Socially Assistive Robotics for Gait Rehabilitation

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11.1 Introduction

Gait is a rehabilitation process that involves physical and cognitive parameters [1]. Rehabilitation may need to be done in a cognitively stimulating context to maximize its impact on neuroplasticity and cognition [2]. Engagement, motivation, and adherence during the process have shown a high impact on the patient's performance. Social Robots have been used to assist the patient physically and cognitively [3] through factors like robot embodiment, social, emotional intelligence, and socio-cognitive skills [4]. Socially Assistive Robotics (SAR) focuses on achieving specific goals in rehabilitation, training, or education [5].

In the first section of this chapter, the basic concepts of social robotics and the importance of the cognitive process are presented. In the second section, the parameters considered for developing patient–robot interfaces based on SAR for gait rehabilitation are described. The application of these concepts is presented through an example in neurological rehabilitation.

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11.2 Social Interaction

To understand social robotics is essential to have a clear meaning of social interaction. The main objective of a social robot is to assist the patient not only physically but also cognitively. Over time, social interaction has been studied, and it has been represented through a variety of theories. However, a general definition of social interaction from a sociology approach is as follows: "social interaction is a dynamic, changing sequence of social actions between individuals or groups" [6]. As a product of social interaction, the partners can modify their actions and reactions.

In this context, social robots have several ways to change and share actions. The channels commonly used for social robots are verbal and nonverbal communication [7]. Verbal communication is considered the exchange of symbols that can be spoken or written [8], and nonverbal communication can be produced through gestures and gaze [6]. For long-term periods, this interaction is expected to be more robust and very similar to the human–human social interaction. Currently, SAR applications for long-time experiences still represent a challenge. Factors such as robot embodiment, social, emotional intelligence, and socio-cognitive skills [4] must be considered during the design of social robots and their applications.

11.2.1 Relevant SAR Characteristics During Social Interaction

Some characteristics differentiate SAR from other forms of social interaction like virtual agents, affecting the relationship with humans in different scenarios [9]. The parameters described here will be social robots' embodiment, social-emotional intelligence, and socio-cognitive skills (Fig. 11.1).

11.2.1.1 Social Robots' Embodiment

Social robots are developed to interact with users in a human-centric way. The robot embodiment is not always the same; robots can have various external appearances (e.g., human-like [10], animal-like [11], or abstract designs [12], see Fig. 11.2), but they share the aim of engaging users in an interpersonal manner [4]. Despite the several social robots, people tend to have a greater acceptance of anthropomorphic robots [13]. This preference occurs as humans attribute their mental stages (e.g., thoughts, emotions, and desires) to this kind of robot [14]. The design of the robot depends on its final application. It is crucial to include whole-body motion proxemics, facial expression, linguistic vocalization, and touch-based communications in some areas. To achieve the correct embodiment features is vital to use methodologies as an inclusive-participatory design [15], where the participants contribute to the decision-making process to increase the acceptance and effectiveness of the impact caused by the robot.

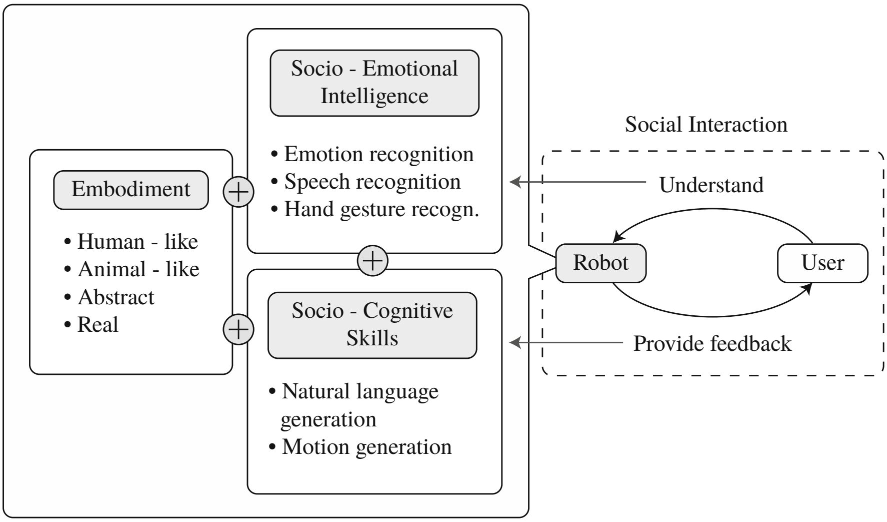

Fig. 11.1 Parameters that differentiate SAR from other forms of social interaction

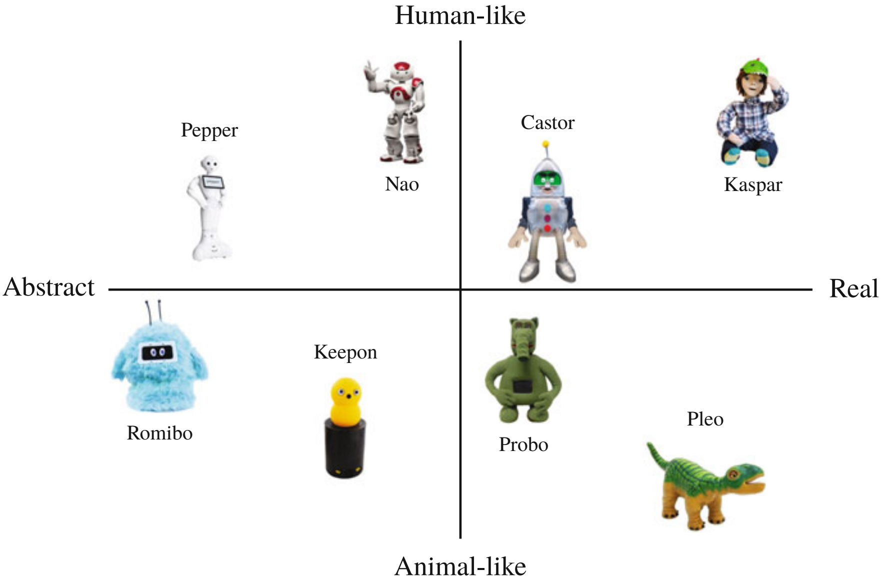

Fig. 11.2 Socially Assistive Robots classification. In this chapter, we consider two main categories: real/abstract referring to their similarity to living beings and human/animal referring to their similarity with humans or in contrast their similarity with animals

11.2.1.2 Socio-emotional Intelligence

Human communication and social interaction often integrate compelling and emotive cues. Thus, social robots need to be able to recognize and interpret affective signals from the users. Theoretical models of emotions for social robots are currently being developed to derive coherent computational models. Two theoretical models are mainly used in social robotics: *appraisal theory model* and *dimensional theory model*.

The *appraisal theory* emphasizes a connection between cognition and emotion. In this model, emotions are evoked from personal significance events (e.g., individual beliefs, desire, and intentions) [16]. This theory can be described as a discrete model, where an emotional event causes a response. For example, the Artificial Intelligence (AI) with if-then rule codes is based on this kind of model. On the other hand, the *dimensional theory* is based on continuous dimensional space [17], where the user's emotional state can be represented in a 3D space. PAD models are based on this theory [18]. PAD models are represented by P (i.e., pleasure/valence), A (i.e., arousal/intensity), and D (i.e., dominance/coping potential).

Emotional Empathy is another factor relevant in order to achieve long-term interactions between robots and humans. Empathy can be broadly defined as an "affective response more appropriate to someone else's situation than the one's own" [19]. Several works are currently focused on empathy approaches to enhance the social robots' capabilities [20]. Most of these studies use mimicking user's affective states to endorse the effects of social robotics [21].

11.2.1.3 Socio-cognitive Skills

Social robots must understand and predict human behaviors. Therefore, robots have to be aware of people's goals and intentions, so the robot's behaviors can be adjusted to help the users in terms of their goals and needs [22]. In this way, several strategies are used. The most common features used in robots are memory (i.e., face recognition) [23, 24] and communicative skills (i.e., speech recognition) [25].

A key challenge in this kind of interaction recalls critical past events during conversations and activities [26]. *Episodic memory* is a core concept to define this challenge. The *episodic memory* stores the data related to past events and adds perspective to the robot to choose actual and emotional events and preserve temporal labels to use them in future referencing. Several applications consider the use of automatic speech recognition (ASR) to produce casual communication and social exchanges [27]. However, this remains a challenge. Limitations on the environmental characteristics and the voice properties are highlighted in various research studies [28, 29].

11.2.2 Importance of the Cognitive Approach in Rehabilitation

Gait rehabilitation is a process that involves a multidisciplinary approach. Several medical specialties are included (i.e., physiatry, internal medicine, and orthopedics), physical therapy, occupational therapy, speech pathology, social work, clinical psychology, neuropsychology, orthotics/prosthetics, nutrition, and recreational therapy [1]. A basic premise of rehabilitation medicine is that optimal patient recovery requires the concerted efforts of some combination of each of these treatment disciplines [1]. It has been proposed that rehabilitation may need to be done in a cognitively stimulating context to maximize its impact on neuroplasticity and cognition [2]. Physical and cognitive training on their own are helpful to some extent for improving cognition, but there may be added benefits to combining the two into a single activity [30]. Social cognitive and system formulations can help revise how we attempt to deliver comprehensive rehabilitation efforts [1]. In this context, Bandura's social cognitive theory of human behavior and cognition suggests that environmental factors, internal factors, and behavioral outcomes combine to shape and direct human learning, cognition, and behavior [31].

The integration of a cognitive approach in physical rehabilitation has been done through different studies. The study by Dhami et al. in 2015 proposed dancing as an alternative to physical therapies as used in neurorehabilitation. This produced a positive impact on physical functioning and cognitive perception, due to the combined, or multimodal framework in therapies, which incorporate simultaneous physical and cognitive activities in a stimulating environment [30]. This can also be achieved through SAR. SAR shares with assistive robotics to assist human users, but SAR constraints that assistance through non-physical social interaction. SAR focuses on achieving specific convalescence, rehabilitation, training, or education goals [5]. Integrating a socially assistive robot can help provide one-on-one support to the patient [3]. It can facilitate the healthcare staff to focus on patients' individual needs, immediately detect any complications during the session [32], analyze the patient's progress within the program in more detail [33], and provide a more tailored plan [34]. Unlike virtual agents [35], socially assistive robots present a physical embodiment, which improves likeability [36, 37], user engagement and motivation [38], adherence [39, 40], and task performance [38], which are essential in long-term healthcare programs. This subsection will further discuss the importance of motivation and adherence and gait rehabilitation and how it can be improved using a cognitive approach.

11.2.2.1 Intrinsic Motivation

Motivation is the most challenging part of the work of the therapeutic profession. Motivated patients are believed to perform better in rehabilitation activities and make more gains than those described as less enthusiastic for treatment [41]. Yet, motivation is recognized as the most significant challenge in physical rehabilitation and training [42]. The more an individual is motivated and engaged in the learning activity, the better the learning outcome [41].

SAR technology can provide novel means for monitoring, motivating, and coaching [42]. Socially assistive robots have been shown to improve user motivation and engagement in several studies in rehabilitation [5, 43–47]. A complementary application where robots are used to motivate and increase the adherence in long-term therapies and medical self-care is diabetes mellitus treatments, where robots play personal assistants in the adult [48] and children [49] population, showing potential results within motivational aspects and treatment engagement.

11.2.2.2 Adherence

Improving adherence to therapy is a critical component of advancing outcomes and reducing rehabilitation costs [50]. Rehabilitative robotics has the potential to enhance adherence to rehabilitation recommendations, which is known to be difficult for those with chronic health conditions [51]. Research suggests that poor adherence compromises health outcomes [52], while high levels of therapy practice optimize motor recovery [53], underscoring the importance of strategies and technologies that bring rehabilitation support into patients' homes. Different studies have shown positive results of social robotics regarding this factor. *Gadde et al.* evaluated an interactive personal robot trainer in the early stages to monitor and increase exercise adherence in older adults [54]. The system was tested with 10 participants, initially showing positive response and a favorable interaction. In another study by White et al., using focus groups, all participants favorably endorsed the potential utility of a socially assistive robot that functioned as a personal coach. They identified three areas in which such a system would be helpful for (1) adherence to therapy recommendations, (2) organizing and remembering things to do, and (3) locating and supporting participation in social and recreational activities [50].

11.3 Patient–Robot Interfaces Based on SAR

Natural human-to-human interaction is performed using senses (e.g., vision, touch, taste, smell, and touch) that facilitate perception of the environment and the ability to communicate employing diverse information channels [55]. This information serves as the input of cognitive processes that are conformed by a sequence of tasks, including reasoning, planning, and execution of a given situation [56, 57]. Unlike human beings, who use their senses to perceive the world, computers and robotic systems implement interfaces composed of a set of sensors that provide the required data to perceive the environment, process the information to define a plan, and perform a determined behavior according to the context [58]. Hence, aiming to generate an effective interaction between the user and the robot, it is of relevance to provide multiple communication channels from different sources. In other words, these interfaces should be multimodal to allow interaction as naturally as possible [56]. For this reason, in most of the Human–Robot Interaction (HRI) systems, there are considered not only humans and robots but also multimodal interfaces that work as an intermediary between both agents [58]. Classic Human–Computer interfaces commonly conform to such interfaces (HCis), such as graphical computer interfaces in conjunction with visual interfaces (e.g., camera-based vision and recognition interfaces) and sensors. Among the most used sensors are Inertial Measurement Units (IMUs), laser rangefinders (LRFs), or wearable devices associated with different communication modalities that are integrated within the HCi [56].

The way an HRI is developed is critical to achieving a natural interaction that can potentiate the intervention with SAR, and over the years, researchers have used different methods to plan and produce these interfaces. A method that has shown promising results is the participatory design. The design of a Patient–Robot interface based on SAR following this methodology is presented in this section. The process is done in a generic rehabilitation program where there is a component of gait rehabilitation. The core activities for which an HCi can be developed are the ones carried out on a treadmill.

11.3.1 Participatory Design

Participatory design (PD) is a well-known method to develop products and services for a target population. The process intends to empower the people involved in a specific activity or situation (users, designers, and stakeholders) by providing them space and a voice to contribute to the decision-making [59]. This way, the real needs, desires, and expectations of the population are met in the final products or services.

PD was initially used in areas like industrial design, but given the effectiveness of designs based on participatory practices, researchers' attention has gained attention in different fields. PD techniques are up-and-coming when transferring knowledge and developments from research to the real world, especially when interacting with humans is vital in the final product or service. Additionally, implementing PD constitutes an opportunity to understand and gain knowledge about the target community's context. An occasion to show the benefits of technological tools and build a relationship based on trust and confidence between researchers and the community.

In health care, PD has been used in the design of social robots for (i) Autism Spectrum Disorder (ASD) [15, 60] and (ii) a children's hospital [61]. In all these contributions, PD methods have been implemented to recognize the target populations and their environment (families, society, groups of allies, and friends) as partners with experience that can be a part of the solution. They are no longer only a source to obtain information and requirements to produce results [62]. All the actors in the project are acknowledged as valuable contributors, which plays a crucial role in ethical, political, and social considerations of the development. The philosophy behind PD is not to provide a step-by-step list of the activities or phases to develop the final product or service, as there are multiple possible ways to implement it. It is up to the researchers to plan and design an appropriate methodology based on the population, context, variables, and objective. A general diagram of the main phases to consider during a PD is presented in Fig. 11.3.

When the participatory process is correctly implemented, it comprises different stages that could lead researchers to:

- obtain contextual information that successfully establishes the needs, interests, preferences, fears, desires, and priorities related to the product or service's functionality,

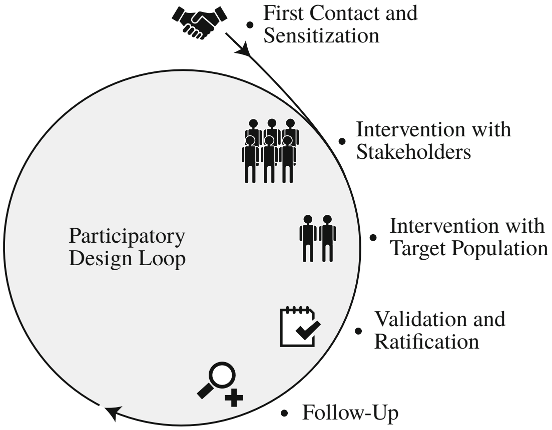

Fig. 11.3 General diagram of participatory design phases to design product and services

- validate or refute the insights gained in previous studies or developments to design the different products or services, and
- generate ideas and creative solutions through reflecting on experiences from the various participants.

11.3.2 Design Criteria

The contextual information found when applying PD leads to the establishment of design criteria or requirements. A natural way to understand and address them in an ordered fashion can be by grouping them according to their characteristics.

Observations from the process that follow the PD steps in Fig. 11.3 set the requirements that the HRI must accomplish. These requirements can be broadly classified into three main groups:

- **Variables:**
  In most rehabilitation scenarios, three types of variables are required to be measured by the system: (i) spatiotemporal, (ii) physiological, and (iii) exercise intensity variables. Spatiotemporal variables include the measurement of items as speed (mph) of the band, cadence (Hz), which is the step frequency of the patient (amount of steps per second), and step length (m), which refers to the distance between legs on each step during exercise. The clinicians typically request the measurement of these variables to monitor the patient's movement. Additionally, the cadence and the step length measurement are used to determine the patients' walking speed. Physiological variables control the patients' physical condition, usually employing the heart rate, blood pressure, and posture while walking. Finally, exercise intensity can be monitored employing the Borg scale and configured with the treadmill inclination.

- **Interactivity:**
  This requirement is provided through a Graphical User Interface (GUI) that allows visual interaction and provides corrections to avoid risk during the session. Similarly, a social robot must be integrated to provide a more natural and social interaction with the system and monitor and motivate patients during exercise.

- **Follow-up:**
  The third requirement is associated with the data management and follow-up of the program. Hence, a database must be included to provide a record of the events generated on each session and record each parameter of the sessions to allow the clinical staff to perform analysis on the patient's evolution.

  The requirements are summarized in Table 11.1.

11.3.3 Patient–Robot Interface Structure

After recognizing the need for the different modules presented in Table 11.1, the structure of the HRI is evident. The system must accomplish a continuous measuring and recording of variables while providing visual interactivity (employing a GUI). These functionalities that comprise the variables, follow-up, and the GUI regarding the interactivity requirement are considered the HCi. Similarly, the robotic social agent can address the interactivity requirements associated with social interaction,

Table 11.1 Requirements for the design of an HRI based on SAR

	Module	Feature
Variables	Sensor interface	*Spatiotemporal* Speed (mph) Cadence (Hz) Step length (m)
		Physiological Heart rate (bpm) Blood pressure (mmHg) Posture correction
		Exercise Intensity Treadmill inclination (°) Borg scale
Interactivity	Graphical User Interface	Visual interaction
	Social Robotic Agent	Social interaction
		Monitoring
		Motivation
Follow-up	Database	Events recording
		Parameters recording

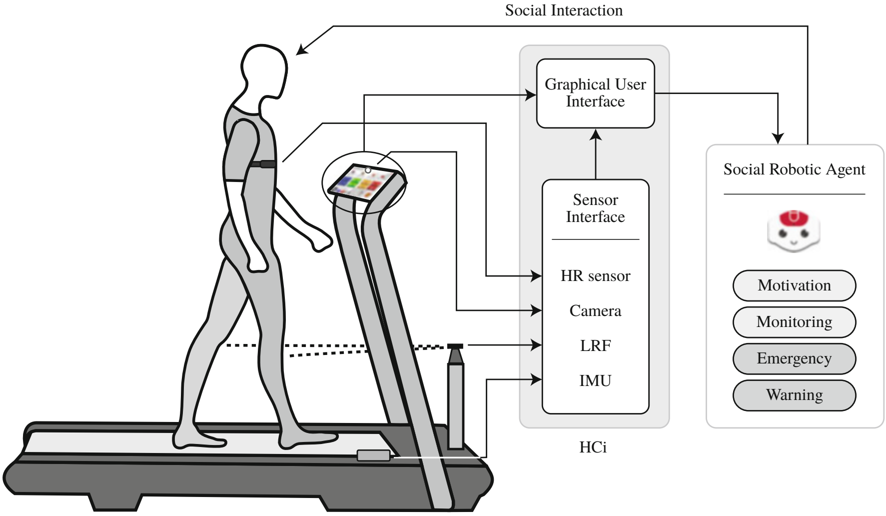

Fig. 11.4 Modules to consider in the design of a Patient–Robot Interface

monitoring, and motivation. Both systems, in conjunction, conform to the Patient–Robot Interface illustrated in Fig. 11.4.

A Patient–Robot Interface focuses on three main properties: acquisition of sensory data, computer interaction, and social interaction between the patient and the system. As depicted in Fig. 11.4, the HCi handles variables described in Table 11.1 utilizing a *sensor interface* and the user requests through the *GUI*. The therapy info is processed in the HCi and sent to the *social robotic agent*. The robot analyzes this information, and based on the result, the state of the therapy and the behavior that must be adopted are determined (i.e., motivation, monitoring, emergency, and warning). These behaviors are established according to the risks associated with the therapy. Hence, with this control loop, the patient's health condition is monitored and controlled, reducing the probability of risk occurrences. While at the same time, the robot can provide feedback and motivation through social interaction.

11.3.3.1 Sensor Interface

The sensor interface measures three types of variables usually selected by the medical staff to monitor the patient's status during the therapy, presented in Sect. 11.3.2. This interface integrates the measurement from a heart rate (HR) monitor, an IMU (reporting the treadmill inclination), an LRF (to estimate gait parameters), a camera (recording the patient's posture), and periodic results from the Borg scale. The system must be designed to present the three primary metrics and examples of the technology that can be involved are as follows:

Gait Spatiotemporal Parameters

As these parameters require tracking the displacement of the patient's legs during exercise, the selected sensor must locate the patient in the band and measure the leg difference distance (LDD). Additionally, the number of steps per second, namely the cadence, must be achieved by the exact measurement. Moreover, the sensor must accomplish the measurement at a frequency higher than the gait frequency. However, gait frequency is low compared to electronic devices. Hence, one sensor that meets all previous requirements could be the Hokuyo-URG 04LX-UG01 (Hokuyo, USA) [63]. This is a laser rangefinder (LRF) used to measure areas using an infrared electromagnetic wave (a wavelength of 785nm), and the distance measurement principle is based on the light phase difference. Similarly, this sensor allows measuring in a range of 240 degrees with a maximum distance of 4m. However, for this application, the measurement range must be limited to 60 degrees to limit the measurement of the treadmill band area. The sensor can perform a scan composed of 683 measurements in 0.1 s, which indicates a sampling frequency of 10 Hz, which is suitable for measuring gait spatiotemporal parameters. As shown in Fig. 11.4, an LRF sensor reports measurements used to estimate the patient's cadence, step length, and speed. The estimation of these parameters was proposed and validated in previous work [56, 64].

Physiological Parameters

The appropriate sensor to measure the HR must meet three main requirements: (1) it must allow physical activity while performing the measurement; in other words, the sensor must resist movement perturbations. (2) This sensor must allow online data transmission since the heart rate must be monitored in real-time during therapy. Finally, (3) the sensor must provide the processed data; namely, the sensor has to measure the signal and provide the heart rate value without requiring any additional processing. Hence, a suitable sensor for this application could be the heart rate monitor Zehpyr HxM BT (Zehpyr, USA) [65]. This sensor is located on the user's chest and reports a wireless and continuous measurement of the heart rate using Bluetooth communication [66].

Additionally, cervical posture corrections (the flexion of lower cervical vertebrae and its inclinations [67]) can be measured with the front camera of the tablet (Microsoft, USA) placed on the treadmill screen. A gaze estimator algorithm can be used. During the exercise, a proper cervical posture is set when the patient looks straight. In most therapies performed on a treadmill, the proper posture is essential to avoid dizziness, falls, and nausea. This measure represents the counting of a binary ("look-straight, not look-straight") value extracted from a gaze vector.

Exercise Intensity Parameters

Two different metrics are used to measure the physical activity difficulty: the inclination of the treadmill and the reported difficulty of the exercise. As the inclination most often cannot be accessed directly from the treadmill, an additional sensor must be installed. This sensor must be capable of measuring inclination angles in a range of 0 to 5 degrees (slope available on the treadmill), and as with the other sensors, it must allow online data transferring. Hence a sensor that meets these requirements is an IMU that will be placed on the treadmill so that one of its rotation angles corresponds to the central rotation axis of the treadmill. This way, changes in the measured IMU angle are equal to changes in the treadmill slope. For example, the MPU9150 IMU (Invensense, USA) [68] is an embedded system that combines a 3-axis gyroscope, one 3-axis accelerometer, a 3-axis magnetometer, and a digital motion processor.

11.3.3.2 Graphical User Interface

The GUI can run in a tactile computer monitor (i.e., Surface Pro-Microsoft, USA). This interface must present basic information and control panels regarding the status of the therapy (e.g., current user, session time, start/stop panel, emergency status, and biofeedback display) (see Fig. 11.5). As was presented in Fig. 11.4, the system receives the sensory data to be processed, stored, and displayed on the screen. With this information, the patient has access to visual feedback provided by the HCi. Hence, the graphical interface should report the synchronized and processed data from the sensors and allow the user to interact and respond to the requests generated by the system or the robot. Additionally, the interface must estimate the patient's fatigue level or related values, which can be captured employing the Borg scale (a qualitative measurement that estimates the perceived exertion of the patient, 6 for low intensity and 20 for very high intensity [69]). This value has to be periodically requested by the system or the robot.

Figure 11.5 presents an example of the main window (i.e., *MainTherapyWindow*) displayed during the therapy time. However, the system can contain additional functionalities and forms that allow the medical staff to register users, log in to the therapy session, and set therapy configuration parameters. Additionally, the system may allow the user to select different modalities of the therapy. In the

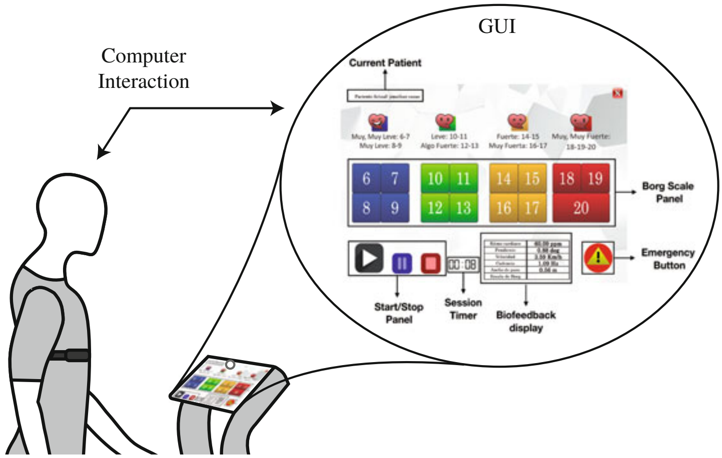

Fig. 11.5 Graphical User Interface to assess the patients' fatigue, view the therapy parameters as a form of feedback, configure the robot, monitor sensors, and control the therapy performance

first modality, the system could only work with the HCi; namely, the system only measures performance through the sensor interface and stores it in the database. Additionally, the GUI could request the Borg scale, even if feedback is not displayed on the screen. This modality is meant to measure a patient's performance without providing any feedback or social interaction and can be used for validation purposes with a control group defined in the baseline. The second modality could incorporate the social robot to provide social interaction, motivation, and monitoring. Similarly, the GUI should provide feedback regarding the state of the measured parameters (biofeedback display, see Fig. 11.5).

11.3.3.3 Social Robotic Agent

The robot module is focused on the interaction between the user and the robot. This interaction is provided through three robot roles: (i) motivational support, (ii) performance monitoring, and (iii) online feedback (emergency and warning). A typical therapy with the robot starts with an initial greeting, where the robot made an introduction of its functionalities during the rehabilitation program. Then, when the patient starts the exercise on the treadmill, the performance monitoring state is activated. During this state, sensory information is analyzed. Depending on the values given by each sensor, the current state can turn to the online feedback state or remain in the same state. If the online feedback is activated, two robot behaviors can be triggered (emergency or warning) when the system detects an increment in the physiological parameters such as training heart rate, Borg scale, and cervical posture.

11.4 Case Study: A Social Robot for Gait Rehabilitation with Lokomat

Patients who suffer from neurological disorders as spinal cord injuries, dementia, and cerebrovascular diseases like stroke are usually recommended to enter a physical rehabilitation (PR) program. PR is an active process to achieve a full recovery or an optimal physical, mental, and social potential to integrate the person appropriately back into society [70]. This is done through a combination of a (1) physiological treatment (e.g., cardiovascular, aerobic, and muscle control training) and (2) cognitive rehabilitation (e.g., language, perception, motivation, attention, and memory training) according to the patient's condition [70, 71]. There are different methods to perform PR. The conventional method is based on the guidance and manual assistance of the therapist in repetitive exercises that are used to improve the patient's performance [72]. In this method, the results depend merely on the expertise of the physiotherapist and the intensity of the exercises [73]. Alternatively, robot-assisted PR therapies combine a body weight support (BWS) system with a lower-limb exoskeleton to train physiological gait patterns on treadmills. Such is the case of PR with Lokomat, a robotic orthotic device that includes a BWS system to retrain gait [74].

Several studies have demonstrated the benefits of robot-assisted PR with Lokomat over the conventional therapies, including improvements in cardiovascular parameters [75], motor control [76], and balance [77], among others. However, even with robotic aids, PR is complex, and its second component, i.e., cognitive rehabilitation, has not been fully integrated. In healthcare, including social robots to rehabilitation procedures has shown progress regarding adherence to the treatments, assistance, and perception [5, 78]. This section presents the design and implementation of a patient–robot interface using SAR during Lokomat therapies.

11.4.1 Patient–Robot Interface

Following the approach presented in Sect. 11.3.3, Cespedes et al. [79, 80] developed and tested the interface. The system was composed of three main modules: (i) the sensory module, which allowed the acquisition and processing of sensory data, (ii) the Graphical User Interface, which was used for the computer interaction and monitoring, and (iii) the social robot module, in charge of the social interaction and the assistance of the patients. Figure 11.6 shows the patient–robot interface proposed for the Lokomat gait rehabilitation therapy using SAR.

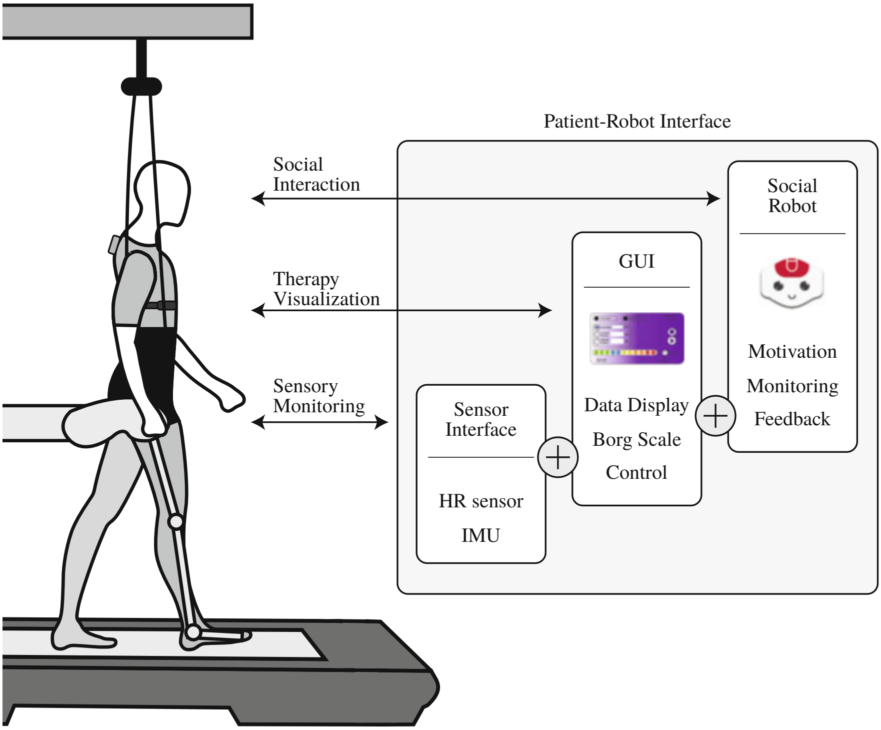

Fig. 11.6 Patient–robot interface for the Lokomat gait rehabilitation therapy using SAR

Sensory Module

The system acquired and processed the following physiological variables:

- The spinal posture (cervical and thoracic postures), measured with an IMU BNO055 (Adafruit, USA).
- The heart rate, measured with a Zephyr HxM sensor (Medtronic, New Zealand).
- The patients' perceived exertion during the exercise, measured with the Borg scale.

Graphical User Interface

The GUI was in charge of visualizing the therapy's data and controlling the session flow. Additionally, it allowed the therapists to interact with the patient and manage the session. A tablet Surface Pro (Windows, USA) was used to display the interface.

Social Robot Module

The robot's role was to provide feedback to the patients regarding their physiological parameters and motivate them during the therapy development. It supported the therapists while performing other tasks during the session, enabling physical distancing between the clinicians and the patient. The feedback given by the robot included nonverbal (imitation of healthy postures) and verbal gestures. The nonverbal gestures and the conversation scheme designed for the robot were developed with a rule-based algorithm. It depended on the events that took place during the sessions and the types of feedback presented. An NAO V6 robot (Softbank Robotics, France) was used to achieve the interaction.

11.4.2 Setup and Results

The study took place at the Mobility Group Rehabilitation Center located in Bogota, Colombia, where patients received Neurological Rehabilitation with Lokomat. A total of 10 patients were recruited to perform the rehabilitation assisted by the robot during 15 sessions. A session was conducted per week and lasted around 50 min. In the end, only 60% of the patients finished rehabilitation with Lokomat. Two conditions were established: (i) a *Control condition* and (b) a *Robot condition*. In the *Control condition*, the participants performed a conventional session of neurological rehabilitation with Lokomat. During the *Robot condition*, the participants performed the sessions assisted by the social robot. Patients were monitored in both conditions through the sensory module and the GUI and received support and additional feedback from the healthcare staff. Test sessions, where physiological parameters were measured, were performed at the beginning, in the middle, and at the end of the study. Afterward, the patients were assigned randomly to start with one of the conditions during six sessions. Finally, considering the start condition, the patients changed the scenario during another six sessions.

Two types of variables were analyzed to evaluate the robot assistance. The first one was quantitative variables, including the unhealthy posture time, the Borg scale, and the heart rate at training. The second group was qualitative variables from a questionnaire to observe the patient's perceptions of the robot's role. A Wilcoxon Signed-Rank test was applied to compare the patient's progress in both conditions. This is a non-parametric test used to compare two related samples and assess their difference [81]. A descriptive analysis was performed for the closed questions in the qualitative parameters, and a textual data analysis test was performed for the open items.

The study provided promising results regarding the inclusion of SAR in long-term PR and expanded the boundaries of robotic-assisted PR:

(i) In the case of patients who started the study with the *Control condition*, the percentage of unhealthy posture time regarding both the cervical and the thoracic postures (for both planes of motion) decreased when performing the session with the robot. The heart rate was maintained in a healthy range considering the exercise performed during the session, and the Borg scale was perceived at a low level.

(ii) Similarly, in the case of patients who started the*Robot condition* study, the percentage of unhealthy posture time regarding both postures was lower with the robot than without it. However, the patients seemed to maintain the posture after the robot intervention (the unhealthy posture time was lower compared to the previous group of patients), indicating that the patient learns how to control the cervical posture on the sagittal plane. Both the heart rate and the Borg scale were performed in healthy ranges.

(iii) Statistical differences in the different measurements between the *Robot* and the *Control condition* were found. For example, the percentages of unhealthy posture time were lower in the *Robot condition* than in the *Control condition*. Contrarily, the heart rate and the Borg scale parameters did not show differences between conditions.

(iv) During the robot condition, many benefits were evidenced. First, the feedback given by the robot allowed the patients to maintain a healthy posture and promote full gait rehabilitation. Patients considered that the system was safe and secure as they were continuously monitored. At the same time, this monitoring gave the medical team the possibility of performing other tasks during the session, which enriched the therapy sessions.

(v) An essential contribution of this study is how a patient–robot interface can enhance the methods in therapy by integrating different sources of information. For instance, the heart rate is not measured in conventional therapies. With the system and the robot's interaction, the clinicians could be warned by the robot and take action during the therapy if the patients had a high heart rate. Additionally, the inclusion of the Borg scale provided the clinicians with precise information regarding the performance of the patients. Altogether, clinicians could evaluate the patient's progress, not only in the gait behavior but also in their cardiovascular functioning and the exertion perceived during each session.

(vi) Although, in general, the robot's sociability was perceived as low by the users, they highlighted the platform's potential in PR with Lokomat. Fluid speech and conversation with the robot is the next step towards better social interaction. At the end of the sessions, most of the patients suggest using the robot with other patients. Clinicians' overall perception was also positive and in accordance with recent findings that evidence the need for social and cognitive support during PR [82]. These results showed the potential of SAR in gait rehabilitation as a tool to enhance the conventional sessions.

11.5 Conclusions

Gait rehabilitation is a primary component of physical rehabilitation processes for many patients with neurological disorders. Robot-assisted methods to perform this rehabilitation therapy have shown many physical benefits for patients. Nevertheless, these methods can still improve substantially as their cognitive component is explored. Social Assistive Robotics have been used in the last years in therapy to include cognitive aspects such as patient motivation and engagement. Starting from the basic concepts of social interaction, relevant characteristics of social robotics and their importance in rehabilitation processes were presented. After that, the methodology to design a Patient–Robot interface based on social robots was guided through a real-world rehabilitation scenario on a treadmill. The impact and promising future of including SAR in physical rehabilitation were at last shown in a case study of long-term gait rehabilitation with Lokomat.

References

1. L.L. Mullins, J.R. Keller, J.M. Chaney, A systems and social cognitive approach to team functioning in physical rehabilitation settings. Rehabilitation Psychology **39**(3), 161–178 (1994)
2. K. Fabel, G. Kempermann, Physical activity and the regulation of neurogenesis in the adult and aging brain. NeuroMolecular Medicine **10**, 59–66 (2008)
3. D. Feil-Seifer, M. Mataric, in *9th International Conference on Rehabilitation Robotics, 2005. ICORR 2005* (IEEE, Chicago, IL, USA, 2005), pp. 465–468
4. C. Breazeal, K. Dautenhahn, T. Kanda, Social robotics, in *Springer Handbook of Robotics* (Springer International Publishing, 2016), pp. 1935–1971
5. M.J. Matarić, J. Eriksson, D.J. Feil-Seifer, C.J. Winstein, Socially assistive robotics for post-stroke rehabilitation. J. NeuroEng. Rehab. **4**, 5 (2007)
6. Understanding Social Interaction|Boundless Sociology, https://courses.lumenlearning.com/boundless-sociology/chapter/understanding-social-interaction/. [Online; accessed 23-July-2019]
7. D. Feil-Seifer, M.J. Matarić, Toward Socially Assistive Robotics For Augmenting Interventions For Children With Autism Spectrum Disorders, Tech. rep., 2008
8. R. Krauss, Psychology of verbal communication. Int. Encyclopedia Soc. Behav. Sci., 16161–16165 (2004)
9. J. Casas, N. Cespedes, M. Múnera, C.A. Cifuentes, *Chapter One - Human-Robot Interaction for Rehabilitation Scenarios* (Academic Press, 2020)

10. D. Casas-Bocanegra, D. Gomez-Vargas, M.J. Pinto-Bernal, J. Maldonado, M. Munera, A. Villa-Moreno, M.F. Stoelen, T. Belpaeme, C.A. Cifuentes, An open-source social robot based on compliant soft robotics for therapy with children with ASD. Actuators **9**(3), 91 (2020)
11. K. Goris, J. Saldien, I. Vanderniepen, D. Lefeber, *The Huggable Robot Probo, a Multidisciplinary Research Platform*, vol. 33 (IEEE, 1970)
12. A. Shick, *Romibo Robot Project: An Open-Source Effort to Develop a Low-Cost Sensory Adaptable Robot for Special Needs Therapy and Education* (IEEE, 2013)
13. Y.H. Wu, C. Fassert, A.S. Rigaud, Designing robots for the elderly: Appearance issue and beyond. Archiv. Gerontol. Geriat. **54**, 121–126 (2012)
14. J. Fink, Anthropomorphism and human likeness in the design of robots and human-robot interaction, in *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 7621 LNAI (Springer, Berlin, Heidelberg, 2012), pp. 199–208
15. A.A. Ramírez-Duque, L.F. Aycardi, A. Villa, M. Munera, T. Bastos, T. Belpaeme, A. Frizera-Neto, C.A. Cifuentes, Collaborative and inclusive process with the autism community: A case study in Colombia about social robot design. Int. J. Soc. Robot. **13**, 153–167 (2021)
16. R.S. Lazarus, *Emotion and Adaptation* (Oxford University Press, 1991)
17. J.A. Russell, Core affect and the psychological construction of emotion. Physchol Rev. **110**(1), 145–172 (2003)
18. A. Mehrabian, J.A. Russell, *An Approach to Environmental Psychology* (MIT Press, 1974)
19. M.L. Hoffman, Toward a comprehensive empathy-based theory of prosocial moral development., in *Constructive & Destructive Behavior: Implications for Family, School, & Society* (American Psychological Association, 2004), pp. 61–86
20. I. Leite, S. Mascarenhas, C. Martinho, R. Prada, A. Paiva, The influence of empathy in human-robot relations. Int. J. Human Comput. Stud. **71**(3), 250–260 (2012)
21. B. Gonsior, S. Sosnowski, C. Mayer, J. Blume, B. Radig, D. Wollherr, K. Kuhnlenz, Improving aspects of empathy and subjective performance for HRI through mirroring facial expressions, in *Proceedings - IEEE International Workshop on Robot and Human Interactive Communication* pp. 350–356 (2011)
22. C. Breazeal, Cynthia, Social robots: From research to commercialization, in *Proceedings of the 2017 ACM/IEEE International Conference on Human-Robot Interaction - HRI '17*, pp. 1–1 (2017)
23. Z. Kasap, N. Magnenat-Thalmann, Towards episodic memory-based long-term affective interaction with a human-like robot, in *Proceedings - IEEE International Workshop on Robot and Human Interactive Communication*, pp. 452–457 (2010)
24. T. Belpaeme, P.E. Baxter, R. Read, R. Wood, H. Cuayáhuitl, B. Kiefer, S. Racioppa, I. Kruijff-Korbayová, G. Athanasopoulos, V. Enescu, R. Looije, M. Neerincx, Y. Demiris, R. Ros-Espinoza, A. Beck, L. Cañamero, A. Hiolle, M. Lewis, I. Baroni, M. Nalin, P. Cosi, G. Paci, F. Tesser, G. Sommavilla, R. Humbert, Multimodal child-robot interaction: Building social bonds. J. Human Robot Interact. **1**(2), 33–53 (2013)
25. E. Tsardoulias, A.L. Symeonidis, P.A. Mitkas, An automatic speech detection architecture for social robot oral interaction, in *AM '15* (2015)
26. Z. Kasap, N. Magnenat-Thalmann, Building long-term relationships with virtual and robotic characters: The role of remembering. Visual Computer **28**, 87–97 (2012)
27. K. Jokinen, G. Wilcock, Multimodal open-domain conversations with robotic platforms, in *Multimodal Behavior Analysis in the Wild: Advances and Challenges* (Elsevier, 2018), pp. 9–26
28. L. Yang, H. Cheng, J. Hao, Y. Ji, Y. Kuang, A survey on media interaction in social robotics, in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 9315 (Springer, 2015), pp. 181–190
29. T. Salter, I. Werry, F. Michaud, Going into the wild in child-robot interaction studies: Issues in social robotic development. Intell. Serv. Robot. **1**(2), 93–108 (2008)
30. P. Dhami, S. Moreno, J.F.X. DeSouza, New framework for rehabilitation - fusion of cognitive and physical rehabilitation: the hope for dancing. Front. Psychol. **5**, 1478 (2015)

31. A. Bandura, *Social Foundations of Thought and Action: A Social Cognitive Theory*. Prentice-Hall Series in Social Learning Theory (Prentice-Hall, Englewood Cliffs, NJ, 1986)
32. B. Irfan, N.C. Gomez, J. Casas, E. Senft, L.F. Gutierrez, M. Rincon-Roncancio, M. Munera, T. Belpaeme, C.A. Cifuentes, *Using a Personalised Socially Assistive Robot for Cardiac Rehabilitation: A Long-Term Case Study* (IEEE, 2020)
33. J. Casas, E. Senft, L.F. Gutierrez, M. Rincon-Rocancio, M. Munera, T. Belpaeme, C.A. Cifuentes, Social assistive robots: assessing the impact of a training assistant robot in cardiac rehabilitation. Int. J. Soc. Robot., 1–15 (2020)
34. N. Céspedes, B. Irfan, E. Senft, C.A. Cifuentes, L.F. Gutierrez, M. Rincon-Roncancio, T. Belpaeme, M. Múnera, A socially assistive robot for long-term cardiac rehabilitation in the real world. Front. Neurorobot. **15**, 633248 (2021)
35. M. Bautista, C.A. Cifuentes, M. Munera, Conversational agents for healthcare delivery: Potential solutions to the challenges of the pandemic, in *Internet of Medical Things*, 1st edn. (CRC Press, 2021), p. 26
36. J. Fasola, M. Mataric, A socially assistive robot exercise coach for the elderly. J. Human Robot Interact. **2**, 3–32 (2013)
37. J. Li, The benefit of being physically present: A survey of experimental works comparing copresent robots, telepresent robots and virtual agents. Int. J. Human Comput. Stud. **77**, 23–37 (2015)
38. V. Vasco, C. Willemse, P. Chevalier, D. De Tommaso, V. Gower, F. Gramatica, V. Tikhanoff, U. Pattacini, G. Metta, A. Wykowska, Train with me: A study comparing a socially assistive robot and a virtual agent for a rehabilitation task, in *Social Robotics*, vol. 11876, ed. by M.A. Salichs, S.S. Ge, E.I. Barakova, J.-J. Cabibihan, A.R. Wagner, A. Castro Gonzalez, H. He (Springer International Publishing, Cham, 2019), pp. 453–463
39. T.W. Bickmore, R.W. Picard, Establishing and maintaining long-term human-computer relationships. ACM Trans. Comput. Human Interact. **12**, 293–327 (2005)
40. C.D. Kidd, C. Breazeal, A robotic weight loss coach, in *Proceedings of the 22nd National Conference on Artificial Intelligence - Volume 2*, AAAI'07 (AAAI Press, 2007), p. 1985–1986
41. N. Maclean, P. Pound, A critical review of the concept of patient motivation in the literature on physical rehabilitation. Soc. Sci. Med. **50**, 495–506 (2000)
42. A. Tapus, M. Mataric, B. Scassellati, Socially assistive robotics [grand challenges of robotics]. IEEE Robot. Autom. Mag. **14**, 35–42 (2007)
43. K.I. Kang, S. Freedman, M.J. Matarić, M.J. Cunningham, B. Lopez, A hands-off physical therapy assistance robot for cardiac patients, in *9th International Conference on Rehabilitation Robotics, 2005. ICORR 2005*, pp. 337–340 (2005)
44. R. Gockley, A. Bruce, J. Forlizzi, M. Michalowski, A. Mundell, S. Rosenthal, B. Sellner, R. Simmons, K. Snipes, A. Schultz, Jue Wang, Designing robots for long-term social interaction, in *2005 IEEE/RSJ International Conference on Intelligent Robots and Systems* (IEEE, 2005), pp. 1338–1343
45. J. Fasola, M.J. Matarić, Using socially assistive human-robot interaction to motivate physical exercise for older adults. Proc. IEEE **100**(8), 2512–2526 (2012)
46. S. Sabanovic, C.C. Bennett, Wan-Ling Chang, L. Huber, PARO robot affects diverse interaction modalities in group sensory therapy for older adults with dementia, in *2013 IEEE 13th International Conference on Rehabilitation Robotics (ICORR)* (IEEE, Seattle, WA, 2013), pp. 1–6
47. K. Swift-Spong, E. Short, E. Wade, M.J. Mataric, Effects of comparative feedback from a socially assistive robot on self-efficacy in post-stroke rehabilitation, in *2015 IEEE International Conference on Rehabilitation Robotics (ICORR)* (IEEE, Singapore, Singapore, 2015), pp. 764–769
48. R. Looije, F. Cnossen, M. Neerincx, Incorporating Guidelines for Health Assistance into a Socially Intelligent Robot, Tech. rep., 2006
49. I. Baroni, M. Nalin, P. Baxter, C. Pozzi, E. Oleari, A. Sanna, T. Belpaeme, What a robotic companion could do for a diabetic child, in *The 23rd IEEE International Symposium on Robot and Human Interactive Communication* (IEEE, 2014), pp. 936–941

50. M. White, M.V. Radomski, M. Finkelstein, D.A.S. Nilsson, L.I.E. Oddsson, Assistive/socially assistive robotic platform for therapy and recovery: Patient perspectives. Int. J. Telemed. Appl. **2013**, 1–6 (2013)
51. P.L. Wilbourne, E.R. Levensky, Enhancing client motivation to change, in *Clinical Strategies for Becoming a Master Psychotherapist* (Elsevier, 2006), pp. 11–36
52. W.H. Organization, Adherence to long term therapies: Evidence for action. *WHO* (2013)
53. D.X. Cifu, J.S. Kreutzer, S.A. Kolakowsky-Hayner, J.H. Marwitz, J. Englander, The relationship between therapy intensity and rehabilitative outcomes after traumatic brain injury: a multicenter analysis11no commercial party having a direct financial interest in the results of the research supporting this article has or will confer a benefit upon the author(s) or upon any organization with which the author(s) is/are associated. Archiv. Phys. Med. Rehab. **84**, 1441–1448 (2003)
54. P. Gadde, H. Kharrazi, H. Patel, K.F. MacDorman, Toward monitoring and increasing exercise adherence in older adults by robotic intervention: A proof of concept study. J. Robot. **2011**, 1–11 (2011)
55. R. Sharma, V.I. Pavlovic, T.S. Huang, Toward multimodal human-computer interface. Proc. IEEE **86**(5), 853–869 (1998)
56. C.A. Cifuentes, A. Frizera, Human-robot interaction strategies for walker-assisted locomotion. Springer Tracts Adv. Robot. **115**(September), 105 (2016)
57. E. Bruno, S. Oussama, K. Frans, E.B. Siciliano, O. Khatib, F. Groen, *Springer Tracts in Advanced Robotics*, vol. 26 (Springer, 2003)
58. M.A. Goodrich, A.C. Schultz, Human-robot interaction: A survey. Found. Trends® Human Comput. Interact. **1**(3), 203–275 (2008)
59. M.L. Guha, A. Druin, J.A. Fails, Cooperative inquiry revisited: Reflections of the past and guidelines for the future of intergenerational co-design. Int. J. Child Comput. Interact. **1**(1), 14–23 (2013)
60. A.A. Ramírez-Duque, T. Bastos, M. Munera, C.A. Cifuentes, A. Frizera-Neto, Robot-assisted intervention for children with special needs: A comparative assessment for autism screening. Robot. Autonom. Syst. **127**, 103484 (2020)
61. N. Vallès-Peris, C. Angulo, M. Domènech, Children's imaginaries of human-robot interaction in healthcare. Int. J. Environ. Res. Public Health **15**(5), 970 (2018)
62. S. Merter, D. Hasırcı, A participatory product design process with children with autism spectrum disorder. Int. J. CoCreat. Des. Arts **14**(3), 170–187 (2018)
63. Y. Maeda Kamitani, Scanning Laser Range Finder Corrector Amended Reason, pp. 1–4 (2009)
64. A. Aguirre, S.D. Sierra M., M. Múnera, C.A. Cifuentes, Online system for gait parameters estimation using a LRF sensor for assistive devices. IEEE Sensors J., 1 (2020)
65. Zephyr Technology, HXM Bluetooth API Guide, pp. 1–21 (2011)
66. J.S. Lara, J. Casas, A. Aguirre, M. Munera, M. Rincon-Roncancio, B. Irfan, E. Senft, T. Belpaeme, C.A. Cifuentes, *Human-Robot Sensor Interface for Cardiac Rehabilitation* (IEEE, 2017)
67. R. Shafer, *Chapter 7: The Cervical Spine*, 2nd edn. (Wiliams & Wilkins, 1987)
68. Invensense, MPU-9150 Datasheet, vol. 1(408), pp. 1–50 (2013)
69. J. Scherr, B. Wolfarth, J.W. Christle, A. Pressler, S. Wagenpfeil, M. Halle, Associations between Borg's rating of perceived exertion and physiological measures of exercise intensity. Eur. J. Appl. Physiol. **113**, 147–155 (2013)
70. WHO, T. Dua, A. Janca, A. Muscetta, Public health principles and neurological disorders. Neurol. Disord. Public Health Challen. **2**, 7–25 (2006)
71. S.B. O'Sullivan, T.J. Schmitz, G.D. Fulk, *Physical Rehabilitation* (F.A. Davis, 2013)
72. L.L. Stanley Fisher, A. Trasher, Robot-Assisted Gait Training for Patients with Hemiparesis Due to stroke (2011)
73. G.L. Shahid Hussain, S. QuanXie, Robot assisted treadmill training: Mechanisms and training strategies. Med. Eng. Phys. **33**, 527–533 (2011)
74. M. Munera, A. Marroquin, L. Jimenez, J.S. Lara, C. Gomez, S. Rodriguez, L.E. Rodriguez, C.A. Cifuentes, *Lokomat Therapy in Colombia: Current State and Cognitive Aspects* (IEEE, 2017)

75. A. Mayr, M. Kofler, E. Quirbach, H. Matzak, K. Fröhlich, L. Saltuari, Prospective, blinded, randomized crossover study of gait rehabilitation in stroke patients using the Lokomat gait orthosis. Neurorehab. Neural Repair **21**(4), 307–314 (2007)
76. R. Banz, M. Bolliger, G. Colombo, V. Dietz, L. Lunenburger, Computerized visual feedback: An adjunct to robotic-assisted gait training. Physical Therapy **88**, 1135–1145 (2008)
77. D.-H. Bang, W.-S. Shin, Effects of robot-assisted gait training on spatiotemporal gait parameters and balance in patients with chronic stroke: A randomized controlled pilot trial. NeuroRehabilitation **38**(4), 343–349 (2016)
78. J.A. Casas, N. Céspedes, C.A. Cifuentes, L.F. Gutierrez, M. Rincón-Roncancio, M. Múnera, Expectation vs. reality: Attitudes towards a socially assistive robot in cardiac rehabilitation. Appl. Sci. (Switzerland) **9**(21), 4651 (2019)
79. N. Céspedes, D. Raigoso, M. Múnera, C.A. Cifuentes, Long-term social human-robot interaction for neurorehabilitation: Robots as a tool to support gait therapy in the pandemic. Front. Neurorob. **15**, 10 (2021)
80. N. Céspedes, M. Múnera, C. Gómez, C.A. Cifuentes, Social human-robot interaction for gait rehabilitation. IEEE Trans. Neural Syst. Rehab. Eng. **28**(6), 1299–1307 (2020)
81. F. Wilcoxon, Individual comparisons by ranking methods. Biometrics Bulletin **1**, 80 (1945)
82. D. Raigoso, N. Céspedes, C. Cifuentes, A.J. del Ama, M. Munera, A survey on socially assistive robotics: Clinicians’ and patients’ perception of a social robot within gait rehabilitation therapies. Brain Sciences **11**(6), 738 (2021)