Socially Assistive Robots for Older Adults and People with Autism: An Overview

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Abstract: Over one billion people in the world suffer from some form of disability. Nevertheless, according to the World Health Organization, people with disabilities are particularly vulnerable to deficiencies in services, such as health care, rehabilitation, support, and assistance. In this sense, recent technological developments can mitigate these deficiencies, offering less-expensive assistive systems to meet users' needs. This paper reviews and summarizes the research efforts toward the development of these kinds of systems, focusing on two social groups: older adults and children with autism.

Keywords: robotics; healthcare; disability; assistive technology; socially assistive robotics

1. Introduction

According to the World Health Organization (WHO) [1], one in seven people experience disability to some extent. However, only half can afford the required healthcare services [1]. This is especially critical when a person's quality of life diminishes and their independence is reduced. In this context, technological advances can play an important role, since they may enable people with disabilities to receive the healthcare necessary to lead a fulfilling life and be independent [2].

A review of the literature reveals the enormous variety of assistive technology currently available. Given the wide ranges of types and levels of deficiency, assistive technology can be classified depending on its complexity. Three concentric spheres of assistive technology can be defined with the user at their center. These are (from the inside to the outside): embodied assistive technology, assistive environments, and assistive robots.

Embodied assistive technology includes mobility devices [3,4] (e.g., wheelchairs, prostheses, exoskeletons, or artificial limbs); specialized aids (e.g., hearing [5], vision [6–8], cognition [9], or communication [10]); and specific hardware, software, and peripherals that assist people with disabilities with accessing information technologies (e.g., computers and mobile devices). Although these systems provide valued help, they usually offer just one functionality and lack much intelligence (intelligence being understood as the ability to receive feedback from the environment and adapt their behavior).

Going a step further, the environment can be adapted to the user's needs, with sensors and actuators, such as cameras or domotic systems, such that more functionalities are covered and more information about the user's health status can be gathered and processed, providing this technology with intelligence. Along those lines, we can find smart homes [11], virtual assistants [12–14] and ambient assisted living (AAL) settings [15–17]. Nevertheless, this kind of technology fails to support independent life when the user has chronic or degenerative limitations in motor and/or cognitive abilities.

As a solution, assistive robotics (AR) emerged. Its main goal is to fruitfully promote the well-being and independence of persons with disabilities. Robots may assist people in a wide range of tasks at home (especially in terms of activities for daily living), and so ongoing research includes household robots [18–20] and rehabilitation robots [21,22], among others. In the case of assistive robots, interdisciplinarity is required to achieve the final goal, integrating research areas such as artificial intelligence, human-robot interaction, and machine learning techniques, among others.

Thus, motivated by the current societal needs of the particular risk groups (i.e., children and older adults), this paper reviews and summarizes the promising and challenging research on assistive robotics aimed at helping older persons and children with autism to perform their daily tasks.

2. Socially Assistive Robots

One of the main difficulties in the acceptance of assistive technology is the way in which this technology is perceived. In this sense, the interaction between the robot and the user is a key issue. This social interaction led to the development of socially assistive robotics (SAR). According to Feil-Seifer and Mataric [23], SAR can be defined as the intersection of AR and socially interactive robotics (SIR), whose main task is interaction with human individuals.

Ideally, SAR should operate autonomously and not require the manipulation of a human operator. The interaction with the user must be intuitive and must not require extensive training. Additionally, the robots have to adapt their behaviors to the new routines and needs of the users, which is currently the most challenging task to be solved [24]. To meet this demand, artificial intelligence and machine learning algorithms must be developed and deployed in these systems, since the robots cannot be programmed in advance to react to every possible circumstance that might occur during interactions with the users.

As mentioned above, there exists a wide variety of applications depending on the needs to be covered and the demands of the target social group. Given that the SAR focuses on improving the user's life conditions, this study reviews the advances in two of the most vulnerable social groups:

- *Older adults;*
- *People with cognitive disorders.*

Section 3 reviews the latest advances in age-related health issues, while Section 4 analyzes the most significant research on children with autism in terms of diagnosis and therapy to train their communicative and social skills.

3. Older Adult Care

The aging population is one of today's major health concerns. This unprecedented situation urgently requires technological solutions to confront the constantly increasing demands of care services, which are currently overwhelmed. In this regard, the WHO identifies two key concepts in its *Global strategy and plan of action on aging and health* [25]:

- Healthy aging, understood as the process of developing and maintaining functional ability for older people's well-being;
- Functional ability, where technology is used to perform functions that might otherwise be difficult or impossible.

Healthy aging has become popular topic in recent decades. In this regard, SAR develops systems to improve older people's health through physical activity, which has a positive cognitive impact [26]. Some research attempts have consisted of companion robots that help users with assisted therapy and activity (see [27] for an overview). However, work is needed to promote for their acceptance among older people, as pointed out in [28], especially in terms of social interactions.

In addition, SAR for promoting physical exercise has been developed. This is, for instance, the case of the robotic *coach* proposed by Görer et al. [29]. It is essentially a technique based on a

learning by imitation approach, which is used to learn the exercises from a human demonstrator. Then, the *reference* joint angles are used to evaluate the user's movements and to provide them with the necessary feedback to improve their performance. Note that two different platforms are used to achieve this goal. A NAO robot is used to describe the physical exercises, while an RGB-D camera captures the movements of the person. This can be problematic, since the correct position of the RBG-D device is essential to properly evaluate the user's performance. In addition, no sitting exercises are used because the skeleton data are insufficient to obtain the required results. Finally, the robot may confuse the user, given that it emulates the exercise as a demonstration and performs certain movements that are not to be carried out, such as head motions.

Another proposal is PHAROS [30,31], a socially assistive robot that monitors and evaluates the daily physical exercise done at the user's home (see Figure 1). For this, machine learning techniques (i.e., a convolutional neural network (CNN) together with a recurrent neural network (RNN)) are used to properly identify and evaluate the exercise performance. In addition, it integrates a recommender that generates the workout every day such that the person is working on what is necessary to stay healthy.

Figure 1. PHAROS robot in a pilot study at a residence of the elderly, Doña Rosa (Alicante).

Assisting functional ability requires more complex systems. In this sense, systems have been evolving over time, integrating an increasing number of functionalities. This is the case of the HOBBIT [32], a robot to help older people feel safe and continue to live in their own home. With this aim, the robot, illustrated in Figure 2, is able to autonomously navigate around the user's apartment, going anywhere they request, being able to pick up objects from the ground, bring a specific object, learn new objects to be found in the future, call in case of emergency, provide games for entertainment, and also remind the user to take their medication.

Analogously, the EU project RAMCIP [33] has developed a robotic assistant for older adults and those suffering from mild cognitive impairments (MCI) and dementia (see Figure 3). This robotic assistant also integrates several functionalities that promote physical and cognitive activity, such as detecting a fall (in which case a relative or external caregiver is informed), checking the cooker has been turned off after preparing a meal or the lights have been turned on when walking at night, picking up improperly left or fallen objects from the ground and moving them to safe storage, reminding users about their mediation, bringing the corresponding medicine and monitoring its taking, and facilitating social interactions with family and friends.

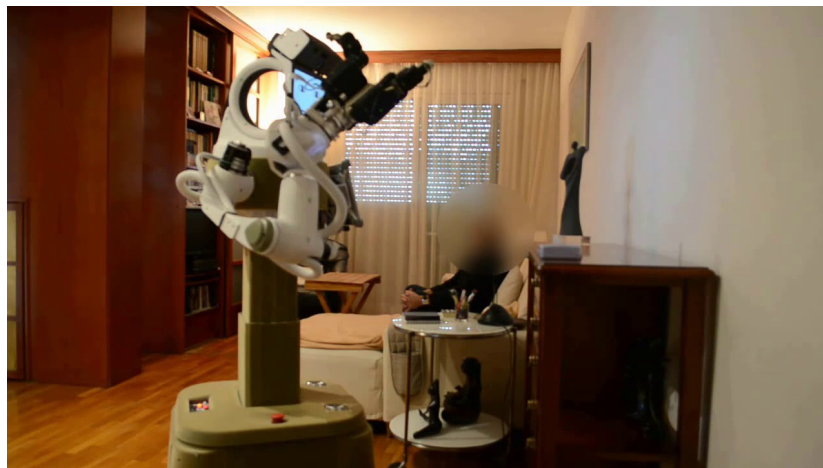**Figure 2.** Hobbit robot in a pilot study at the Doña Rosa senior care home.

Figure 3. RAMCIP robot in a pilot study at a user's home.

Other solutions consider the possibility of integrating a robot platform into a smart home environment such that its functionalities may be augmented. An example is the robot activity support system (RAS) created by Washington State University [34] for adults with memory problems and other impairments to help them to live independently. Thus, the smart home has sensors in the walls to track the user's movement and feeds their data into the robot's neural network. This allows the robot to integrate activity detection technology to provide assistance when required. However, it is still at an early stage of development, and can only provide video instructions on how to do simple tasks, such as assisting a person through the steps of taking a dog for a walk or guiding them to an object. In addition, the need to install additional technology at home makes this option difficult and costly to implement.

Alternatively, other developments aim to assist people in nursing homes and healthcare facilities. In these kinds of systems, the key issue is the social component, with the aim being for the older adult user to perceive the robotic platform as a social companion rather than a machine to perform predefined tasks. This is the main focus of Rudy [35], an assistive robot created by INF Robotics in 2017. This robot offers telemedicine capabilities, such as remote patient monitoring (RPM), medication reminders, and medication dispensing (shown in Figure 4). In addition, it integrates a social component that, together with its friendly appearance, engages users. In fact, the social interactions are the most appreciated functionality of this system, since loneliness is a major issue among the aging. Nevertheless, it costs $5000, which is a significant amount which is not within all budgets.
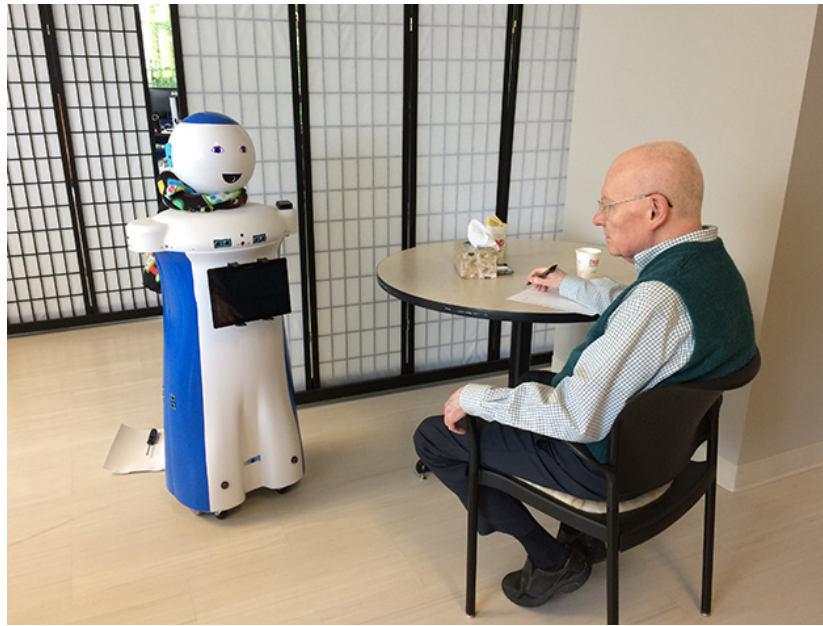
Figure 4. Rudy in a pilot study.

Along similar lines, Trinity College Dublin developed Stevie in 2017, which they improved in 2019 as Stevie II (Figure 5). The aim of this socially assistive IA robot was to augment the role of caregivers in long-term care environments, allowing them to concentrate mainly on person-centered tasks. Its functionalities range from medication reminders to keeping residents cognitively stimulated with quizzes and games. For this, enhanced expressive capabilities and a well-defined social component are used.
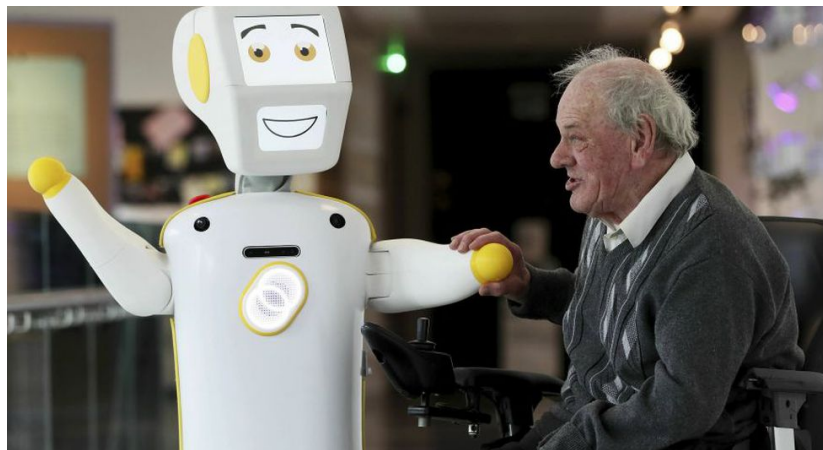
Figure 5. Stevie II in a pilot study.

4. Training Communication and Social Interaction in Children with Autism

In recent years, the use of SAR has become popular for the treatment and diagnosis of autism [36]. Indeed, the research in this field has presented an increase in user therapy acceptance and improvements in their social skills [37].

Applied behavior analysis (ABA) is one of the most extended therapies for the treatment of autism. It consists of improving specific behaviors, which are divided into simple and repetitive tasks that are presented sequentially and strategically while measuring and analyzing the patient's performance during the therapy [38].

The automation of some aspects of the therapy using technology with different devices and tools has been widely studied (videos, virtual and augmented reality, and robotics [39]). ABA therapies

combined with SARs have exhibited substantial advantages and demonstrated their effectiveness in obtaining positive results in patients, such as high enthusiasm, increased attention, and increased social activity [40].

These results may be explained by the fact that children with autism feel more comfortable interacting with robots, because their behavior and reactions are more predictable [41]. Furthermore, the social skills of the patients could be gradually improved by increasing the complexity and unpredictability of the robot's behavior, making it more similar to actual human behavior [42].

These robotics systems can be used to manage therapy sessions, collect data and analyze the interactions with the patient, and generate information from this data in the form of reports and graphs. For this reason, they are a powerful tool for the therapist to check patient's progress and facilitate diagnosis.

The visual appeal of the robotics platform is a key factor to engaging the attention of children with autism. In general, these robots tend to use bright colors, rotating mechanical parts, striking shapes, and lights [43]. Additionally, some studies have reported that children with autism prefer to interact with robots with less humanoid characteristics [44]. However, some anthropomorphic robots have been succesfully used in research, especially in imitation and emotion recognition activities. Tables 1 and 2 present different SAR robots used in experiments. Following [45], there are several robot types depending on their location on the humanoid spectrum:

1. **Android**. They look like humans.
2. **Mascot**. They have humanoid forms but abstract or cartoonish appearances.
3. **Mechanical**. Humanoid forms with visibly mechanical parts.
4. **Animal**. Meant to look like pets.
5. **Non-Humanoid**. No resemblance to any living being.

Table 1. Robots used in autism therapies.

Robot	Appearance	Type	Description	Publications
Zeno R-50		Android	Child-sized robot (height = 0.64 m and weight = 6.5 kg) with a simplified expressive face. Its face has a motor that can be animated using software.	[46–48]
Nao		Android	Humanoid (height = 0.57 m and weight = 5 kg). Appearance of a human toddler. 11 DOF for its lower limbs and 14 DOF for its upper body.	[49–58]
Pepper		Android	Humanoid (height = 1.21 m and width = 0.48 m). It has almost the same articulations than a human, except for its mobile base and the impossibility of moving every finger independently. It has 4 microphones, two loudspeakers, two RGB cameras and a depth sensor (Asus Xtion). It has tactile sensors in the head and the back of its hands. It has a speech recognition engine that is able of identifying multiple variations in the human voice.	[59–62]
KASPAR		Android	Child-sized humanoid robot with minimal expressions. Can create body movements and gestures using its hands, arms, torso, head and show facial expressions.	[63–69]

Table 1. *Cont.*

Robot	Appearance	Type	Description	Publications
Keepon		Animal	Small creature-like robot (height = 12 cm). Simple, like a yellow snowman, and made of soft materials (silicone rubber).	[70–72]
Popchilla		Animal	Chinchilla-looking robot with movable arms, ears, mouth and eyes (teleoperated) with programmable speech output (Interbots). Provided with a iPad app.	[73]
PABI		Animal	Penguin-like small robot. 8 DOF in eyes, head, wings and opening beak. It carries a single board computer for autonomous operation and wireless communication for teleoperation. Speaker mounted behind its beak for communication. 2 independent video cameras in its eyes for tracking and monitoring. It carries a tablet as an interface with the onboard computer.	[74–76]
Pleo		Animal	Dinosaur-like robot. Developed to learn and repeat dances. 14 DOF, with movable legs, torso, neck, eyes, tail and mouth. Touch sensors in its whole body. Camera in its nose for object tracking and microphones. Capability to show emotions by making noises.	[77–80]
Robota		Android	Small robot (height = 45 cm and width = 14 cm) with the form of a young girl. 1 DOF of movement in its limbs (up and down), head rotation, 1 DOF for every arm, coordinated motion of the two eyes, individual blinking of the eyes and touch sensibility. Capabilities for vision tracking and machine learning.	[81–85]

Table 2. Robots used in autism therapies.

Robot	Appearance	Type	Description	Publications
i-Sobot		Android	Biped robot (height = 16.5 cm and weight = 350 g). 17 pieces of micro servo motors for walking and 180 different actions. 180 voice and sound commands. Remote controller or spoken commands.	[86–88]
Tito		Mascot	Robot (height = 17 cm) Coloured red, yellow and blue with washable clothes made of soft material. Wheels to move but with fake feet and legs to emulate human shape. Movable arms and head, lighting mouth for smiling. Wireless microphone-camera device inside one eye for tracking. Touch sensibility. Autonomous and teleoperated modes.	[89]
GIPY-1		Mechanical	Cylindrical mobile robot (diameter = 20 cm and height = 30 cm). Its face is the cladding of the robot: round eyes and nose triangle, with elliptical mouth. Can move forward, backward and turn on its own axis. Wireless controlled by a joystick.	[90,91]

Table 2. *Cont*.

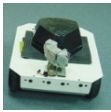| Robot	Appearance	Type	Description	Publications
HOAP-3		Android	Humanoid robot (height = 60 cm and weight = 8.8 kg), commercialized by Fujitsu. 28 DOF for head, arms, legs and body movement. Inbuilt camera in its eyes for tracking and recognition. Microphones and speaker for audio recognition and speech. Expression LEDs to show emotions. Autonomous operation and teleoperated through WIFI.	[92]
Labo-1		Non-humanoid	Robotic mobile platform with form of a flat-topped buggy. 8 infrared sensors pointing in 4 directions for obstacle avoidance and a singLe positional heat sensor. Autonomous operation with an onboard computer and two buttons for behavior selection.	[93]
Ifbot		Mascot	Humanoid robot (height = 45 cm). 2 moving arms with 1 DOF and two wheels to move. 10 motors for facial expressions: eyes, eyelids and neck. 104 LEDS in its head and mouth to show emotions along with the facial expression.	[94]
Cosmobot		Mascot	Movable head, arm and mouth. Wheels to drive the robot in 4 directions. Pressure sensors and a built-in microphone for the interaction with the children. Expandable play station (Mission Control) for interaction, with external ports for joystick, wearable head and arm sensors. Teleoperated and controllable from a desktop computer software.	[95,96]
Ryan Companionbot		Android	Rear-projected humanoid. It shows 3D avatar models with speech and facial expressions. The animated face is projected into a face-shaped translucent mask. The 3D models are compatible with Maya design software.	[97–99]

Since the therapist's availability is limited, SARs must be developed with a certain level of autonomy in order to carry out the treatments. This autonomy is directly correlated with a SAR's level of intelligence in adapting to the environment and the patient's responses. This is where machine learning comes in, providing solutions to the problems these systems must address, such as eye-tracking, and face or automatic speech recognition.

Eye-tracking is the process of measuring the point of fixation of the gaze or the movement of an eye with respect to the head. It is used to measure a patient's attention to the robot. There exist commercial solutions for this purpose, but they are high cost or depend on special and invasive hardware (Tobii EyeX). However, there are many works focused on inferring the gazes of the users from images of their faces. Traditional techniques usually rely on shape-based methods, such as [100,101], observing geometries such as pupil centers and iris edges; and in appearance-based methods, such as [102,103], they directly use the images of the eyes for the prediction, with handmade features along with neural networks. In recent years, the focus has been on deep learning techniques to accomplish this task using standard and inexpensive camera devices. This is the case of [104], which uses a convolutional neural network to predict the gaze of the user from a color image of their face, previously trained with a large-scale dataset of faces and correlated gazes. More recent works such as [105] predict emotions and the patient's mood states from eye tracking data using recurrent neural networks.

The study of the patient's gaze is a crucial technique that helps with the diagnosis of autism and measures the effectiveness of the interaction between the robot and the user. In [106], the researchers carried out a study comparing the gaze attention of patients with autism when they interacted with humans and with robots . Similar to the previous example, in [107] the authors compare the gaze attention of people with autism while maintaining conversations with a human and a realistic android, which could serve as a diagnostic tool. In [84,85] the authors report the effects of repeated exposure to the humanoid robot Robota, which includes an increase in gaze attention and imitation.

Most of the experiments with these robots do not specify the kind of eye-tracking technique they use, or even whether they use external hardware, but recent works in this topic show that deep learning techniques outperform traditional ones without the need for invasive tools, so developments may move in this direction in order to ensure the best experience for users.

Face recognition has been one of the most widely studied research topics in computer vision since the beginnings of computer science, as it provides the recognition of subjects in a non-intrusive manner. The first step involves the detection and delimitation of the region of the image containing the face. Traditionally, detection has been conducted by searching for handcrafted features, like in [108], which uses cascade classifiers with different resolutions, trained with the Adaboost technique, based on Haar-like features. Subsequently, a vector of characteristics is extracted to describe the face, using global techniques like Eigenfaces [109] or Fisherfaces [110] based on Principal Component Analysis, or using local descriptors, like Local Binary Pattern Histograms [111], which codify the local structure of the image by comparing every pixel with its neighbourhood. However, traditional methods suffer when the conditions of the face are not ideal: recognition rates decrease with variations of the pose of the face and changes in the lighting conditions. Recent works have adopted end-to-end architectures based on deep learning that greatly outperform the traditional methods. Studies such as [112–115] use variations of convolutional neural network architectures trained with large-scale face datasets, obtained without pose restrictions, with good results on tests. Along with face recognition, recent studies like [116,117], classify the user's emotions by means of variants of convolutional neural networks, with promising results.

These characteristics are important for socially assistive robots in order to identify the patient and their mood and keep track of the history of the interaction. In [59], the researchers used face and emotion recognition to make a Pepper robot adapt a story to the mood of the children. In [118], the authors propose a technique for face recognition using a humanoid robot NAO to track the faces of the children with autism and measure their concentration during social interaction. In [61], the authors propose several activities through the interaction with a Pepper robot, receiving feedback by measuring the users' smiles.

Finally, *automatic speech recognition* is considered the most important bridge to enable human-machine communication. However, the technical difficulties of speech processing led to the keyboard and mouse becoming the most accurate interfaces for this purpose. Traditional methods in speech processing used statistical models, such as hidden Markov models [119,120], to process the wave signal and recognize the words pronounced and understand the sentences. However, these methods were very limited in vocabulary and the complexity of the sentences that human users could use and the recognition rates were far from perfect. Today, with the advent of GPUs, as in the previous sections, deep learning techniques are becoming the focus for researchers. End-to-end architectures, such as that proposed in [121–123], mainly based on a combination of convolutional neural networks, for extraction of features, and recurrent neural networks, for temporal information analysis, are taking the lead and obtaining interesting results.

In the case of social robotics, speech recognition is an important feature, as we need an intuitive, organic, and more natural method of communication than the old-fashioned peripherals. In [58], the researchers propose the use of the Nao robot to maintain conversations with children with autism and automatically extract crucial information on their interests to recommend them picture books. In [57], the authors propose a conversational therapy using a Nao robot that encourages the child to

talk about their experiences and help them to recognize objects and imitate facial expressions. As a different approach, in [62], the authors use a Pepper robot to teach people with typical development to communicate with people with autism spectrum disorder.

All of these studies show that not only can patients with autism benefit from the advent of the SAR and artificial intelligence techniques, but therapists and family members also have more tools to help them with therapy and day-to-day living.

5. Conclusions

Socioeconomic changes and the lack of healthcare professionals to cover the unceasing demand of services and care have led to the need for technological solutions to mitigate this situation. In addition to intelligently interacting with the environment, the techniques developed must be successfully adopted by users. In this sense, neuroscientific evidence shows that users, especially children, tend to engage with robots better than traditional screens and their design must make the user feel comfortable and increase their well-being. As a consequence, the scientific response to these issues is assistive robotics, and more precisely, socially assistive robotics, which integrates a human-robot interaction in a social way.

This paper presents an overview of the state-of-the-art SAR solutions for helping and assisting older adults in their daily activities, such as activity scheduling and rehabilitation; and for helping children with autism spectrum disorders by means of diagnosis and social therapies. These solutions benefit from new advances in artificial intelligence, as these increase the autonomy levels of assistance robots, allowing them to adapt to unforeseen circumstances without the direct intervention of a human. Thus, the advent of SAR along with AI can help users with their day-to-day living, promoting their daily functioning, well-being, and independence.

Despite the active development in (social) assistive technology, there is still work to be done. Indeed, the current solutions do not provide ideal solutions to all needs of people with disabilities, but the results are highly promising.

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