera to identify the food on a plate, and then an online learning framework is developed for successful bite acquisition. However, the algorithms converge after ten failures per food item and all food items are discrete and solid. Bhattacharjee et al. [73] used the same robotic system to explore the preferences of autonomy that users with mobility impairments have in robot-assisted feeding. By evaluating the system with ten users with limited mobility, the authors found that the users did not have a preference between partial or low autonomy when controlling the robotic arm.

Goldau et al. [74] developed a system to autonomously assist people with severe motor impairments during drinking. This work presents a robotic solution to enable independent, straw-less drinking using a smart cup. The seven-DOF Jaco 2 robotic arm with a three-finger gripper was used. An RGB-Depth camera was mounted on the robot's end-effector with a custom 3D-printed holder. The robot arm grasped the smart cup,

which consisted of a beak, two force sensors, and a Bluetooth module that transmitted the force values to the system's computer. The authors developed a vision-based robot control system used to serve a drink, which handled the delivery of the grasped cup to the user's mouth based on camera input, and a robot force control system for the drinking process, which enabled the user to control the process of tilting the cup based on the force s/he applied. Two experimental studies have been conducted with mostly able-bodied participants and one with quadriplegia, and the first results show a high user acceptance rate and positive feedback. Shastha et al. [75] extended the robot force control system for the drinking process by introducing Reinforcement Learning (RL) approaches and by using a smart cup with one force sensor and without a beak. Five of the commonly used RL algorithms were compared to find the best fit for the robotic drinking task, and the system was tested in an experimental study. The preliminary results showed a high degree of acceptance by the participants (mostly able-bodied and one with quadriplegia). However, a user study with several participants suffering from quadriplegia is needed to evaluate the proposed system.

The approaches discussed so far focus on partially autonomous approaches, where the robot autonomously performs the task and the human is in the loop to provide high-level inputs. In recent years, there is research on how to enable users with quadriplegia to directly control the robotic arm by controlling the robot's end-effector in three-dimensional space. Several hands-free methods have been developed to enable direct robot control, such as employing the use of head gestures [76,77], eye trackers [78], or Brain-Machine Interfaces [79]. However, direct robot control is time-consuming. Kyrarini et al. [80] developed a robot learning framework where a person with quadriplegia (end-user) was able to 'teach' a seven-DOF Jaco 2 arm to serve a drink. The end-user was able to control the translation and rotation of the robot's end-effector and the gripper actuation through a state machine and a hands-free Human-Robot Interface. The presented system was evaluated by twelve able-bodied participants and one person suffering from quadriplegia, as shown in Figure 9. The feedback from the end-user was very positive, because she was 'in control', a feeling that she described as essential.



**Figure 9.** The Jaco 2 learns how to serve a drink from a person with quadriplegia via a head gesture-based human-robot interface [80].

Besides drinking and eating tasks, assistive robots have also been used for other ADLs. The Baxter humanoid robot from Rethink Robotics [81] has been used to assist a user with dressing [82]. The proposed robot-assisted dressing system combines a tracking method with hierarchical multitask control to minimize the force between the person and the robot. The experimental results showed that the Baxter robot was able to provide personalized dressing assistance in putting on a sleeveless jacket for users with simulated upper-body

impairments. Jevtic et al. in [83] developed a robotic assistant to help with shoe fitting. The authors utilized Barrett's seven-DOF WAM robotic arm [84] as a robotic assistant and the user-provided verbal instructions to the robot. Additional modalities, such as users' pointing gestures and adjustment of the robot's shoe delivery position, were used to enable a successful shoe fitting process. Other assistive robotic tasks that require a higher degree of direct physical contact between the robot and the human have also been explored, such as beard shaving [85], hair brushing [86], and bathing [87]. However, these robotic tasks are still in a preliminary phase and more research is required to ensure safety and acceptability.

## 6. Rehabilitation Robots

Rehabilitation robots are a special robot type designed primarily for aiding humans with physical impairments during the process of rehabilitation. There are many debilitating motor disability diseases such as stroke, multiple sclerosis, injuries to the head and spinal cord, and spina bifida [88,89]. Physiotherapy helps patients suffering from these infirmities, as mentioned earlier, to regain their natural motor skills to the maximum extent possible. Physiotherapists design a rehabilitation program for their patients where they try to improve their patients' motor skills [90]. Rehabilitation robots can assist physiotherapists during the rehabilitation process. Therapists who use rehabilitation robots can enhance gross motor skills better than conventional therapists. The robots can help patients perform repetitive tasks and collect data from sensors for analysis [91,92]. In that way, the therapist can readjust the rehabilitation process by better recognizing the different intricacies of different patients. In this paper, we divide the rehabilitation robots into two subcategories, upper-limb and lower-limb rehabilitation robots, which focus on helping humans with upper body and lower body impairments, respectively.

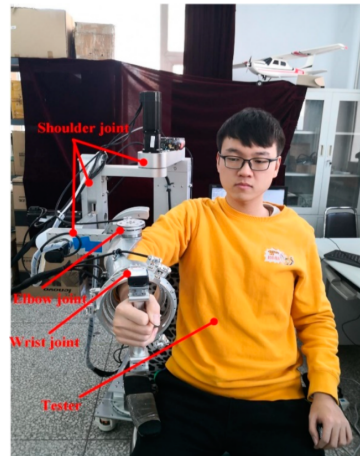
### 6.1. Upper Limb Rehabilitation

With respect to upper limb rehabilitation, there are robotic systems that are designed for various purposes and functionalities such as assisting various upper limb movements and rehabilitation of affected upper limbs due to paralysis caused by various conditions. Many robotic systems and frameworks have been developed mainly for the rehabilitation of upper limbs with disabilities caused by paralysis due to stroke and hemiplegia [93–96]. According to Maciejasz et al. [97], there are robotic systems developed to assist the following types of upper limb joint movements—shoulder movements, elbow movements, forearm movements, wrist movements, and finger movements. The authors also stated that there are robotic systems developed to assist the combination of the previously mentioned movements [97]. There is also research that utilizes different approaches with respect to upper limb rehabilitation robots, such as implementing visual and auditory feedback [98] and computer vision [99] along with robotics. The upper-limb rehabilitation robots are divided into primarily two classes, exoskeletons and end-effector-based rehabilitation robots [100–102].

Exoskeleton robots are a kind of wearable robot that is used to assist and aid humans primarily in movement. With respect to rehabilitation, exoskeleton robots are designed as wearable robotic machines that help a patient with limb impairments in the process of rehabilitation. Rehmat et al. [103] and Zhang et al. [101] stated that the exoskeleton rehabilitation robot has three different kinds of control strategies—a patient-driven strategy (a.k.a. active mode), a robot-driven strategy (a.k.a. passive mode), and a challenging strategy where the robot resists the force applied by the patient. In patient-driven or active mode, the patient performs the movement with the robot acting passive and helping the patient during rehabilitation. Robot-driven or passive mode is the exact opposite of the active mode as the robot performs the movement with the patient being passive during rehabilitation. Under the category of exoskeleton based rehabilitation robots, several forms of implementation have been done to create wearable robots that assist in upper body movement. Bouteraa et al. [104] developed an exoskeleton robot with two degrees of freedom that uses Kinect skeletal tracking for upper limb rehabilitation and specifically

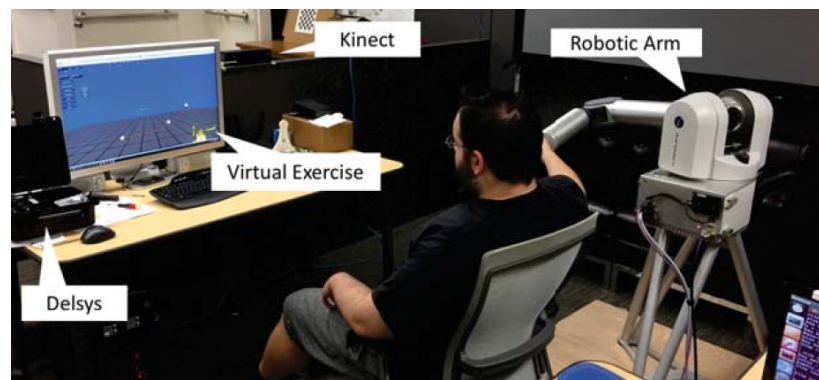


focuses on elbow and forearm movement. Pang et al. [105] developed a tension mechanism for an exoskeleton rehabilitation robot, shown in Figure 10, that utilizes the principle of ensuring minimum driving torque.



**Figure 10.** Wearable upper limb rehabilitation robot with characteristics of the tension mechanism [105].

In end-effector based rehabilitation robots, the work of research ranges from the development of a new robot framework to the implementation and analysis of the rehabilitation robot. Liu et al. [96] developed a two-link end-effector based robotic arm which was tested by using it to perform line and circle tracking tasks for rehabilitation. Ponomarenko et al. [106] designed an end-effector based rehabilitation robot that is electromagnetically powered and has five independent degrees of freedom in the shoulder and elbow joints. There are also several other end-effector based upper body rehabilitation robots, such as MIT MANUS which uses motor drive with impedance control, MIME of Stanford University which uses motor drive with an EMG signal control and force control, and others [101]. Moreover, Barrett Medical has developed a commercially available end-effector based rehabilitation robot called Burt [107]. Burt has multiple therapy modes and enables game-based rehabilitation to engage patients and to increase the number of repetitions reached in therapy sessions. A prior model of Burt Barrett Medical, called the Barrett WAM arm [108], is used in research. It is a robotic arm available in two main configurations, four-DOF and seven-DOF, and it can be controlled by force. The Barrett WAM arm, shown in Figure 11, has been used as a part of systems for game-based upper limb rehabilitation [109–111].



**Figure 11.** Game-based upper-limb robotic rehabilitation [109].

Apart from exoskeleton and end-effector based robots, there are also other forms of implementation with respect to upper-limb rehabilitation robots. Mohamaddan et al. [95] developed an upper limb rehabilitation robot for a home setting that uses an armrest and

a scissors lift mechanism. Ding et al. [98] proposed a robotic arm skate for upper body rehabilitation equipped with a user interface that provides instructions and visual and auditory feedback.

Although there are many research works in developing exoskeleton based rehabilitation robots, many of the exoskeleton robots are either in the prototype stage or have not yet been put up to evaluation with patients [97,101]. In addition to that, Rehmat et al. [103] stated that only a few of the exoskeleton robots have been subjected to clinical trials. While comparing between end-effector and exoskeleton upper body rehabilitation robots, Meng et al. [100] states, both robot types have certain deficiencies such as the end-effector robot having less degree of freedom, and the exoskeleton robot being heavy and not easy to carry. The authors have also stated concerns about improving safety while dealing with such robots and also improving gravity support in robots while patients are continuing recovery [100].

### 6.2. Lower Limb Rehabilitation

This subsection mainly concentrates on Lower Limb Rehabilitation (LLR) robots. LLR robots help rehabilitate the motor skills of human body parts below the waist. One of the many types of LLR robots is an exoskeleton. An LLR exoskeleton is an external skeleton with motors and levers that helps patients with their gait. Over the years, many LLR exoskeletons have been developed. A recent survey by Hobbs and Artemiadis [112] has addressed several LLR robots from 1999 to 2017. In this section, our focus is on recent advances in LLR robotic research.

ReWalk [113,114] is a motorized exoskeleton with an onboard controller and battery within a backpack, a wristwatch style selector where a user can choose between sit, stand and walk options, and tilt sensors to measure the tilt of the patient. The robot also has a pressure sensor to detect ground contact in footplates. The exoskeleton supports the patient's hips and legs through a strap worn around the hips and has frames supporting the upper and lower legs connected by a knee joint, as well as footplates. For extra safety, crutches are also provided. This robot is especially suitable for patients who have intact upper extremity control and only need lower limb rehabilitation. ReWalk is the first exoskeleton to get FDA approval for use within the United States. ReWalk does not offer full body weight support. Hence, this robot cannot be used by patients with limited or no upper extremity control of their bodies.

Lokomat [115] is a robot designed by Hocoma to support full body weight. Patients can use it irrespective of their upper extremity control. Lokomat is a bilateral orthosis robot. The difference between bilateral orthosis and an exoskeleton is that bilateral orthosis can support the patient's full body weight while an exoskeleton does not. Lokomat has a treadmill and an exoskeleton. The treadmill is used for in-place walking, and the exoskeleton is used to support the hip and knee joints and is driven by back drivable actuators. Back drivable here means that the patient can move his/her legs freely without resistive torque. The Lokomat can help patients perform predefined gait rehabilitation tasks that follow a specific trajectory set by the patients' physiotherapists. Apart from this, the Lokomat also has passive foot lifters to help with gait training. Straps (bilateral orthosis) support the exoskeleton for gait training.

Kuzmicheva et al. [116] stated that systems like Rewalk might not help patients with their balance. To overcome that, MOPASS was introduced. MOPASS (Figure 12) has four caster wheels, a main motor, and smaller motors that drive the front two wheels. Similar to ReWalk, there are hip and knee joints for leg movement and an extra DOF at the trunk. This DOF is to facilitate pelvis motion in patients. There are four FlexiForce force sensors placed inside a shoe for fall detection and a pulse oximeter to measure the patient's vital signs. The data from the sensors is sent to the control PC via Bluetooth. Software is provided to analyze the data from the sensors and generate gait trajectories for the patient. MOPASS allows patients to move in both sagittal (such as when walking, running, etc.) and transverse planes (such as during trunk rotation).

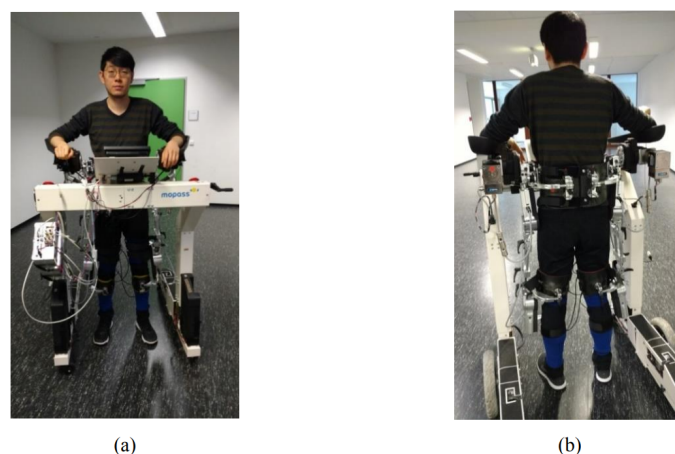


Figure 12. MOPASS gait rehabilitation system from frontal (a) and back (b) sides [117].

Matjacic et al. [118] developed a Balance Assessment Robot for Treadmill walking (BART) that assesses the balancing abilities of a patient during walking. BART consists of a wide instrumented treadmill and an actuated pelvic link with a pelvis brace to deliver perturbing force impulses at the pelvis level during treadmill walking [119]. Evaluation of BART in a study of forty-one post-stroke and forty-three healthy subjects showed that a substantial number of post-stroke subjects had reduced balancing capabilities. Therefore, further rehabilitation for improving their balance is needed.

There are multiple tests to measure the effects of robot rehabilitation on patients in comparison to traditional physiotherapy. Some of these tests include the Timed Up-and-Go Test, the Fatigue Severity Scale (FSS), the Six-Minute Walk Test, and the Berg Balance Score (BBS) to measure balance during the standing and sitting postures of patients. Straudi et al. [120] performed rehabilitation using the Lokomat robot with sixteen subjects. The subjects were divided into two groups of eight, and their Expanded Disability Status Scale (EDSS) was calculated. The first group had an EDSS score of  $5.8 \pm 0.8$ , and the second group had an EDSS score of  $5.7 \pm 0.7$ . The subjects who underwent twelve RAGT sessions had an improvement in their gait speeds (0.07 m/s) and walking endurance measurements (33.2 m), compared to the control group ( $-0.01$  m/s and  $-0.7$  m). Walking endurance is a constant-load exercise test that measures the participant's ability to sustain a given sub-maximal exercise capacity, such as walking in patients' cases. In another recent study conducted by Zheng et al. [121] RAGT using Lokomat had a positive effect on balance, as shown by the BBS score. The mean difference between the scores of patients with RAGT and without RAGT is 4.25. In conclusion, robot-assisted rehabilitation with a physiotherapist's oversight yields better outcomes than traditional physiotherapy.

## 7. Walking Assisting Robots

Walking assistants are designed to help people with limited walking abilities in their everyday lives and to provide additional support in everyday functioning. Depending on the level of disability, different types of walking assistants can be used. For instance, people with complete paralysis due to spinal cord injury or traumatic brain injury can benefit from using an intelligent wheelchair [122,123], whereas people with a weak lower limb due to stroke or accidents may benefit from a wearable exoskeleton that may help in rehabilitation and recovery [124]. There has also been significant research in the development of an intelligent prosthesis for use by amputees [125]. While all these options for walking assistants exist, a separate class for Intelligent Walking Assistants (IWA) was introduced to classify a set of robots that aids persons with moderate upper and lower body strength and patients in a hospital that need support for daily ambulation and walking exercises [126]. The IWAs provide additional support to the users by monitoring their gait, velocity, and intent while fulfilling the basic requirement of traditional walkers like crutches or canes. IWAs are one

of the most commonly researched topics in medical robots. In this section, we will see some of the common approaches to designing a robotic walking assistant.

Traditionally IWA design follows two standard approaches: cane-based walker or walking-frames-based walker. The IWA's standard functionalities are obstacle avoidance and guidance, user intent prediction, user gait estimation, user velocity estimation, and fall detection and prevention. These robotic devices are usually equipped with several sensors, such as force-torque (FT) sensors, Laser Rangefinders (LRF), acoustic sensors, Charge-Coupled Device (CCD) cameras for localization, and RGB-Depth cameras to be able to perform these activities.

Cane-based walking assistants (CWA) closely resemble a cane, and owing to their relatively small size, they are easily usable indoors and outdoors. The CWAs, even though small, provide the required stability for people that are confident enough in their walking and only need little to no support while doing so. Di et al. [127] proposed a novel intelligent cane robot, which consists of an omnidirectional base, a universal joint connecting the cane to the base, an LRF sensor, an FT sensor, and a touch panel. They propose a fall detection and prevention scheme which uses an insole load sensor to be worn by the users inside their shoes. The load sensor data, in combination with the LRF and FT sensor data, can provide an impedance-based fall prevention controller for the robot. The above works do not, however, discuss any user gait estimation techniques for the CWAs.

Yan et al. [128] proposed a different design, where the handle of the CWA is attached to a ball joint to improve human-robot stability during walking and falling/stumbling scenarios. The user must wear a sensor on their torso while using the walker to measure posture for the human-robot system's stability measurement. An LRF at the front is used for obstacle detection and avoidance, and an LRF at the back is used for motion control and fall detection. In their paper, Van Lam and Fujimoto [129] proposed a slim new CWA design consisting of a single omnidirectional wheel. The robotic cane can maintain the user's balance by moving in the appropriate direction of the fall. Here, however, the authors fail to consider important safety features like obstacle avoidance, guidance, and user gait estimation.

Another type of IWA is the Walking-Frame based Walking Assistants (WWA), as shown in Figure 13, which closely resembles a four-legged walker and provides more stability and support. These walkers are usually large and are helpful in indoor scenarios. In addition to the features provided by canes, walkers incorporate additional assistive features like sit-to-stand assistance and rehabilitation exercise monitoring, to name a few. These additional features are the reasons why these walkers are more suited for long-term assistance for the elderly in an assisted living facility or for patients who require rehabilitation and additional support after surgery. Xu et al. [130], proposed a robotic walking helper that consists of frames for the user to place their arms in for support. A Force Sensing Resistor (FSR) sensor is placed inside each frame's handle, which is used in combination with an LRF sensor to analyze the user's motion. A Support Vector Machine Algorithm is trained to classify the user's motion state to either the falling mode or normal walking mode, based on which the robot is controlled.

A user-following smart walker, UFES smart walker, is proposed by Cifuentes et al. [131]. One Inertial Measurement Unit (IMU) sensor is mounted on the robot while the second IMU sensor is mounted on the user's pelvis region to detect pelvis rotation for angular velocity computation. An LRF sensor is mounted below the knee-level to compute gait parameters for estimating the robot's linear velocity. The robot uses a combination of the resulting data sets to follow in front of the user's gait while supporting the user's walking. While the robot system considers the user's gait for robot motion control, safety features such as fall detection and prevention and obstacle avoidance are not discussed.





**Figure 13.** Walker frame based walking assistants (WWA)—the walking-aid robot [130].

An intelligent shared-control robot, Walbot, is proposed by Jiang et al. [132]. The robot consists of an omnidirectional mobile base and a handrail designed to give maximum motion capacity and support to the user. It consists of an LRF sensor in the front to localize obstacles and an IMU sensor for measuring the slope of the ground. The user's intent is detected using a sensor-less force impedance controller by using an external disturbance observer. The robot's velocity is then computed to be compliant with the user's intent. The robot behaves passively by allowing the user to control the robot's speed while actively monitoring obstacles. The system does not include other features like gait parameter estimation and fall detection and prevention.

Advanced assistive robotic systems have been proposed with state-of-the-art technologies and novel sensors in recent times. For instance, the assistive robotic system iWalk that consists of an RGB-D RealSense camera for gait tracking, gait stability, and mobility assessment, has been proposed by Chalvatzaki et al. [133,134]. iWalk employs an LRF sensor for gait phase estimation and microphones and speakers for speech recognition and voice feedback. The system is also able to monitor human activity during exercises and provide fall detection. The only drawback is that the system does not provide fall prevention. Song et al. [135] propose a walking assistant robot that uses a passive-compliant control to move the robot and an active obstacle avoidance controller. The robot consists of two six-DOF robotic arms interlocked using a special mechanism to form a handrail. Two LRF sensors are present on the robot. One sensor on the front estimates the gait parameters while the other is used in the rear for obstacle location and avoidance. The robot's motion is computed using the user's motion intentions, which are estimated using two sensors. The gait parameters estimated using the front laser are used to determine the robot's linear velocity, while the angular velocity is determined using the FT sensor on the robot's arm and is based on the user's steering intentions. Fall prevention is provided in case of freezing gait, where the user may fall forward on the robot. During this scenario, the robot can bear the user's gait to prevent falls. Nevertheless, this system does not consider all fall cases where the fall direction cannot be determined. Falls due to freezing gait are the only fall types considered.

## 8. Open Challenges for Robots in Healthcare and Conclusions

As service robots diffuse into non-traditional robotic environments, such as hospitals, care facilities, or homes, it is important to the readiness of the technology and to investigate the impact of robots on our society. Table 1 summarizes the robotic platforms discussed in this paper. As seen, several robotic platforms are still in the research phase. From commercially available robots, only some of them are deployed in real work environments. Lokomat, for example, is available in 25 rehabilitation centers in the U.S. [136]. Recently, ReWalk entered into a contract with a German Private Health Insurer to ReWalk Exoskeletons to individuals with Spinal Cord Injuries [137]. However, commercially available robots

are expensive and the cost does not allow the ubiquitous use of robots. According to ARK's research [138], the cost of industrial robots has been declined in the last 15 years. As machine learning and computer vision advance in recent years, this decline in costs may cause an inflection point in the demand for robots. However, there are no statistics about the cost of robots in healthcare, but a similar trend will follow as for industrial robots, depending on the maturity of the technology and the demand for such products.

**Table 1.** Overview of the robotic platforms presented in this paper.

Robotic Platform	Platform Status	Robot Category	Tasks	Ref.
Pepper	Commercial Product	Care/Hospital	Therapy, Cognitive and Physical Training, Providing Information, Human Activity and Health Monitoring, Conducting Surveys	[21,23–27,29,30]
Nao	Commercial Product	Care	Therapy, Cognitive and Physical Training	[31–35,39]
Care-O-Bot4	Research	Care	Collection and Delivery Services, Serving Drinks, Providing Information	[41]
Lio	Commercial Product	Care	Collection and Delivery Services, Entertainment and Motivation, Automatically Entering Rooms and Reminding Important Tasks	[47]
Hobbit	Research	Care	Collection and Delivery Services, Recognition of a User's Instability	[50]
RAMCIP	Research	Care	Collection and Delivery Services, Recognition of Potential Emergencies	[51]
Kosecki et al., 2016	Research	Care	Collection and Delivery Services, Medication Reminder	[53]
Moxi	Commercial Product	Hospital	Collection and Delivery Services	[55]
YuMi	Commercial Product	Hospital	Collection and Delivery Services	[57]
TUG	Commercial Product	Hospital	Collection and Delivery Services	[58]
Relay	Commercial Product	Hospital	Collection and Delivery Services	[59]
ROBEAR	Experimental	Hospital	Patient Lifting	[60]
Veebot	Research	Hospital	Drawing Blood, Inserting IV	[61]
ARNA	Research	Hospital/Walking Assistance	Collection and Delivery Services, Patient Monitoring and Walking Assistance	[63–65]
DeKonBot	Research	Hospital	Disinfection	[66]
FRIEND	Research	Assistive	Workplace Assistance, Drinking and Eating Assistance	[68]
Jaco 2	Commercial Product	Assistive	Manipulation Tasks, Drinking/Eating Assistance	[71–75,80]
Baxter	Commercial Product	Assistive	Dressing	[82]
Barrett's WAM	Commercial Product	Assistive/Rehabilitation	Shoe Fitting/Game-based Upper limb rehabilitation	[83,109–111]
Rehmat et al., 2018	Research	Rehabilitation	Upper Limb Rehabilitation	[103]
Zhang et al., 2018	Research	Rehabilitation	Upper Limb Rehabilitation	[101]
Bouteraa et al., 2016	Research	Rehabilitation	Upper Limb Rehabilitation	[104]
Pang et al.	Research	Rehabilitation	Upper Limb Rehabilitation	[105]
Burt	Commercial Product	Rehabilitation	Game-based Upper Limb Rehabilitation	[107]
Mohamaddan et al., 2015	Research	Rehabilitation	Upper Limb Rehabilitation	[95]
Ding et al., 2019	Research	Rehabilitation	Upper Limb Rehabilitation	[98]
ReWalk	Commercial Product	Rehabilitation	Gait Rehabilitation	[113,114]
Lokomat	Commercial Product	Rehabilitation	Gait Rehabilitation	[115]
MOPASS	Research	Rehabilitation	Gait Rehabilitation	[116]
BART	Research	Rehabilitation	Balance Rehabilitation	[118,119]
Di et al., 2016	Research	Cane-based Walking Assistance	Sit-to-Stand Assistance, Walking Assistance, Walking on a Slope, Emergency Aid, Fall Prevention, Guidance, and Obstacle Avoidance	[127]
Yan et al., 2016	Research	Cane-based Walking Assistance	Walking Assistance, Fall Detection and Prevention	[128]

Table 1. Cont.

Robotic Platform	Platform Status	Robot Category	Tasks	Ref.
Van Lam and Fujimoto, 2019	Research	Cane-based Walking Assistance	Walking Assistance, Self-balance, and Fall Prevention	[129]
Xu et al., 2018	Research	Frame-based Walking Assistance	Walking Assistance, Fall detection and Prevention	[130]
UFES smart walker	Research	Frame-based Walking Assistance	Walking Assistance, Gait Parameter Estimation	[131]
Walbot	Research	Frame-based Walking Assistance	Walking Assistance, Walking on a Slope, Obstacle Detection and Avoidance	[132]
iWalk	Research	Frame-based Walking Assistance	Walking-Frame Based Walking Assistants, Patient Monitoring, Human Stability Estimation, Mobility Assessment, Exercise Monitoring, and Gesture Recognition	[133,134]
Song et al., 2017	Research	Frame-based Walking Assistance	Walking Assistance, Fall Prevention, Obstacle Detection, and Avoidance	[135]

However, the *maturity and readiness of the technology* is still an open challenge. Wan et al. [139] provided a recent review on the technological advantages in human–robot interfaces, environmental perception and user monitoring, navigation, robust communication, Internet-of-Things, and Artificial Intelligence for mobile healthcare robot. Moreover, Wan et al. identified several open research issues in intelligent communication, biosensors, AI, and state-of-the-art deep learning algorithms that need to be addressed to achieve robustness and safety. Moreover, safety standards require to be updated. For example, the ISO 13482:2014 [140], which defines the safety requirements for personal care robots has not been updated since 2014. Villaronga [141] discussed in detail the confusions that may arise from ISO 13482:2014. Villaronga has included the following statement [141]: “ISO 13482:2014 classifies personal care robots from a technical perspective. That might be very useful to create new robot applications, but not to give protection to consumers in legal terms. In fact, compliance with some technical safety requirements does not necessarily imply compliance with the entire existing legal framework.” The law requires to provide guidance not only for safety, but also data protection, responsibility, transparency, autonomy, and dignity [142].

In terms of attribution of *liability issues*, the mechanical nature of healthcare robots makes it impossible to assign them liability in case of malfunctioning or any other adverse consequence related to their usage. This could make it extremely complicated to attribute civil and criminal liability to natural and legal persons in relation to a harmful event caused by the robot. By having AI involved along with this, accountability is made even more complex and ensuring safety is one of the main challenges [143]. As robots and AI advance at a fast speed, lawmakers should be more concerned to fill in the legal gaps.

One important concern is the *privacy* of the patients. Nursing care robots are usually equipped with cameras that are capable of monitoring their patients, recording related data, and communicating information wirelessly. Although such a feature can be useful in safeguarding elderly patients, establishing virtual proximity with their family and caregivers, it could also lead to a violation of the patients’ privacy. Without adequate regulations, responsible corporate policies and protocols, these robots’ capabilities can become a threat to the private lives of patients [143].

Moreover, there is the question of *acceptability* by the patients. Most of the robotic systems discussed in this paper are evaluated by volunteers willing to interact with robots. However, in a critical health-related situation, there is not only a question of whether the patients would accept robotic assistance but also of whether their families and caregivers would accept them. Caregivers see robots with a fear that they may replace them, as in other industries robots are replacing humans. Therefore, the issue of *employment* is a widespread concern. However, human-social contact is very crucial, especially when a patient needs care. It should not be believed that robots can fulfill the emotional and physical needs of the patients, especially the elderly [144]. For example, the study by Carros et al. [27] showed clearly that the participants do not want robots to replace caregivers. Taylor et al. [145]

performed a three-month study in five US-based hospitals to co-design a robotic assistant in interprofessional team settings that would empower nurses. The results of the study show that a nursing assistant robot could identify errors and inform them or could have the role of a neutral party to challenge the hierarchical culture in hospitals and the asymmetric power dynamics when interacting with higher-ranking healthcare professionals, among other tasks. Taylor et al. [145] concluded that nurse empowerment is an important issue for patient care and safety.

Another important aspect of robots in healthcare is the *long-term HRI* and its influence on the wellbeing of humans. Most HRI studies focus on short-term interactions between humans and robots [146]. For example, Rajavenkatanarayanan et al. [147] investigated the cognitive load of a human while collaborating with a robot during an assembly scenario and Kanal et al. [111] investigated the physical and cognitive fatigue a human may feel during upper-limb rehabilitation. However, many real-world robot applications will require repeated interactions and building a relationship over the long term [146]. To the best of our knowledge, the impact robots may have on humans in the long term is underresearched. For example, there are news reports [148,149] that there is a higher rate of worker injuries at Amazon's warehouses equipped with robots. The reason may be that robots increased productivity, and subsequently, human co-workers require to work faster, which led to a higher rate of injuries. Therefore, there is a need to research the impact of long-term HRI in healthcare but also other robotic applications.

In conclusion, to ensure seamless integration of robots in healthcare settings, it is vital to ensure reliable performance and customizability and anticipate the societal impact. Reliable performance is crucial as we want robots to operate effectively and safely in real-world environments, which are unstructured and unpredictable. Customizable robots will be required to perform a wide variety of tasks in new situations and while cooperating with a wide diversity of people, even people that are not comfortable with their presence. The societal impact of robots is essential as they may influence the quality of healthcare for patients and the quality of work for caregivers, and their potential privacy concerns remain to be addressed. The open challenges we have addressed in this paper are not only related to healthcare robots. Similar challenges face any robotic application that requires interaction between humans and robots in a real-world environment, such as manufacturing, industry, logistics, search-and-rescue, and others.

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