25 Telerehabilitation Technology

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Abstract

Due to physical and cognitive deficits, it is often difficult and costly for individuals who have suffered a stroke to access on-site neurorehabilitation. Telerehabilitation offers the opportunity to improve the rehabilitation process as it can provide intensive supervised rehabilitation in the home environment. The term telerehabilitation refers to the provision of therapeutic services at a distance, enabled by electronic telecommunication and information technologies. Services are provided through a variety of technical systems with different purposes and capabilities. This chapter provides an overview of technical solutions for providing telerehabilitation services to treat the main consequences of stroke, namely paresis of the upper and lower extremities, and communication difficulties. We describe the communication tools, sensor technologies, virtual reality systems, and robots for service delivery and explore the facilitators and barriers to successful implementation. Evidence is summarized in the context of teleassessment, telemonitoring, and teletherapy.

Keywords

Telehealth · Teletherapy · Telemonitoring · Teleassessment · Stroke

25.1 Introduction

In neurorehabilitation, clients face numerous barriers to accessing usual on-site appointments including geographic isolation, limited resources, and shortage of time; all these may lead to the lack of compliance with rehabilitation regimens [1]. Telerehabilitation may help to overcome these barriers and is a suitable supplement or even substitute to usual rehabilitation. The term *telerehabilitation* describes the use of information and communication technologies (ICT) for the delivery of rehabilitation services to people at a distance, for example, in the home environment, in the out-client area, in the in-client sector, or at school [2, 3]. Early attempts to use phones for teletherapy of people with aphasia were made as early as the 1970s. Vaughn et al. designed a device that combined phones “with a

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variety of terminal devices, such a speaker phone for speech, handset for other auditory signals, a “Touchtone” keypad for pointing responses, a teletypewriter for typing, a “Telenote” device for handwriting, and computer terminals for more generalized applications” [4, 5]. Standardized assessments such as the modified Barthel Index were also successfully carried out on the phone in the 1980s [6]. In the age of digitalization and the Internet, technologies are advancing, becoming cheaper, more accessible and ubiquitous, and available to a greater number of people. As ICT continues to develop, telerehabilitation is becoming a global treatment option.

25.1.1 Benefits

Telerehabilitation offers many advantages as compared to conventional in-person therapy: By eliminating the need to travel long distances, telerehabilitation helps clients comply with treatment protocols. The remote delivery of service is especially important for those who have difficulties traveling due to physical impairments or who live in rural or remote settings. Telerehabilitation can increase the frequency of services and enhance continuity of care [2].

Perhaps even more importantly, telerehabilitation promotes clients’ involvement and empowers them to care for and manage their medical needs and therapeutic interventions [2, 7]. Clients’ empowerment and engagement are key elements to enhance neuroplasticity and facilitate functional recovery in neurological disorders [8, 9]. Most health care, perhaps as much as 85%, is self-care [10, 11]. The home environment as an authentic environment for the experiences of functioning encourages clients to develop problem-solving skills and actively engages them in the rehabilitation process [7]. Through the use of new technologies, the client is not alone in his home rehabilitation. As therapists have access to data from home, clients can self-train knowing that their therapist is tracking their progress. Automatized real-time feedback from technologies motivates and engages the client, thus, further promoting neuroplasticity [12, 13].

Educational materials that directly address the current state (as assessed during therapy) can be delivered promptly when needed and improve client knowledge. “The greater the understanding and comprehension that clients have in terms of the rehabilitation process, goals, diagnosis, and healing process, the more invested they will be in their own recovery” [8].

Clients with neurological disorders have often complex healthcare needs that require a multidisciplinary coordination of their rehabilitation. Services are provided by many professionals including physicians, psychologists, rehabilitation engineers, audiologists, nurses, and educators, out-client rehabilitation, and, above all, by occupational and physical therapists as well as speech–language pathologists [3]. Telerehabilitation can be integrated into telemedicine platforms that allow to connect all stakeholders including the client and share all relevant information in real-time.

25.1.2 Interaction from a Distance

In telerehabilitation, therapists and clients communicate from a distance and exchange health data with the use of technologies. These include video conferencing systems, instant messaging platforms, mobile health (mhealth) applications, electronic client portals, and digital client platforms. By incorporating additional technologies, telerehabilitation enables not only audiovisual interaction but also real-time exchange of ``hands-on' information. Wearables, for example, monitor specific types of physiological parameters that are readily accessible from outside the human body. Robotic devices can give assistance and transmit information about forces and movements to give therapists a deeper understanding of the client’s sensorimotor performance [14, 15]. Environmental sensors provide information about how clients interact with their environment. Taken together, the potential of interaction between therapists and clients is not restricted to audiovisual communication. Innovations in medical devices such as nanosensor technologies and virtual reality may expand the possible information exchanged in the future [16].

25.1.3 Synchronous and Asynchronous Therapy

Telerehabilitation may be delivered synchronously when therapist and client communicate in real-time [17]. Usually, they speak via video conferencing and telemedicine systems. Telerehabilitation may also be performed asynchronously when information for therapy or education is delivered to the client so that he/she can train alone, or when the client trains alone and recorded data is transmitted to the therapist [17]. After a familiarization phase under therapist supervision, clients can continue therapy independently. Thus, telerehabilitation shifts from remote one-to-one therapy to (partially) supervised self-training.

Self-training may involve medical applications (apps) or gaming software run on flat screens, head-mounted devices, or projection systems, that provide clients with visual and auditory feedbacks (but may also include other sensory inputs such as touch, movement, balance, and smell) [18]. The user interacts with the virtual environment by a mouse or joystick, cameras, sensors, or haptic (touch) feedback devices. The data may be further analyzed or processed (e.g., to recognize trends of recovery over days or weeks). Robotics for self-therapy enable clients to practice independently with mechanical assistance [19]. Self-training with integrated feedback may empower and motivate clients to engage in therapy.

25.1.4 Acceptance of Telerehabilitation

Although telerehabilitation is applied regularly in rural regions, its general implementation and acceptance was rather limited among therapists and clients until the Coronavirus disease 2019 (COVID-19) pandemic forced a rapid adoption of telerehabilitation. Because severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) is highly contagious, vulnerable persons were isolated starting in 2020. Unfortunately, those who require rehabilitation are often vulnerable (e.g., 90% of stroke clients in Switzerland are 65 or above) [3]. Furthermore, the pandemic went along with very early in-client discharge and a suspension of rehabilitation services in out-client settings in 2020, which decreased the access to rehabilitation services and their availability [7, 8]. To aggravate the situation, SARS-CoV-2 infection is not only associated with pneumonia, but also with neurological complications: The hypercoagulable states may lead to stroke and other neurological manifestations. Thus, COVID-19 did not only decrease the supply of rehabilitative services but also additionally increased the number of persons who required these.

Telerehabilitation was a promising way to fill the supply gap of rehabilitative measures during the pandemic. As telerehabilitation reduces the contact between vulnerable persons and the environment, it enables the therapy of persons in strict isolation [15]. Thus, traditional in-person visits were often replaced by tele-services. In Switzerland, for example, about two-thirds of occupational therapists (OT) provided telerehabilitation during the COVID-19 pandemic lockdown although they were often not reimbursed and the pandemic did hardly allow to implement measures associated with the successful implementation of telerehabilitation such as education and training, as well as administrative and technical support [20]. The service relied mainly on audiovisual interaction. The media used most was phone followed by chat services, email, video conferencing systems, and short messages services (SMS). One reason for this rather low use of modern technologies may be clients' preferences. 95% of people aged 65–69 already use the Internet, but only 35% of people aged 85 and over do (numbers from Switzerland 2020 [21]). Three-quarters of the OTs rated their clients' experience of telerehabilitation as positive or rather positive during the lockdown [20]. About two-thirds of OTs described their own experience as broadly positive or rather positive, and about one-quarter as negative or rather negative [22].

Usually, it needs two for out-client telerehabilitation: clinicians and clients. What does it take to improve the telerehabilitation experience for both user groups? The uptake of tele-services is influenced by facilitators and barriers. Almathamy et al. [23] reviewed scientific literature regarding factors that influence clients' adoption of telemedicine. The telemedical counseling they focused on was delivered with synchronous video conferencing systems or software, most studies reported on specially developed systems. The authors distinguished internal and external factors that influence the adoption. While the former describes the users' behaviors and motivations, the latter refers to the system and the surrounding environment. External barriers described were mainly technical (e.g., low internet speed or difficulty to use the system). Internal barriers included resistance to technology, the lack of eye as well as physical and social contacts with telemedicine, and clients' security concerns. Accordingly, understanding of the technology and high internet speed were important facilitators. Family involvement during treatment facilitated the use of systems.

For the service to be effective, clinicians do not only need to find it useful for clients, but they themselves require to be ready for system uptake [24]. To achieve successful implementation and sustainable use of telerehabilitation, it needs preparation, teaching, and support from an organization. Jafni et al. adopted findings from a critical care information system and identified seven significant factors that influence the adoption of telerehabilitation by therapists [25, 26]:

- The system's functions and features should be more useful, faster, and easier compared to existing systems.
- The delivered information must be accurate and understandable for every stakeholder including the client.
- Service quality requires follow-up services and responsiveness to support requests.
- Users should receive regular training that targets technology skills, safety, and security. Implementation plans help avoid problems.
- System performance must be reliable.
- Factors that influence users' decisions on system use include professional hierarchy, age, education, system ease of use, and cutting-edge technology [26]. The system must be effective and useful to meet the expectations even of stakeholders with limited IT skills.
- A strategy is needed to get stakeholders to adopt the new system. This includes stakeholder involvement, interactive communication (e.g., meetings), and a "champion" who can influence and encourage others to use the system.

25.1.5 Effectiveness of Telerehabilitation

The effectiveness of telerehabilitation has not yet been sufficiently proven. There are several studies showing that telerehabilitation interventions have either better or equal salutary effects on motor, higher cortical, and mood disorders as well as quality of life compared with conventional in-person interventions. However, evidence is based mostly on pilot projects that are small in sample size and proof-of-concept in nature, and randomized controlled trials (RCT) are scarce. A meta-analysis in 2020 by Laver et al., involving 22 RCTs, examined the efficacy of telerehabilitation after stroke [12]. The authors concluded that data are not sufficient to draw definitive conclusions as there was variance in interventions and comparators among studies, few adequately powered studies, and several studies with risk of bias. However, at this point telerehabilitation seems not inferior to in-person services or usual care regarding improvement in upper limb function, improvement of health-related quality of life, independence in ADL, or reduction of depressive symptoms [12].

Therapy is an important part, but it is not the only service that is delivered in rehabilitation: Rehabilitation involves also monitoring, assessment, prevention, assistance, supervision, education, consultation, and coaching [3]. We focus on telemonitoring, teleassessments, and teletherapy because current research, especially in these areas, employs new technologies that go beyond audiovisual interaction. Telemonitoring is based on the observation of behavioral, biological, or psychological signals. Standardized teleassessments complement this continuous real-world data in providing metrics that mirror clinical assessments [27]. The term teletherapy describes the delivery of sensory motor and cognitive rehabilitative treatment.

25.1.6 Stroke

We focus on stroke as the manifestations and the recovery process after stroke are good examples of how different technological advances may cover the entire neurorehabilitation spectrum of a client. Stroke is one of the leading causes of long-term disability in the world and survivors often need long-term neurorehabilitation treatment. About 26% remain disabled in basic ADL and 50% suffer from reduced mobility due to hemiparesis [28]. Aphasia and depression are other frequent causes of disability. Thus, stroke is a disease of immense public health importance with growing economic and social consequences [29].

We focus on telerehabilitation for the main complications of stroke, namely paralysis or loss of muscle movement of the upper and lower extremities, and communication difficulties.

25.2 Upper Extremity

A frequent consequence of stroke is a decline in functioning of the upper extremities, like the shoulders, arms, hands, and fingers [30–32] which, in turn, is often associated with a deterioration in life quality [33, 34].

After a stroke, stroke survivors enter a recovery process. Recovery refers to the improvement in one or more components of an individual's functioning over time [35]. Importantly, at the level of motor behavior, recovery must be distinguished from compensation [36–38]. Behavioral recovery refers to actions that reflect restitution of pre-morbid movements, that is, actions using the same anatomical body parts (i.e., muscles, joints, effectors) for task accomplishment as before the neurological disease, whereas compensation refers to performing a task with different/additional body parts [35]. For example, when an individual reaches for a cup on a table, only shoulder, elbow, wrist, and finger movements may be employed before a stroke. Conversely, after a stroke, a person might make additional trunk movements in direction of reach to support arm and hand movements.

25.2.1 Assessment of Motor Functioning

25.2.1.1 Clinical Assessment

Observation-based Clinical Assessment
Neurorehabilitation research examines the factors of interventions that optimize recovery, like the type of therapy approach and the time of delivery in clients' rehabilitation journey [35]. Evidence for the effectiveness of an intervention is key for generation and accumulation of knowledge, which is fundamental for decision-making in the treatment of individuals [39]. However, the effectiveness of an intervention study is often not comparable to the effectiveness of other studies, due to differences in measured constructs and assessment tools [39]. Therefore, many efforts were made, like systematic reviews and Delphi studies, to determine a set of outcome measures for motor functioning that should be used universally [39–45].

Outcome measures are typically sorted according to several categories [39, 44]. First, they are categorized by the International Classification of Functioning, Disability, and Health (ICF) domains.

The ICF uses the term functioning to refer to an individual's health and disability status. Functioning is regarded as a general term and is defined by three sub-domains [46]:

1. *Body structure and body functions* are anatomical parts of the body and physiological and psychological functions. Problems in body structure or function are defined as impairments.
2. *Activity* is the execution of tasks by an individual. Problems with task accomplishment are referred to as activity limitations.
3. *Participation* is an individual's involvement in life situations. Problems during participation in real-life situations are called participation restrictions.

For example, when an individual experiences a stroke, the incident might result in impairments to the motor cortex (body structure) and the execution of shoulder movements (body function), which might limit reaching movements for objects (activity), which might be a restriction when shopping for groceries (participation).

Clinical outcome measures are often based on the observation of individuals' behavior by a clinical evaluator [44]. Technology-based outcome measures are obtained from sensor data that are usually transformed (e.g., the spatial position of the wrist over time is transformed to movement speed or the number of movement units [45]. Moreover, technology-based outcome measures at the ICF activity level can be classified as capacity (i.e., maximal activity, performed in a controlled environment) and performance measures (i.e., activity in a real-life setting [39, 47, 48]). Outcome measures must fulfill strict criteria regarding validity, reliability, responsiveness, clinical utility, and expert consensus to be recommended [39, 44].

Widely recommended examples of clinical outcome measures of the upper extremity are the Fugl–Meyer Assessment for Upper Extremities (FMA-UE [49, 50]; function level of ICF) and the Action Research Arm Task (ARAT [51, 52], activity level of ICF). The ARAT is an example of a capacity measure.

The FMA-UE covers 33 items that examine reflexes, voluntary movements, and movement synergies of shoulder, elbow, wrist, and fingers. Required materials are a reflex hammer and objects for movement task, like a sheet of paper or a tennis ball. Evaluators rate the degree of function for each item on a three-point scale. Administration time is about 30 minutes [53]. To provide a specific example, in one item of FMA-UE individuals need to abduct their arm. The behavior of interest is the shoulder abduction function (which, after stroke, may be accompanied with undesired elbow movement).

The ARAT comprises of 19 movement tasks, in which clients make reaching, grasp, grip or pinch movements, using standardized objects, like wooden blocks, marbles, pieces of metallic tubes, etc. Evaluators rate clients' ability to perform each task and quality of movement on a four-point scale. Testing time is about 5–20 minutes [52, 54]. One task, for example, is to pick up a wooden ball from a table and put it onto a shelf that is placed within reach. Of interest is the entire sequence of movements.

Clinical outcome measures at the ICF participation level are usually questionnaires that assess participation in daily life as perceived by clients [39, 43]. An example of a recommended questionnaire is the Stroke Impact Scale [43].

Clinical outcome measures, such as the FMA-UE and the ARAT, are well established in clinical practice and have excellent psychometric properties [43]. However, they rely on direct observation, with client and evaluator being present at the same location. Hence, the question arises of how the assessment of motor functioning can be realized in remote settings. One solution is to video-record clinical assessments remotely and to evaluate the videos at a different location [55]. This method has excellent psychometric properties but implies additional time and material costs for cameras and the operation of standardized video-shooting procedures. Thus, for remote assessment, technology-generated outcome measures might be a more actionable solution.

Technology-Based Clinical Assessment

Technology-generated outcome measures are considered as an important complement to clinical outcome measures because of several advantages [39]: They are objective [45] (as they do not depend on the interpretation of an observer) and more sensitive [56] (as they yield continuous scale data). Thus, they can gather more detailed information about recovery which provides better information for the personalization of treatment regimina [56, 57]. Another advantage is that technology-generated outcome measures can distinguish between behavioral recovery and compensation, as they can measure both types of behavior separately, which extends information yielded by the ARAT [57, 58].

For the ICF function level, an expert committee recommended to employ a reaching task in the horizontal plane and capture kinematic outcome measures with an optoelectrical camera system [45, 59]. Optoelectrical systems use multiple cameras with infrared illuminators and triangulation algorithms to reconstruct the three-dimensional (3D) position of reflective markers [60]. Markers are placed at defined anatomical landmarks of individuals' body segments to measure their position and to derive kinematic measures. Position measurement of a marker has less than 1 mm error and measurement of joint angles has an error range of 1–degrees [61]. Alternatives are networks of IMUs and markerless camera systems (multiple high-quality video cameras and computer vision-based analysis). Compared to marker-based systems, these are slightly less [62] or similarly accurate [63], respectively. IMU networks are mobile, whereas markerless camera systems leave individuals' bodies free of markers and sensor straps. However, both systems are similar to optoelectrical systems in price range and complexity of analysis. Hence, these systems imply similar barriers to the widespread use in clinical practice and at home as marker-based systems.

Moreover, various force measurement devices are recommended to measure grip strength (entire hand), precision grip [64] strength (individual fingers), and assess finger individuation [65] (control of one finger independently of the others). An advantage of the assessments for hand and finger strength is that they are quick and easy to administer as compared to other clinical or technology-based assessments, and that muscle strength early after stroke is a good predictor in statistical models of motor improvement capacity [66, 67].

For the ICF activity level, an expert committee recommended a 3D reaching task ("drinking task") and optoelectrical cameras for kinematic measurement [57, 68–70]. For this task, recommendations extend to the analysis of kinematic outcome measures [45], such as the number of movement units of the arm endpoint and angular velocity of the elbow, and trunk displacement and arm abduction angle [58]. Recovery, as opposed to compensation, corresponds to a smaller number of movement units of the arm endpoint, higher angular velocity of the elbow, less trunk inclination, and less arm abduction [57].

While the 3D reaching task assesses capacity at the ICF activity level, experts recommended to assess performance by monitoring arm use in real life, using measures like threshold activity counting [71], which can be obtained with accelerometers or inertial measurement units (IMUs) [39, 72]. However, a standardized way for application and analysis of this assessment is still missing and requires further research [39].

The described technology-based outcome measures are rather established in research than in clinical application. The equipment is expensive (about 10′000–20′000 USD), application is time-intense, and analysis is rather complex, especially in the case of optoelectrical camera systems [39]. Hence, their immediate application in remote settings appears to be impracticable.

25.2.1.2 Tele-Assessment

Low-cost sensor technologies, such as IMUs and depth-sensing cameras, and advances in video-based pose tracking algorithms are expected to enable technology-based assessment in clinical practice and real-life settings, once usability and standardization application and analysis have matured [42, 45].

Accelerometers and IMU sensors are the most frequently used wearable sensors in neurorehabilitation research [73, 74] (see Wang et al. for more types of wearable sensors). Accelerometers measure linear acceleration, gyroscopes measure angular velocity and magnetometers measure magnetic fields; an IMU is an assembly of these three components and captures the mentioned quantities in three orthogonal dimensions, which are usually aligned with the device's housing [75]. Usually, 2–4 sensor units are used and placed at wrists or lower arms, upper arms, or the sternum [74]. Data are frequently used to estimate the orientation of the device in order to estimate orientation of body segments or joint angles [74], with errors lying in the three to eight-degree range [60].

Another technology for clinical practice and home-use are standard digital RGB (Red–Green–Blue) video cameras (e.g., like those of a webcam) combined with infrared depth sensors [76] (RGB-D). Algorithms use these video and depth data to estimate and track 3D joint positions. The position data can be used to estimate joint angles, which have a similar error to IMUs depending on the viewing angle [60, 77].

Pose estimation algorithms [78] are based on computer vision and deep learning, and only use videos of standard digital RGB cameras [79]. The algorithms detect and track joint positions and yield two-dimensional (2D) or 3D position data, depending on the capabilities of the algorithms. Validation studies showed that accuracy can be similar to that of depth-sensing cameras when the plane of body motion and camera viewing angle are aligned (e.g., trunk movement in the frontal plane is captured by a frontal camera [80].

Stereo cameras might be the key technology to provide accurate but low-cost motion sensing [81]. Stereo camera systems consist of two or more RGB video cameras. Depth information is inferred by the difference in an object's positions in the two camera images.

These low-cost technologies can be used to capture motion data and measure motor functioning at each ICF level [73].

Motion data are commonly used to classify the degree of motor function impairment or activity limitation [73]. Observation-based assessments such as the FMU-UE or the ARAT yield ordinal values. Supervised machine learning algorithms can estimate the observation-based scores from the motion data, captured during the clinical assessment tasks [82, 83] or during different functional tasks [84, 85]. For example, FMA-UE scores were estimated from sensor data that were recorded during eight functional motor tasks [85]. Hence, this approach may require fewer movement samples than FMA-UE or ARAT assessments [84]. A drawback of wearable sensors is that they require donning, while camera systems do not have this disadvantage [73].

Estimating clinical scores at the ordinal level has the advantage of linking motion data to validated assessments of motor functioning, but it does not take advantage of the continuous scale data that is provided by the sensors [73]. However, the use of continuous data requires the identification and psychometric validation of the kinematic metrics, as it is the case with the recommended outcome measures obtained with optoelectrical cameras [57].

As mentioned above, motor functioning at the ICF activity performance level has already been quantified by assessing arm motion in real-life, for several hours to several days [73]. Accelerometer data were used, with sensors being placed at one or both wrists [73], and measures as activity counts were employed [71] Activity counts measured whether acceleration magnitude was above a particular threshold [71]. In neurological clients, arm use of the more affected upper limb was compared with the less affected or with data from healthy individuals [71, 73, 86, 87].

Function can be defined as the functionality of a body structure as is the case in the ICF framework. Functional motion can be also defined as the goal-directed and volitional motion of the upper limbs in relation to an object or target during ADL [88]. One approach aims to detect this functional motion and identify its nature during ADL in real-life settings [73]. In these studies, functional motion is defined as the goal-directed and volitional motion of the upper limbs with regard to an object or target in ADL [88]. Functional motion covers functional primitives (e.g., reaching, transporting, repositioning) that can be combined into functional movements (e.g., drinking from a cup) and functional activities (e.g., having dinner). For this approach, usually, IMUs are used and placed at individuals' wrists and/or various other positions [73]. First, several repetitions of each functional task are executed in a standardized setting and categorized by human observers. Then, supervised machine learning is used to estimate the category using the motion data [89–91]. This approach ultimately allows quantification of individuals' functioning on all ICF levels, for example by counting the number of functional activity executions (activity performance) or by measuring movement quality within functional activities [89].

25.2.2 Teletherapy

Neurorehabilitation research and guidelines suggest that recovery of motor functioning is positively influenced by interventions that follow principles of motor learning, such as high intensity and repetitive practice [92–97]. Recovery is positively influenced by the use of technology, as it facilitates the provision of therapy that follows these suggestions [39, 98].

In clinical application, rehabilitation technology may comprise of end-effector and exoskeleton rehabilitation robots linked to multimodal virtual or augmented reality environments [99]. Moreover, low-cost rehabilitation systems may be used that require less direct supervision by health professionals to deliver additional therapy in clinical and home-based settings [12, 98].

Rehabilitation systems for home use can be broadly categorized as feedback systems, virtual reality (VR) systems, and robotic systems [100]. Feedback systems use human motion data to provide feedback about motor performance, primarily in real-life environments [74, 101], whereas VR systems use individuals' motion data to provide interaction with artificially generated environments [102]. The systems may complement each other, as feedback systems are specialized in monitoring and feedback, whereas VR systems focus on training [103]. Robotic systems are usually seen as a separate class [100], even when combined with VR displays, because they comprise of extensive robotic apparatus [104].

25.2.2.1 Feedback Systems

Feedback systems usually consist of wearable sensors (accelerometers or IMUs) on the wrist of the impaired upper limb and sometimes on other body segments (for reviews see [73, 74]). Motion data are used for the estimation of arm use intensity, recognition of specific arm movements, recognition of particular exercises, and movement quality [73]. These analyses yield feedback such as information about upper limb use, the number of completed arm exercises, or numeric values for the degree of compensation [74]. In several studies, feedback was provided in form of vibrotactile signals, as these do not require visual attention. For example, vibrotactile feedback was applied to the affected arm as a reminder to use the arm more frequently [105, 106]. In another study, visual feedback was provided on conventional laptops or tablet screens in form of numbers or graphs which showed summary information of relevant metrics [107–109]. Several studies provided evidence that feedback systems improve motor performance and suggest that feedback systems have the potential to motivate individuals to move, increase adherence, and support motor learning [105, 106, 109]. However, evidence is sparse, especially in form of RCT [74, 110]. Further research is required to explore the full potential of feedback systems, notably with respect to systems that provide feedback during motor performance [73].

25.2.2.2 VR Systems

VR systems use data from motion sensing technologies to allow interaction between individuals and virtual environments [102]. The rationale behind VR systems is that immersion and use of games motivate individuals to practice [111].

VR systems can be classified by the type of motion sensing system and display technology [111]. Motion sensing systems (for lists of systems see [104, 112]) can be grouped into desktop (e.g., joysticks), body-mounted (e.g., IMU systems, sensor gloves, head-mounted displays), and contact-free systems (e.g., camera-based systems). Individual motion sensing systems may contain various motion sensing technologies (e.g., force sensors, pressure sensors, IMUs, depth sensors).

Display technologies of VR systems can be categorized into visual (e.g., 2D flat panel displays), auditory (e.g., two speakers for stereo sound), and haptic displays (e.g., vibrotactile actuators, force feedback [102]).

VR systems differ in the degree of immersion and, hence, can further be classified as non-immersive systems (e.g., systems with conventional tablets) and immersive systems (e.g., 3D stereoscopic vision head-mounted displays with surround sound [104]). Immersion in this definition is a technical quality and refers to the capability of systems to simulate the real world and generate authentic virtual experiences [113, 114].

Individuals may experience the virtual environment from a first- or third-person view. Motion data of individuals' body segments or joints are used to enable synchronous action in the virtual environment.

Examples of commercialized VR rehabilitation of the upper limbs can be found in a recent review [104].

An umbrella review of the meta-analysis concluded that there is evidence of a benefit of VR on motor function, but that evidence is weak as study quality is low or very low [114]. According to the review, important moderating factors for a benefit of VR are the quality of immersion, interactivity, and customization of VR environments. Immersion and interactivity are important because differences in perceived distance between VR and real life, as well as system delays, might hinder the transference of skills from VR environments to real life [115]. This is critical as clinical evidence for the transfer of skills from VR training to real life is inconclusive [116]. Customization of VR environments is an important capability of VR systems as individuals with motor deficits might also have deficits in perception or cognition (e.g., individuals with attention deficits might require environments with reduced distraction [103]). Thus, VR systems engineered for neurorehabilitation are preferable to commercial VR gaming solutions that rather are designed for able-bodied individuals [114].

Several reviews examined the efficacy of VR-based training in home-based settings [103, 117]. Across reviews, only a few randomized controlled trials were identified. These generally showed a benefit of VR telerehabilitation that is comparable to conventional therapy, but the numbers of participants per study were low, VR Systems and intervention protocols differed strongly, and there was a wide variety in outcome measures. One RCT [118] that observed a benefit of VR-based telerehabilitation (and demonstrated noninferiority to conventional face-to-face therapy) applied several techniques to influence therapy outcomes such as behavioral contracts, stroke education, high ease of use, many input devices to cover a large range arm movement functions, frequent interaction with clients, multiple means of providing client feedback, solutions for creating appointment, and reminders. In several clients, this led to more than 1000 arm movement repetitions per client and day. This points to the conclusions that many aspects of therapy require optimization to obtain the desired doses of practice and beneficial effects on arm movement recovery.

25.2.2.3 Robotic Systems

There is a large and quickly increasing number of rehabilitation robots and robotic devices for the upper extremities (a recent review lists commercial devices for home use [119]). Robotic devices can be classified into grounded end-effectors, grounded exoskeletons, and wearable exoskeletons [120]. End-effector devices are usually only attached to individuals' distal arm parts, such as the hands or fingers. Exoskeletons target one or more joints of a paretic limb and are attached to adjacent segments. Systems can be further divided into passive, active, and interactive systems, depending on whether they merely stabilize, actively control, or react to individuals' movement input (for further classification see [121]). Systems are often equipped with sensors and, hence, can measure kinetics and kinematics that can be used to control VR-based exercises. Robotic devices for home use mainly target wrist, hand, and fingers [120]. Figure 25.1 shows an example of an interactive end-effector robot, the ReHandyBot, a portable robot for hand rehabilitation [122].

In clinical settings, robot-assisted therapy resulted in similar or larger improvements in upper extremity motor function as conventional interventions [123–125], regardless of the type of robotic arm training device [126]. Furthermore, for home-based settings, studies also suggest a benefit of robot-assisted therapy that is similar to conventional therapy, but the number of studies is rather small [127]. Drawbacks of robotic systems are their obtrusiveness, low comfort, and high costs [128, 129]. A recent trend are soft robotic gloves [130]. Soft robotic gloves are wearable and can facilitate hand and finger movements during activities of daily living or while playing VR-based serious games. Many studies report beneficial effects on motor recovery in clinical and home-based settings [130].

25.3 Lower Extremity

While upper limb impairments are common after stroke, the same is true for gait impairments. Over 80% of stroke survivors demonstrate a gait impairment [131] that recovers to some extent in the first two months after stroke [132]. Despite this, community ambulation often remains compromised in most survivors [133–135]. Gait ability specifically has major implications for health; it is an essential predictor for functional independence [136, 137] and long-term survival [137, 138] after stroke, along with participation and quality of life [139, 140]. Regaining gait ability is hence one of the most frequently prioritized goals of stroke survivors [131, 141].

25.3.1 Assessment of Motor Function

25.3.1.1 Clinical Assessment

Observation-Based Clinical Assessment

Gait ability can be separated into two major domains: Functional gait ability and gait quality. Assessments commonly employed in an in-clinic environment typically target the first domain. Best practice guidelines [43, 44] include the 10-m walk test (10MWT) [142], 6-min walk test (6MWT) [143], and timed-up-and-go test (TUG) [144], as they provide a complementary representation of a client's functional gait status and are feasible to implement clinically. These tests are commonly performed throughout stroke rehabilitation, albeit with a variability in terms of protocol and also time/distance criteria [145].

The 10MWT aims to measure maximal gait velocity and reflects the maximal capacity that a client has at a given point in time. For stroke survivors throughout all phases of recovery, the test demonstrates excellent sensitivity (MDC90 = 0.34–0.1 m/s from acute to chronic, respectively), and reliability (ICC = 0.83–0.95 from acute to chronic, respectively [145–147]). The MCID for this test in subacute stroke is estimated between 0.16 and 0.22 m/s [148].

The 6MWT aims to measure gait endurance. Equally, the clinometric properties of this assessment are well understood, and it demonstrates excellent reliability (ICC = 0.97–0.99 from acute to chronic, respectively) and sensitivity (MDC90 = 52 - 28 m from acute to chronic, respectively) [149] in stroke survivors throughout their recovery [150]. In terms of construct validity, the 6MWT correlates significantly with aerobic capacity, mobility, walking speed, strength, balance, and participation [150].

MCID for slow walkers in the subacute phase is estimated at 44m [148].

The TUG represents a compound test that measures the ability to perform sequential motor tasks relative to walking and turning [144, 151]. In this capacity, it can be considered a representation of complex movement [147]—one of the four pillars considered necessary for successful community ambulation [139]. In terms of clinometric properties, the TUG is considered reliable (ICC = 085 - 0.96) [152] and measures with an MDC95 of 2.9–3.5 s [147, 153].

Technology-Based Clinical Assessment

The second domain of gait assessment—gait quality—is not typically breached in clinical routine [154]. Procedures informing on this domain, in order of complexity, include observational gait assessments, pressure mat recordings, monocular video recordings (RGB/RGB-D), inertial-measurement-unit-based recordings, insole-based recordings, multi-camera video recordings, and 3D motion capture with force measurements. The objective and time-efficient quantification of gait quality has long carried the promise of identifying key deficits and guiding therapeutic intervention, however, this has yet to manifest on a large scale in clinical settings [155]. The barriers to large-scale adoption lie mainly in the cost, complexity, training requirements, and unwieldiness of current technology [156]. Advances especially in two domains carry the potential to overcome these limitations and have been frequently evaluated: Improved spatial reconstruction algorithms for IMUs, and improved computer vision pose estimation [157]. Typically, gait quality is described in three domains: Spatio-temporal metrics that describe the spatial and temporal characteristics of the endpoint within the resolution of a single gait cycle (e.g., step length, stance time, double support phase), joint kinematics (time-series of angles between segments that span from one gait event to the next), and kinetics (time-series of the ground reaction force for each limb) [158]. Gait events are considered when the foot strikes the ground (Foot-strike) and when the foot leaves the ground (Foot-off) and are used as anchors to normalize all cycles to a common timescale [159]. For brevity, this chapter will forgo technologies that are not translatable to the home environment, e.g., force plates. The clinical utility of metrics derived within these domains is not yet well understood and pathology- and deficit-dependent [160, 161].

Camera-based systems are typically best suited for pre-defined walkways or treadmill situations [161], where a large amount of gait cycles can be collected within a small movement volume. For gait, the same optical technologies introduced above are applicable for the calculation of joint angles and segment positions during walking: Multi-camera RGB and RGB-D setups, and single-camera RGB and RGB-D. The benefits and drawbacks are equally largely comparable to the application for the upper extremities, however for walking, the capture volume and movement amplitude are larger, and occlusions are less frequent. Compared to optoelectrical 3D motion capture, the accuracy for multi-camera RGB systems using contemporary pose estimation networks is in the range of 2–3° joint angle deviation [162] and 1–15 mm deviation in 3D joint center position estimation [80]. Multi-camera systems remain complex, as the camera locations must be calibrated relative to each other before measurement. Moving to a single RGB-D camera with an added depth channel results in a reduced accuracy between 5 and 6° for joint angles [163], however, this is at least partially dependent on the camera placement [77]. This is equally applicable when using 2D monocular RGB video to estimate 3D pose [164–166], where out-of-plane errors in the major movement directions can be reduced by strategic camera placement [167]. In synthesis, these values compare favorably to estimated MCIDs for lower limb angles in stroke survivors, which range from between 3 and 9° for the major lower extremity joints and planes [168, 169].

Associated, nascent technologies that may enrich the industry are event-based cameras [170], 2D LiDAR sensors [171–173], or moving camera setups [174–176]. These technologies offer various benefits (high framerate, reduced setup complexity, and increased capture volume, respectively), however, have not yet reached a level of maturity and accuracy for gait analysis that is sufficient for clinical application.

Inertial measurement technology provides a series of additional benefits compared to camera solutions, that are especially relevant to gait. The measurement becomes location-independent and can be performed for long distances overground. Individual measurement units however need to be attached to the subject and calibrated, leading to additional setup time and potential inaccuracies. In a recent review, Poitras et al. report accuracies for joint angle estimation in contemporary commercial systems that are slightly lower than camera-based systems (Hip: < 9.3°; Knee < 11.5°; and Ankle < 18.8°) [177]. However, concerning spatio-temporal parameters [178], IMUs demonstrate accuracy sufficient to describe clinically relevant metrics such as stance duration and asymmetry within the limits of meaningful change after stroke [179–183].

25.3.1.2 Tele-Assessment

Although the advances in technology-based assessments bring the flexibility to perform gait assessments outside clinical environments and without supervision, the link between in-clinic and assessments performed in clients' domestic environments is not yet well understood. The International Classification of Functioning Disability and Health (ICF) suggests that there is a difference between these two settings [46]. The measurements that are carried out in standardized environments such as the clinic reflect the best performance of the clients or their capacity and the assessments that are carried out during daily activities are more representative of the clients' actual performance. Within this thought framework, it can be imagined that a 1:1 translation of clinical fixed-time/distance tests to home rehabilitation may not be trivial, especially concerning functional gait ability. Concerning gait quality, comparisons between clinic and home have been performed using both IMU and camera-based systems [184].

In these comparisons, the accuracy of the technology remains comparable with the clinical setting, however usability and feasibility challenges must be considered.

For cameras, an important aspect is the capture volume: Treadmills are rare in client's typical homes. Furthermore, the calibration of multiple cameras is a time-consuming and painstaking process that is not feasible for clients to perform autonomously. Fixed-camera installations that require minimal calibration are costly to install and require building modifications. Home-recording technologies are thus practically limited to monocular RGB/RGB-D video and stereoscopic cameras that house the sensors in a single discrete unit. In either case, due to the limited field of view camera-based gait analyses are limited to very short walkways or discrete lower limb movements performed on the spot [185]. As a complicating factor, the non-standardized scenes as backgrounds which are common in home applications can confound the tracking algorithms, leading to decreased accuracy [186, 187]. The practical use of cameras for gait analysis in home settings is hence quite limited and confined to a dedicated space.

For IMUs, the limitations concerning the volume of capture do not exist. As these systems are fully portable, they cannot limit the assessment space. However, IMU-based systems also bring challenges that are not yet fully addressed [188]. These are mainly in the usability spectrum, for example, the client-friendly attachment of IMUs to skin/clothing while retaining sufficient data quality, or zero-interaction data transfer and charging solutions [189]. Novel solutions, such as seamlessly including sensing units into shoes with wireless chargers [190], can be expected to provide solace to these usability barriers as costs to components fall and new form factors become available. Finally, many IMU systems require a calibration step in which predefined movements are necessary which may not be possible for a given client or which may lead to recording errors if performed too rapidly or erroneously.

Having scoped the limitations of each technology, there remains the question of which activity to record in a home environment, especially in the context of gait quality. Optimally, the same time/distance tests as performed in the clinic would translate seamlessly to the home environment for both functional gait ability and gait quality. Practical considerations, however, put the use of these tests into question. Specifically, few home environments provide the space necessary for a 6MWT (per clinical definition a 40 m straight walkway), nor even for a 10MWT with acceleration and deceleration phases. These tests are then performed outdoors, which complicates the question of a standardized setting with even surfaces [191]. Furthermore, there remains the question of how to initiate and end recordings for time/distance-limited tests. User interaction at the extrema of the tests invariably leads to a dual-task situation, therefore recording should best be triggered automatically. In the case of time, this is relatively trivial relying on a simple countdown timer. In the case of distance, however, the cumulative error in real-time spatial reconstruction of an IMU can lead to a roughly 5% error in the distance estimation [192]. A 10MWT for instance could be 9.5 m or 10.5 m long, hardly sufficiently reproducible for a reliable clinical outcome. Augmenting IMUs with other technology such as GPS can be helpful in improving the distance estimation [193], however, this is limited to longer tests such as the 6MWT and is strongly sensitive to satellite coverage which can limit its applicability in large cities [194].

The question here arises, whether there is a need for fixed-time/distance tests, or whether the continuous data collection during a portion of a day provides sufficient gait data to either extract representative test segments [195] or predict test performance [196–198]. Continuous data collection or “gait monitoring”, holds the promise to also generate novel digital mobility outcomes (DMOs) [199–201] that can enable greater insight into a client’s status. A plethora of algorithms are available to extract sequences of interest, such as gait, from the continuous data stream [202, 203]. From the current technology situation and a clinical utility perspective, it is unsurprising that the state of the art is gyrating towards continuous monitoring of gait using IMUs [204–207]. Open questions that remain are the location of the sensors (common are shoe [180], ankles [208], pelvis or pocket, and wrist [209] or a combination of these) and the form factor (dedicated gait monitoring hardware, smartphone sensors, or smartwatch sensors) [210].

25.3.2 Teletherapy

Concerning teletherapy, applications focus either on gait volume and intensity or on gait quality. Volume and intensity are collected throughout the day and presented as summative feedback on demand via web or tablet applications [211], similar to what is present in the lifestyle and wellness segment. Indeed, significant effort has been expended in evaluating lifestyle and wellness wearables for gait monitoring in elderly and clinical populations [212–216].

Applications for gait quality are typically proposed as gait training movements in a stationary setting [13, 217]. This can be performed asynchronously [218] or synchronously [219] with a health professional. There are countless exergaming-like applications that use IMU and/or camera systems coupled to visual displays that provide training programs and movement feedback in various levels of detail [220–224]. This segment is evolving rapidly, accelerated by readily available open-source and lightweight pose estimation algorithms for 2D RGB systems. An overview of commercial offerings would exceed the scope of a single chapter and probably be outdated before the book is printed.

A few research studies [225, 226] have engaged in the challenge of providing continuous real-time feedback on gait quality during ecological activity [227, 228]. While biofeedback is a promising approach in clinical settings [229, 230], challenges remain that limit the transfer to real-world scenarios. Outside of technical and usability limitations such as mounting points and battery capacity, the challenges here entail the appropriate detection of movement context [231] and the careful selection of relevant movement features and feedback modalities and mapping [101, 232, 233]. This area is expected to demonstrate significant innovation in the near future [234–239].

Mixed reality (MR) is a promising pathway for gait training scenarios (Fig. 25.2) [240, 241]. Compared to the previously described VR systems, MR enables the client to mix digital and real worlds through different technologies [242]. One approach for MR environments uses a video stream of RGB video cameras mounted to a headset to display a video of the environment onto a closed head-mounted display (HMD). The environment can be augmented with digital creations that are anchored in physical space, appearing in the HMD along with the video feed. These systems can be highly immersive; however, lag of the video feed and a corresponding mismatch of vestibular and visual information is still a challenge [243, 244]. To compensate for this, video resolution can be scaled down, resulting in a visually jarring imperfect representation of the surroundings. A further issue is the question of video white balance, which is adapted automatically to the lighting of scene and can lead to jumps in brightness of the video stream [245]. Equally open is the question of the matching of light source positioning and environmental situations between virtual and real objects [245]. As technology progresses on the fronts of mobile processing and graphics performance, camera, and display technologies, these issues may be resolved. A second approach uses translucent displays to superimpose a hologram image into the real world [246]. This elegantly circumvents the questions of lag and environment resolution as only the digital portion of the mixed reality needs to be rendered. There is rapid development in this sector, however, the field of view remains limited leading to a low level of immersion. In both cases, the usability of the device for remote deployment to clients [247, 248] and realistic multimodal feedback [249, 250] are remaining challenges that a new generation of rehabilitation-friendly devices should address. The perspective is that MR provides a pathway for highly promising VR-based training interventions from the clinic to extend to a client's home [16, 251, 252].

In synthesis, the technology situation is highly favorable to expand on the solutions currently available for gait in home environments. Improvements in device form factors, usability, measurement accuracy, presentation quality, and visualization of gait data synergize to unlock powerful new insights and provide training over a much longer rehabilitation period than previously feasible.

25.4 Communication

Effective communication in neurological conditions requires intact language, motor speech, and voice production. Aphasia is a language disorder where the use and the comprehension of meaningful speech are affected while motor speech disorder refers to a condition where a person has problems creating or forming speech sounds needed to communicate [253, 254]. In neurological voice disorder, the coordination or strengths of muscles that are needed to produce phonation are affected. All three conditions can occur after stroke, both, independently of each other or in combination, leaving roughly a third of all stroke survivors with some sort of communication impairment [255–257].

These impairments have a great impact on those affected as the majority of labor force depends nowadays on communication skills [258] but also social participation and independent living are dramatically affected by impaired communication. Clients with aphasia after stroke "described intense feelings of frustration, hopelessness, isolation, and depression at not being able to talk" [259].

Telerehabilitation is nowadays attracting broad interest in the field of speech and language therapy. For successful telerehabilitation, there is a need for optimal technology use in both, synchronous and asynchronous therapy delivery. To guide therapists along the recovery path, reliable and meaningful remote measures of voice, speech, and language functions are essential.

Besides the direct need of valid measures for therapy delivery, communication measures might also serve as a general indicator of well-being

Fig. 25.1 The ReHandyBot (picture: Rehabilitation Engineering Laboratory, ETH Zurich/Stefan Schneller). Fingers and thumb are fixed to separate grippers. Grippers' movement is coupled which allows training hand opening and closing. Moreover, assistive or resistive forces allow haptic feedback and interaction with virtual objects

including emotional load and measure of participation, or early sign of cognitive decline [260, 261].

25.4.1 Assessment of Speech and Language Functions

25.4.1.1 Clinical Assessment

Observation-Based Clinical Assessment
Clinical assessment of functional voice, speech and language impairments consists of a wide range of measurement instruments. They largely depend on the perceptual evaluation by professional speech and language pathologists or task-specific performance measures (dysarthria [262], aphasia [263]). Many of these measurement instruments may not be specific to the stroke population but are used in the respective conditions (i.e., voice, speech, or language impairments) independent of the underlying disease. Most of the functional assessments related to communication are obviously highly language-specific. In the following paragraph, we will give only a few examples of voice, speech,and language scales in English or German to point out the limitations of remote assessments.

The German Bogenhausener Dysarthrieskalen (BoDyS) is a tool to assess voice and speech impairments in different tasks such as picture description [264]. For each task, the speech and

Fig. 25.2 A client after stroke performing a mixed reality gait training parkour with a holographic head-mounted display. Obstacles that require specific gait adaptations are placed throughout a given physical environment, transforming the space into a virtual rehabilitation gym (from [240])

language pathologist rates different symptoms perceived, such as hoarseness or slow talking speed. Even though audio recordings for potential algorithmic analysis are created during the assessment, the analysis requires manual scoring of voice and speech pathologies.

An expert panel has recently defined a core outcome set to assess language impairments in aphasia research [263]. It includes the Western Aphasia Battery-Revised (WAB-R), a diagnostic tool widely used by clinicians to assess language skills [265]. In German-speaking countries, the Aachener Aphasie Test (AAT) is a widely used diagnostic tool for differential diagnosis and follow-up assessment of language impairment [266].

Scales were also developed to assess communication in a more general term. No consensus, however, was reached by Wallace and colleagues on which measures to use in a core outcome set for research, and the discussion on how to best measure communication is ongoing [263].

Measurement instruments related to participation—especially important once a client is at home—are usually complemented by self-reported outcome measures and questionnaires related to emotional well-being and quality of life—measures which seem more meaningful to assess the impact of a disorder on a client's daily living, but may not give much information on the underlying impairments [263, 267].

Taken together, many of the clinically used assessment tools strongly rely on subjective observational methods, i.e., speech and motor behavior are observed by a professional speech and language pathologist and require (rather time-consuming) manual scoring. There is a call for more technology-dependent outcome measures which may help to understand underlying impairment and treatment effects as stated by Elisabeth Armstrong in her commentary article: Let's utilize technology to the maximum and contribute our expertise at the highest level, while at the same time not simply counting what can be counted and neglecting "what counts" [268].

Technology-Based Clinical Assessments

Voice Analysis

Instrumented acoustic voice analysis is a quantitative noninvasive method to complement a multidimensional approach for evaluation of initial impairment and the recovery/therapy progress [269].

Over the past decades, several acoustic measures have been proposed to be sensitive to (overall) voice quality or specific perceptual dimensions such as hoarseness or breathiness ([270] and other reviews). In standard acoustic voice assessments, a voice profile (vocal intensity and pitch measures), frequency and amplitude perturbation (jitter, shimmer), and harmonicity measurements (harmonic to noise ratio) are usually determined that provide information about the underlying functional impairment and recovery progress [270, 271]. The feasibility and validity of such metrics highly depend on the client's task (e.g., sustained vowels vs. reading) and instructions (e.g., comfortable loudness vs. maximal loudness) as well as room setup and technical specifications (e.g., microphone quality, setup, and calibration). An expert panel of the American Speech-Language-Hearing Association has recently approached this issue and published a standardization protocol defining instructions and specifications for qualitative acoustic voice analysis in great detail [269]. Even in a very standardized setup, acoustic parameters are highly variable due to dependence on the vocal intensity used [272]. Most of the traditional perturbation measures depend on the computation of the fundamental frequency which may not be reliable in severe dysphonia. For this reason, Patel et al. further suggested the calculation of cepstral peak prominence, a measure based on spectral analyses for estimating general dysphonia severity and overall breathiness from connected speech, i.e., during a reading task or a conversation [269, 273–275].

Several computer programs exist which enable instrumented voice analysis also in a clinical setting. One example used in research and clinic is the comprehensive open-source program PRAAT, which was initiated and continuously developed by Jan Boersma and David Weenink from the University of Amsterdam (http://www.PRAAT.org/). Many commercially available voice analysis software exist that come with technical equipment that allows for rapid voice assessment without requiring complex calibration and in-depth technical knowledge.

Speech and Language Analysis

Similar to acoustic voice analysis, certain speech and language parameters can be automatically calculated from audio files using algorithms integrated into voice analysis software such as PRAAT. Such parameters may include speech rate and overall talking time, but also more complex estimates of fluency extracted from connected speech [276, 277].

Fully automized analysis of audio samples to assess language functions is often limited to macroparameters. More relevant [278, 279] linguistic parameters such as lexical diversity, mean utterance lengths, repetitions, and self-corrections can be extracted from transcripts with the aid of specialized speech analysis systems [279]. Examples include the "Aachener Spontansprachanalyse" [280, 281] for German or the "Computerized language analysis" (CLAN) for English [282] which, once the audio sample is manually transcribed, assists with word tagging and linguistic analysis. More content-dependent discourse measures can be assessed using natural language processing by computerized systems [283, 284].

As part of the Aphasia Bank Project, large amounts of standardized speech samples (e.g., the English story-retelling task "Cinderella") from aphasic clients were—and still are—collected, transcribed, and made available to researchers for in-depth discourse analysis [285, 286]. This Big Data approach contributes to the understanding of discourse differences in mildly impaired stroke survivors that may not with scales such as the WAB-R due to ceiling effects [287]. Even though computer-assisted methods facilitate manual transcription, the process is still time-consuming and thus often not feasible in daily clinical practice. Advances in Automated Speech Recognition (ASR)—the automatic *conversion of audio files into written text* [288]—could solve this problem in the future. A recent study suggests that ASR could be used in a clinic setting for aphasic clients. However, the quality of transcripts needs to be investigated separately for each communication disorder [289].

25.4.2 Tele-Assessments

In a remote setting, one way to assess speech and language functions may be to apply standardized assessment batteries or scales via video call in a synchronous session with a speech and language pathologist. This way of applying assessments is limited by the availability of analog equipment on the client's side, and for many tools, a fully computerized adaptation is still lacking. Furthermore, the validity of such teleconference-based application of standardized test batteries needs to be investigated—as has recently been done for the widely used WAB-R [290]—and standards need to be developed [291]. Overall, remote assessments via teleconference systems are feasible, but a revised computerized version rather than ad hoc digital adaptation of valid analog tools would be highly desirable.

Recording audio samples during a tele-assessment via video call for automated analysis is possible, however, signal processing circuits such as automatic gain control or noise cancellation may modify the original microphone signal [269, 271]. Setup and implementation at a client's home may not (easily) be controllable. Audio samples may still be used for synchronous or asynchronous manual scoring of voice, speech, or language impairment or transcription.

Some automated tele-diagnostic instruments are also available for web-based administration or use with smartphone applications. Smartphone applications have been developed for self-administration of acoustic voice assessments in clinical telepractice settings which can produce valid calculations of acoustic parameters [292]. As described above, a highly standardized setup in a clinical setting is crucial for valid acoustic voice assessments. It is thus questionable whether such smartphone-based audio recordings achieve the quality to successfully guide teletherapeutic interventions. For speech and language, there are applications mainly used for research purposes which allow remote application of certain standardized speech and language assessments (e.g., [293]).Tele-monitoring.

Using microphones for monitoring voice, speech, or language functions in daily living is feasible. However, it faces several limitations: Privacy, environmental noise, recording quality, and interference with speech from communication partners. One solution for the privacy issue is to only store information that does not need content recording, such as overall talking time, as done in people with aphasia after stroke [294]. However, this metric does not seem to provide much information about functional recovery as it lacks correlation to impairment level but might be an indicator of participation [294]. Accuracy of measuring talking time is highly dependent on environmental noise. Researchers have started to address this limitation by measuring voice functions via neck surface vibration measures with a single accelerometer placed on the subglottal neck surface [295]. Relevant metrics such as fundamental frequency and sound pressure level as well as spectral parameters can be captured through skin acceleration and correlate for the most part with the parameters received from acoustic measures through a microphone [275, 296, 297].

25.4.3 Teletherapy

25.4.3.1 Synchronous Therapy

Many therapists, clinics or specialized telerehabilitation providers offer speech and language therapy via video conferencing [298], also called telepractice [299, 300] (ASHA 2018). Some use available video call platforms such as Webex or Zoom with standard video call features [301, 302]. Others may use specialized speech and language tele-therapy platforms with integrated digital exercises or social functionality [303]. Such synchronous speech and language therapies were found to have similar effects as in-person therapy (reviewed by [304]). With increasing functionality such as joint editing of digital material and integrated audio recordings, an increased range of therapy content may be provided in the future.

A high-quality microphone and high-speed internet connection are crucial, especially for vocal tele-therapy, and technical hurdles might limit use in the elderly. There are, however, also advantages of video-based synchronous over in-person therapy. Group therapy and group chats for people with communication problems are easily implementable. Group therapy was found to be a valuable and cost-efficient way of delivering therapy. Group chats that socially connect people with similar impairments, medical history, and interests have a positive effect on participation and well-being which in turn can improve specific linguistic effects [305–307]. Another advantage is the high context specificity in which the therapy takes place, allowing speech and language therapy to be tailored to a client's functional environment [308].

25.4.3.2 Asynchronous Therapy

Many commercially available computer programs exist which have digitalized logopedic exercise material and can be used by clients for independent functional training at home. Commercially available programs, such as *Tactus Therapy Solutions, Lingraphica, Constant Therapy,* or *Neolexon* are built to supplement clinician-delivered therapy; the therapist creates a personalized training program and has access to training results or audio recordings via a specialized therapist interface. In many exercises, difficulty levels are automatically adapted based on errors and response time, allowing training without constant evaluation and exercise adaptation by the therapist. Automated detection of errors is mainly available for written input. Thus, any form of automated result or performance feedback is mostly restricted to receptive exercises (i.e., the correct answer can be chosen among suggestions) or to written content. Advances in automatic speech recognition will open the path to more independent verbal training in the future [309]. Feedback during voice training does not rely on speech recognition and helps to adapt vocal behavior—namely pitch and/or loudness—during training [310]. The use of neck vibration monitoring system enables biofeedback during daily living and promotes changes in vocal behavior [311, 312]. Retention of the adapted behavior, however, seems to be strongly dependent on the type and frequency of feedback used [312].

Taken together, such computerized asynchronous therapies are usually well received by stroke survivors and seem a valid option to increase training time, even though efficacy may not exceed in-person therapy effects [313] (see [314] for a review). The field of telerehabilitation is still in its infancy and technologies are developing rapidly. Comprehensive combinations of synchronous and asynchronous options might be more successful in the future. The Australian Tele-CHAT (i.e., Comprehensive High-dose Aphasia Treatment) program is an example of a combination of synchronous, asynchronous, and group therapy and it also supports education and social exchange among stroke survivors. Feasibility and acceptability of this program is still under scientific investigation, but it seems clear that for an efficient and effective therapy delivery, the use of different therapy modes needs to be optimally coordinated.

25.5 Final Remarks

Technological solutions are expected to become an integral part of telerehabilitation. These should be complemented by data platforms that consolidate the diverse streams of information into a coherent and actionable whole. These data can be leveraged by healthcare professionals to gain unprecedented insights into recovery profiles, individual therapeutic needs, and requirements for sustainable technological solutions. AI is already demonstrating some promising performance in specific medical tasks. However, the details of decision-making of the algorithms are often poorly understood, and there is still no robust interpretability and explainability, thus hindering the widespread use of AI in medicine. Ongoing developments of methods for visualization, explanation, and interpretation of AI models aim at making AI transparent and explainable (XAI), and thus robust for application in the medical field [315]. In the future, XAI may allow to target and scale interventions based on a large amount of data precisely and reliably to the needs of the individual.

Clinical trials show promising results with telerehabilitation. The Corona pandemic has promoted the acceptance of telerehabilitation among therapists and clients. To promote widespread and long-term implementation in routine clinical practice, it is up to stakeholders to increase adoption through measures on telecommunications infrastructure, legal certainty around digital health policies and legislation, data security, technical support, teaching, and reimbursement.

The combination of increasing digital literacy, scalability requirements of the neurorehabilitation industry, regulatory changes, and an increased enthusiasm for new technologies are creating a breeding ground for tele-neurorehabilitation to gain wider acceptance and fully deliver on its promise.

In the long term, telerehabilitation could become a ubiquitous tool that enables access to health care and intense, personally optimized neurorehabilitation regardless of geographical location.

Note that this book chapter primarily focused on technology and services for assessment and treatment at the levels of ICF function and activity. Future work will certainly also cover clients' functioning at the ICF participation level, especially because improvements in quality of life and participation in social activities are the higher-order goals of neurorehabilitation. Thus, technology and service design will increasingly need to incorporate clients' social and environmental contexts. Barriers in social contexts can be reduced, for example, through simulation of clients' motor limitations to healthy individuals, using VR and robotic systems [14]. Healthy individuals can thus experience and gain an intuitive understanding of clients' motor limitations [14]. Moreover, caretakers can aid clients to leverage smart homes and smart cities to reduce barriers to social context and increase engagement in these. For example, smart door locks might reduce the stress of clients when entering new social interactions [316] and social games in smart cities can engage to move and interact with others [317].

Hence, as we press on into the future, new technologies and services will become increasingly pervasive in our everyday lives. These technologies can be leveraged for rehabilitation at a distance and might enable a more direct impact on participation than previous approaches.

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