Mobile Technology for Cognitive Rehabilitation

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Abstract

Many barriers currently prevent persons living with acquired brain injury (ABI) from receiving an adequate "dose" of cognitive rehabilitation therapy via the traditional clinic-based service delivery model. The application of mobile technology to cognitive rehabilitation is an emerging area of great interest. Advances in mobile technology provide new opportunities for cognitive rehabilitation, with the potential to improve access to care, as well as increase patients' opportunities to practice and apply skills in their everyday environments—a notion referred to as *ecologically valid treatment*. The aim of this chapter is to provide an overview of mobile technology in the context of cognitive rehabilitation, with a special focus on applications and interventions targeted towards patients with ABI. We provide a general background on cognitive rehabilitation as a treatment model, discuss opportunities and considerations for developing mobile rehabilitation solutions for users with cognitive impairment, and provide a general overview of the state of the research on mobile cognitive rehab treatments. The vast majority of mobile health apps are not evidence based at present (Ramey et al. in Phys Med Rehabil Clin 30(2):485–97, 2019), however, a small but growing literature is now speaking to the use of smart technologies to both help improve functioning and monitor functioning for persons with ABI. We highlight several areas for future development needed to move towards developing clinical practice guidelines for integrating mobile technology into cognitive rehabilitation.

24.1 Introduction

Many barriers currently prevent persons living with acquired brain injury (ABI) from receiving an adequate "dose" of cognitive rehabilitation therapy via the traditional clinic-based service delivery model. This critical service gap exists for a number of reasons, including insufficient clinical resources, poor access to care, and

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limited insurance coverage [1]. Some patients with cognitive disabilities are sent home from acute care without any outpatient cognitive rehabilitation at all. Those fortunate enough to access services often receive coverage that is fragmented and front-loaded, with the majority of therapy provided in the weeks and months after a traumatic brain injury (TBI) or stroke. Support dwindles as patients stabilize and return to the community. Studies suggest that the majority of individuals receive inadequate support after discharge from inpatient rehabilitation, at which point caregivers report a progressive decline in both the quality and quantity of services [2]. The short duration of care is a concern. For example, the field increasingly acknowledges that moderate-severe TBI is a chronic, and even progressive disease process [3, 4], for which ongoing rehabilitation is needed to prevent increasing disability. The evidence from the stroke literature strongly suggests that greater intensity therapy over a longer duration, at least within the first year post-stroke, is associated with greater functional improvements [5, 6]. Without sustained access to services many patients are likely to fall short of achieving their optimal level of functioning, and may even be at risk of experiencing further cognitive decline years later [7]. Given all of this, there is a compelling need for remote delivery of cognitive rehabilitation services to address the needs of those living with acquired brain injury (ABI).

The application of mobile technology to cognitive rehabilitation is an emerging area of great interest. Advances in mobile technology provide new opportunities for cognitive rehabilitation, with the potential to improve access to care, as well as increase patients' opportunities to practice and apply skills in their everyday environments—a notion referred to as *ecologically valid treatment*. The aim of this chapter is to provide an overview of mobile technology in the context of cognitive rehabilitation, with a special focus on applications and interventions targeted towards patients with ABI. We provide a general background on cognitive rehabilitation as a treatment model, discuss opportunities and considerations for developing mobile rehabilitation

solutions for users with cognitive impairment, and provide a general overview of the state of the research on mobile cognitive rehab treatments. Finally, we provide recommendations for future development and research in this area.

24.2 Cognitive Rehabilitation

Cognitive rehabilitation has been defined as "a systematic, functionally oriented service of therapeutic cognitive activities, based on an assessment and understanding of the person's brain-behavioral deficits. Services are provided by qualified practitioners and are directed to achieve functional changes by [1] reinforcing, strengthening, or reestablishing previously learned patterns of behavior, or [2] establishing new patterns of cognitive activity or compensatory mechanisms for impaired neurological systems" (p. 62) [8]. The process of cognitive rehabilitation can be broadly categorized into interventions which are either restorative or compensatory. **Restorative** interventions, also referred to as direct training or process-specific, are aimed at the impairment level and involve repetitive stimulation of a domain, typically in a systematic, methodical manner. **Compensatory** approaches are targeted at the functional level and are based on the assumption that although damaged neurological functions cannot be restored, one's intact strengths and abilities can be used to circumvent impairments. To this end, compensations can reduce the extent of limitations on activities and participation and promote successful community reintegration in spite of residual physical and cognitive impairments. Cognitive rehabilitation initially focused on the use of restorative approaches. Within the past few decades, the focus has been more on compensation for areas of impairment [9]. Historically, the goal of the restorative approaches has been to reduce or eliminate underlying cognitive impairment [10]. Restorative interventions are focused on exercises targeting specific cognitive impairment after brain injury or disease. Although the notion of directly diminishing cognitive impairment is appealing, many have

noted that a program of rehabilitation will only have relevance to patients and their families to the extent that it improves daily functioning. In other words, successful cognitive rehabilitation should produce functional improvements in patients' daily lives, and not just higher scores on laboratory tests of cognition.

The International Classification of Functioning, Disabilities, and Health (ICF) model was developed by the World Health Organization (WHO) to operationalize the functional changes associated with known medical conditions [11]. This model classifies changes associated with brain injury into changes in (1) body functions and structures, (2) activity, and (3) participation. Body functions and structures are measured by assessment of physical or mental functions, and impairment is measured by deviation from expected levels of performance. Activity limitations are an individual's inability to complete basic or instrumental activity of daily living (ADL/IADL) (e.g., inability to recall appointments, follow a recipe while cooking, and follow a medication regimen or balance a checkbook). Participation restrictions are a loss or change in social roles (e.g., loss of a job or inability to parent children). Participation is highly individualized and needs to be assessed by self or family report regarding the degree to which an individual is [1] a productive member of society and/or [2] integrated into family and community life. Participation restrictions reflect, for example, the degree to which individuals are limited in their life roles (e.g., ability to run a household or maintain a network of friends and family, employment, education, and volunteer activities). In this model, there is a dynamic interaction between impairments (both physical and cognitive), activity limitations, and participation restrictions which collectively determine an individual's reintegration into the community. The ICF proposes that ADLs and participation in life roles are the two domains which measure the impact of an injury or illness on daily functioning. It then follows that these same domains best measure treatment effectiveness. Not surprisingly, recent studies of the effectiveness of cognitive rehabilitation largely focus on ADLs and participation as their main measures of treatment outcomes [12].

Cognitive rehabilitation is often time- and labor-intensive and can require multiple sessions to help teach and apply new skills to improve daily functioning. While the restorative approach alone may not be adequate for significant gains in functioning, these approaches are used within the framework of the ICF to rebuild discrete skills in coordination with other approaches tied to functional outcomes. Restorative approaches have a clear and important role in the rehabilitation process by being paired with compensatory approaches towards the goal of improving functioning. Distinct compensation skills, such as those used to increase visual scanning, decrease impulsivity, and/or decrease episodes of forgetfulness will only be effective to the extent that they are reliably and consistently used. While it may seem that once a skill or strategy is learned, it will then be readily applied, that in fact is not necessarily the case [13]. No matter how effective a strategy may be in practice, it will not be effective for the patient until they have the appropriate skills in place to use that strategy in their day-to-day life. This process requires repeated practice, particularly within the patients' usual environments (i.e., their homes and communities).

A compensation strategy designed to enhance functioning can be beneficial only to the extent that its purpose is understood and it is reliably and consistently implemented. Implementation can be accomplished in one of two ways: external cueing or skills training. External cueing can be helpful for giving both reminders to complete a task as well as instructions on how to complete it. This may involve, for instance, setting a timer to remind the patient to use the appropriate strategy, possibly including information on how to use that strategy. A caregiver may also provide a direct cue to the patient to use the correct strategy when needed. While such a reminder from a caregiver may be effective, it also means remaining dependent upon some external agent which reduces independence. It also places an

increased burden on caregivers which can add to caregiver burnout. Skills training, in contrast, works to ensure that strategies are used correctly by teaching the patient-specific skills which will help them to directly apply the strategy. In this case, a targeted intervention is used to (re)learn some discrete skills. Training is delivered using trials of mass learning until skill mastery is consistently demonstrated. The patient is then able to independently execute the specific strategy, although some level of cueing may still be necessary for this to happen. Given that this approach involves improving performance on a specific task or skill, it does not always have direct relevance to ADLs. However, these discrete skills are crucial, if not necessary, to using strategies that ultimately lead to improvement in overall functioning. This approach, though often more time-consuming, ultimately results in the individual acting with a greater level of agency.

An example of evidence-based cognitive rehabilitation approach which combines compensatory and restorative approaches is planner acquisition method described by [14]. This has long been a centerpiece of cognitive rehabilitation, into which other compensation strategies are woven. While this strategy is focused on improving memory functioning, the calendar/planner has also been demonstrated as a strategy to address problems including organizational skills, behavioral control, and other areas of cognitive impairment which impact daily functioning. This approach has been supported in multiple subsequent studies as a powerful method to improve functioning in persons with severe memory impairment [12]. The approach works by using both restorative and compensatory approaches in concert, using a three-step process of acquisition application, and adaptation. The acquisition phase focuses on learning the names, location, purpose, and use (i.e., acquiring semantic knowledge) for the components of the calendar/planner. Restorative approaches (e.g., errorless learning, spaced retrieval) are used to learn the components of the

calendar/planner. Errorless learning is a restorative approach designed to teach specific information to patients by leveraging preserved procedural memory abilities. Learning of the target behavior occurs through the active involvement of the therapist and occurs without their conscious control over its use.

In the application phase, the patient practices using the memory notebook in various real-life and/or role-play tasks in the clinic. Working together the patient and therapist choose tasks that are relevant to the patient's life and develop strategies which help to compensate for impairments which interfere with daily functioning. In the final adaptation phase, skills learned in the first two stages (acquisition and application phases) are applied within community and naturalistic settings. A task that was previously performed in the clinic can now be performed in the patient's own environment (e.g., remembering to take medications, returning phone calls, and remembering scheduled appointments). The impact on daily functioning in this approach is tied to the use of a specific compensation strategy (in this case, the planner/calendar). However, the use of this strategy is dependent upon the use of restorative approaches that help ensure the strategy is used effectively. Thus, while both the restorative and compensatory components are necessary, neither used in isolation is sufficient to reach goals of greater independence. Success is achieved by using both approaches in concert. The three-stage approach using a combination of both restorative and compensation methods has also been effective to address problems in other cognitive domains, including impairments in attention, executive skills, visual-spatial skills, and communication abilities [15]. Thus, while both restorative and compensatory approaches are important, describing cognitive rehabilitation as making a choice between the two is a false dichotomy and can even be counterproductive. Rather, it is useful to understand the unique contributions of both approaches and how they are used together to achieve goals of greater independence.

24.3   Mobile Technology for Rehabilitation

The WHO defines mobile health (mHealth) technology as "medical and public health practice supported by mobile devices", including (but not limited to) smartphones and tablets and biometric/activity monitors (e.g., wearables). Mobile health (mHealth) has the potential to enhance rehabilitation care in multiple ways, including by providing evidence-based education, supporting compliance to treatment plans, supporting monitoring and management of biometrics and chronic symptoms, facilitating patient–provider communication, and promoting effective long-term self-management [16]. Through mHealth technology, healthcare providers can both collect and share health-related information with their patients. When communication via mHealth occurs in only one direction, as in the case of devices that remotely track biometrics (e.g., heart rate monitors) or apps that collected self-reported data (e.g., symptoms trackers), this is considered a one-way system. Another example of a one-way system would be an app that provided information or guided intervention without collecting any data from the user (e.g., a daily meditation app). A two-way system involves a back-and-forth exchange of information between the user (patient) and healthcare provider. Evidence suggests that two-way systems may be preferred by patients, family members, and clinicians [17].

Mobile technology provides new opportunities for delivering interventions in the "here and now" as patients go about their usual activities—a model referred to as ecological momentary intervention (EMI). EMI has recently garnered widespread interest in healthcare technology development for two principal reasons—its ability to extend an intervention beyond the standard treatment context (e.g., clinician's office) and into individuals' daily lives, and the advantage of providing an intervention in individuals' natural environments, encouraging them to apply new skills and behaviors to their actual experiences [18]. Evidence suggests that EMIs

encourage the practice of new behaviors and skills [19–21], which may improve generalization and increase the impact of interventions (e.g., [22, 23]) when combined with face-to-face clinical contacts. For cognitive rehabilitation, this means interventions could be delivered at the very moment that a person with ABI is performing a cognitively demanding task in their home or community, such as planning a shopping list or preparing a meal.

Most adults across all age groups, including adults with disabilities, persons with TBI, use smartphones [24–26]. Beyond being beneficial for using mHealth technology, smartphones are the central hub around which most mHealth technology functions, addressing the frequently voiced need from persons with cognitive disabilities for a single interface to manage a variety of cognitive and health needs [16, 17, 27]. It is therefore not surprising that applications of mHealth technology to health management have grown exponentially in the last decade. In 2017, there were more than 325,000 mHealth apps available, representing a 25% increase over the prior year [28] Apps addressing cognitive issues represent a relatively small share of the market. Most mHealth apps focus on fitness (36%), stress management (17%), and diet (12%), with the remaining 35% focused on disease management [29]. Despite this tremendous growth in the general market, evidence points to a dearth of products that address the particular needs and concerns of users with disability. Disability-focused apps represent less than 2% of all mHealth apps examined [30].

A recently published study evaluated the current state of mobile health care for people with disabilities based on reviews of the scientific literature and web-based resources for locating apps, as well as a survey of 377 users with disabilities [31]. They concluded that mHealth development and application for people with disabilities is in its early stages, with only a handful of mHealth tools targeted towards persons with disability and virtually no scientific evidence of their effectiveness. Furthermore, despite reporting a relatively high rate of

adoption of mHealth apps (40%), survey respondents pointed to problems with accessibility and concerns about the accuracy or relevance of the content in mainstream mHealth apps for disabled users. A recent systematic review of mHealth apps specifically within the domain of *rehabilitation* found only seven apps focused on TBI rehabilitation [32]. These apps addressed a variety of issues such as symptom monitoring, wayfinding, memory problems, and emotional and behavioral concerns. Only three apps were evaluated with a quantitative outcome assessment, and only two of these were in randomized controlled trials (RCTs) [32]. The authors concluded that early app design and evaluation efforts show promising results, but clearly, more research is clearly needed.

24.4 Ethical Considerations

The commercially, rather than scientifically, driven proliferation of mHealth apps presents additional challenges to applying mHealth technology in practice. Even as research on effective mHealth technology grows, clinicians may struggle to find evidence-based mHealth apps, particularly those addressing the specific needs of individuals with cognitive disabilities, amid the sea of apps available (less than 1% of currently available mHealth apps are evidence-based) [33, 34]. A survey of over 500 rehabilitation clinicians reported that only 23% felt knowledgeable about available rehabilitation technology and only 51% felt comfortable using this technology in practice [35]. Similarly, in another study of healthcare professionals working with youth with brain injuries, despite 75% of patients using mHealth technology, only 42% of providers discussed or facilitated this mHealth use in their patients [36]. Mirroring this, one study found that only 10% of participants with brain injury reported that a clinician discussed the use of mHealth services with them following their injuries [36, 37]. This highlights a critical issue—individuals want to use mHealth technologies, but they are not receiving informed recommendations from their healthcare providers. This

creates a high risk that these individuals may use mHealth technology that is inappropriate for (or even detrimental to) their health, unique needs, and rehabilitation goals. This concern is heightened for those individuals with cognitive impairments that limit insight and decision-making. A 2018 systematic review of studies on evaluating mHealth apps concluded that clinicians assess the following about mHealth apps to determine if they are appropriate for patients: (1) design, (2) information/content, (3) usability, (4) functionality, (5) ethical issues, (6) security and privacy, and (7) user-perceived value [38]. Inclusion of the patient in this process is essential, to ensure a match between the patient's needs, values, and preferences and the features, potential risks and benefits, and costs of the mHealth technology.

Individuals with cognitive disabilities do report that smartphones generally provide accessible, convenient, effective, and acceptable support. However, they also desire simplicity, better training and support for learning and continuing to use new technology, and better accessibility features (e.g., larger font) [17, 37, 39–42]. Poor accessibility may explain the disparity in mHealth use between those with and without a disability [16]. Inclusion of people with disabilities in the development and evaluation of mHealth technology is essential, though remains a critical gap in current mHealth development that contributes to this ongoing disparity [16]. Even in the growing literature supporting mHealth use for rehabilitation in populations with cognitive impairment, very little work has been done to identify the best approaches to training individuals to use the technology in their daily lives, leading to frustration and technology abandonment. Broadly, practitioners could support the use and adoption of mHealth by their patients by helping them identify appropriate and evidence-based mHealth apps specific to their needs, values, and preferences and providing hands-on opportunities for their patients to practice with the technology itself before moving on to use it independently [27]. The same approaches used in cognitive rehabilitation (e.g., errorless learning, vanishing cues) could also be

used to acquire the skills needed to use mHealth technology [43], though instruction should be tailored to the individual learner rather than adopting a one-size-all approach. Further, several strategies should be designed within mHealth platforms themselves, to support ongoing use and reduce abandonment, as we discuss later in this chapter.

Despite its potential, mHealth is not a magic bullet and should not replace—nor be implemented in the absence of—health providers. Careful consideration of privacy, safety, and emotional well-being when using mHealth technology is paramount. Mobile technology is a primary part of the future of health care, presenting opportunities to provide quality care to more individuals, but we need to address the challenges inherent in mHealth—especially for those with cognitive impairment—to maintain an effective and ethical practice.

24.5   Mobile Technology for Cognitive Assessment

Mobile technology has a number of capabilities that hold promise for enriching the assessment of cognitive function. Built-in sensors—such as positional sensors (e.g., accelerometer, gyroscope, and GPS), media sensors (e.g., microphone and camera), inherent sensors (e.g., device timer), and participatory user–device interactions (eg, screen interactions, metadata input, app usage, and device lock and unlock)—could provide helpful information for assessing individuals' behavior for the purposes of training, monitoring, diagnosis, or rehabilitation [44]. For example, sensor-enriched mobile assessment of memory could leverage information from human–device interactions—such as the number of times an individual interacts with the screen to gather necessary information to complete a memory task. Furthermore, mobile technology could serve as a platform for administration, scoring, interpretation, and storage of adapted versions of traditional "paper and pencil" neuropsychological tests. A scoping review published in 2021 found encouraging evidence for

the use of mHealth technology to collect patient-reported outcomes after acquired brain injury, including those capturing neurocognitive functions in day-to-day life [27]. However, despite this great promise, the application of mobile technology for neurocognitive assessment is still in its infancy, and to date, there are no validated mobile assessment tools for neurocognitive assessment in individuals with ABI.

24.6   Mobile Technology for Cognitive Rehabilitative Treatments

There are clear opportunities within the traditional framework of cognitive rehabilitation for mobile technology to enhance treatment. Mobile devices can provide external cueing via alarms and notifications. Using mobile technology in the home and community can support the repeated practice of skills and habits without relying on limited therapist availability for direct supervision in the clinic. Furthermore, mobile technology's ability to deliver instruction and support practice within the home and community allows skill acquisition and practice to take place in the very contexts in which they will be applied. These features have been leveraged by targeted cognitive rehabilitation applications.

In addition to targeted applications, many standard smartphone functions and apps geared towards the general population are now regularly incorporated into cognitive rehabilitation. As indicated earlier, training in the use of external aids—planners, calendars, memory notebooks—has always been a critical aspect of compensatory treatments. Traditional paper and pencil aids however can be bulky and easily misplaced, while smartphones allow users with cognitive impairment to easily and discretely take advantage of electronic alarms, calendars, to-do lists, GPS, and other cognitive aids as they go about their daily lives. A recent study from the TBI Model Systems National Database study on internet use ($N = 337$) of individuals with TBI found that 95% owned a mobile phone and over 75% used their smartphone to access the internet

[24]. A smaller survey of individuals with TBI ($N = 29$) found that use as a memory and organizational aid was a commonly cited benefit of smartphones for this population [37]. A 2007 review of the literature on efficacy of using external memory aids for managing memory disorders identified critical research gaps in the study of electronic external aids for users with TBI, including, a poor understanding of factors that lead to long-term adoption of external aids [45]. The authors also note that further research is needed on the design and selection of aids and the evaluation, instruction, and ongoing monitoring of people using the devices [45].

The vast majority of mHealth apps are not evidence-based at present [16]. There is however a small but growing literature speaking to the use of smart technologies to both help improve functioning and monitor functioning for persons with ABI. In a systematic review looking at literature through May 2019, Kettlewell and co-authors (2019) were only able to identify four studies that employed a randomized controlled trial methodology and focused on functioning. They concluded that there was insufficient evidence available to support the benefit of personal smart technologies to improve outcomes in this population [46].

In a scoping review, published the same year, Juengst and co-authors (2019), found that mHealth showed some potential for persons with TBI to use as a compensation strategy for cognitive impairment, as well as a method for monitoring reducing symptoms and a way of addressing social educational goals. Looking at literature published between 2012 in 2019, the authors identified 16 papers which met their criteria. These studies used multiple approaches, with most studies focusing on everyday memory functioning and using simple prompts to help complete a specific task at a given time. The studies also collectively show the importance of the involvement of a human component in the intervention and the need for the contact to be meaningful to the person served. Also evident was the importance of understanding the cognitive difficulties experienced by persons with TBI that may cause greater difficulty in learning or using the technology itself. The qualitative evaluation of these interventions indicated encouraging outcomes in terms of better symptom management, decreasing memory problems and mood difficulties, and improving overall well-being than more formal outcome measures showed alone [47].

More recently, Juengst and colleagues (2021) conducted a scoping review of literature from 2015 to 2019 of studies which used mHealth technology for assessment of patient-reported outcomes in community-dwelling individuals with ABI which included ecological momentary assessment for data collection. 12 manuscripts were identified which met inclusion criteria. The interventions were at various stages of development and testing, supporting a range of cognitive skills from everyday memory to executive function (planning, organization, goal setting) to community participation (social, academic/vocational) [27]. Though the evidence remained insufficient to inform clinical guidelines, it did show promise for the future, and overall users with TBI were enthusiastic about using mHealth technology as a compensatory strategy [17].

Given the great variability with respect to what constructs were measured as well as the frequency duration and timing of the exact data collection, the authors were unable to make recommendations regarding either the optimal content or timing of specific mHealth platforms for capturing information. The authors did note that, as with previous reviews, personalization of the technology to account for the unique needs and abilities of each person was crucial to success. This idea has long been one of the main tenants of formulating rehabilitation treatment: to gather data and ask questions to determine which approach has the best "goodness of fit" between technology and a given individual [48].

24.7 Future Directions

Though the extant evidence for use of mHealth technology for cognitive rehabilitation is certainly promising, there are several areas for

future development so that we can move towards developing clinical practice guidelines. As discussed in this chapter, mobile technology has the potential to extend the duration and intensity of cognitive rehabilitation (including the delivery of 'booster' sessions or maintenance therapies), provide assessment and treatment in ecologically valid contexts, and permit time-sensitive interventions. Long-term use of mobile technology for cognitive rehabilitation should consider patients' evolving needs as they progress through their individual recovery trajectory, as well as their meaningful life roles and personal treatment goals, which are also subject to change over time [49].

Future design efforts should capitalize on the complimentary expertise of various stakeholder groups from both the "technology domain" (technology developers) and the "healthcare domain" (clinicians, consumers with brain injury, and their caregivers). This co-design approach engages stakeholders representing patients, clinicians, and healthcare administration at the front-end of design to identify clinically meaningful problems and concerns, while still allowing for the opportunistic exploration of "technology-inspired" approaches that envision new healthcare technologies that would be overlooked by strictly "problem-driven" design approaches. That said, we should not forget to pause and ask not just what we *can* do but also what we *should* (or should not) do. Inclusion of relevant stakeholders—from patients to their family members to clinicians to payors—is crucial to ensuring meaningful, feasible, scalable, and ethical development of mHealth to support cognitive rehabilitation [49].

Ongoing work is needed not only in the development and scientific evaluation of specific mHealth technologies and platforms but also in how we operationalize, implement, and reimburse for cognitive rehabilitation services provided via mHealth. For the reasons discussed above, the goal of cognitive rehabilitation is predominantly on compensation and adaptation—that is, long-term behavioral changes to support function—rather than restoration, hence, we also need to carefully consider long-term consumer engagement and technical support for using these technologies independently and indefinitely. Lastly, the rapid evolution of mHealth often leaves us scrambling to keep up, both with high-quality evidence (especially as technologies rapidly develop, rendering earlier technologies obsolete) and with important ethical considerations. Below we offer suggestions of some specific promising directions for future development.

First, we need to employ a framework for thinking about how to operationalize the specific therapeutic components to include in mHealth technology for different cognitive rehabilitation targets. This is an important, but often over-looked, step for both research and clinical implementation. For research, we cannot test what components are most effective if we do not have a concrete way to measure those components directly. For clinical implementation, we need standardized definitions for documentation and reimbursement. The Rehabilitation Treatment Specification System (RTSS) provides this kind of framework for defining specific treatment components in rehabilitation interventions. The RTSS characterizes rehabilitative treatments according to the targets, ingredients, and mechanisms of action. Thus, RTSS provides a coherent theory-based framework that researchers can use to systematically test the effects of specific ingredients on specific targets [50]. Classifying mHealth treatments for cognitive rehabilitation according to this approach could greatly accelerate development, as it would enable researchers to test the effectiveness of mobile delivery of specific treatment ingredients, and these evidence-based treatment ingredients could then be implemented across various platforms as technology continues to advance.

Second, we need to develop processes for including mHealth technology in the ongoing treatment process and in clinician workflow. This includes processes for adapting mHealth technology use in response to patient progress or decline [49]. Adaptations may be required for the content, timing, and/or frequency of assessments or EMI in response to these changes. Processes may be external to the technology—such as plans

for ongoing re-evaluation to ensure the technology is still meeting the patient's and family's needs, and process internal to the technology—such as built-in flexibility and customizability within the apps themselves. Individuals will need feedback from providers as well, so the use of mHealth should continue to be paired with, rather than replace, contact with healthcare providers. Input from clinicians and developing training for clinicians to enable them to identify evidence-based mHealth apps and to provide effective training in the use of mHealth technology to their patients will be critical. Further, clinicians may have different preferences and needs for how they access the data collected from their patients via mHealth, how the data are presented to them (e.g., design of a "clinician portal" in a two-way mHealth system), and how mHealth use would impact, and be incorporated into, their clinical workflow.

Third, we need to develop strategies for engaging individuals with disabilities and their caregivers in the use of mHealth technology, both in the short and long term. This can be done in several ways. One critical approach is to include end-users in the development of mHealth technology. Doing so will promote accessibility, design consistent with patient needs, preferences, and values, and long-term adoption. It will also allow us to identify—and hopefully, circumvent or prevent—barriers to mHealth technology use that result in frustration with technology abandonment. In addition to addressing external factors, like appropriate and accessible tech support, strategies need to be embedded into mHealth technology design to promote engagement and long-term use. Such strategies that have been identified in several past studies include iterative feedback about progress (e.g., not only having individuals track symptoms but also providing feedback and what these symptoms mean), ability to customize mHealth content and notification based on personal needs and preferences (e.g., limiting notifications only to the most salient components for that individuals), and including "gamification" (e.g., use of in-app challenges and rewards based on engagement). Such "gamification" has been successfully employed in other

mHealth technologies, such as those targeting exercise, weight loss, or smoking cessation [51–53], and in one study targeting symptom management after youth concussion [54].

Last, we need to develop better training and early support for learning how to use mHealth technology, to ensure that individuals are able to continue using mHealth technology independently. Training should be individualized based on users' familiarity and comfort with mHealth technology and on their cognitive strengths and limitations.

As technology rapidly develops, so do the future directions that can be explored for using mHealth in cognitive rehabilitation. Technology developers refer to a new era of personal technology—the "post-app era"—wherein the way that users interact with their smartphones is becoming more streamlined. Increasingly users will rely on mobile technology to carry out day-to-day tasks without ever needing to open a traditional mobile application. Cloud computing, advancing in machine learning and artificial intelligence (for example, conversational user interfaces know as virtual assistants or "chatbots"), and the seemingly inevitable transition into the "post-app era" are currently paving the way for previously unthought-of mHealth technology. Exciting as this may be, we cannot rush ahead without considering the ethical implications. These include, but certainly are not limited to the following. First, we must consider what we are tracking or providing to individuals with cognitive disabilities in the absence (or synchronous presence) of a human clinician. Second, we must carefully determine what mHealth technology can replace in current practice versus how it would be best used to complement or supplement current practice. Third, advances in mHealth technology should be made to *close* rather than *widen* health disparities. While high-income countries remain at the forefront of developing the latest mobile technologies used in health care, the rate of penetration of such technologies in low- and middle-income countries has recently exceeded that of their wealthier neighbors [26]. Together, there is much potential for mHealth technology to improve the

effectiveness and reach of cognitive rehabilitation interventions, but we must ensure it is done with the same consideration afforded to clinician-delivered care.

References

1. Cullen N. Canadian Healthcare Perspective in traumatic brain injury rehabilitation. J Head Trauma Rehabil. 2007;22(4):214–20.

2. O'Callaghan AM, McAllister L, Wilson L. Experiences of care: perspectives of carers of adults with traumatic brain injury. Int J Speech Lang Pathol. 2011;13(3):218–26.

3. Green R, Colella B, Maller J, Bayley M, Glazer J, Mikulis D. Scale and pattern of atrophy in the chronic stages of moderate-severe TBI. Front Hum Neurosci. 2014;8:67.

4. Masel BE, DeWitt DS. Traumatic brain injury: a disease process, not an event. J Neurotrauma. 2010;27(8):1529–40.

5. Teasell R, Foley N, Salter K, Richardson M. Evidence-based review of stroke rehabilitation (16th edition). Top Stroke Rehabil. 2003;10(1):29–58.

6. Breitenstein C, Grewe T, Flöel A, Ziegler W, Springer L, Martus P, et al. Intensive speech and language therapy in patients with chronic aphasia after stroke: a randomised, open-label, blinded-endpoint, controlled trial in a health-care setting. The Lancet. 2017;389(10078):1528–38.

7. Till C, Colella B, Verwegen J, Green RE. Postrecovery cognitive decline in adults with traumatic brain injury. Arch Phys Med Rehabil. 2008;89(12, Supplement):S25–34.

8. Harley J, Allen C, Braciszewski T, Cicerone K, Dahlberg C, Evans S, et al. Guidelines for cognitive rehabilitation. Neuro Rehabil. 1992;2(3):62–7.

9. Ylvisaker M, Hanks R, Johnson-Greene D. Perspectives on rehabilitation of individuals with cognitive impairment after brain injury: rationale for reconsideration of theoretical paradigms. J Head Trauma Rehabil. 2002;17(3):191–209.

10. Ben-Yishay Y, Silver SM, Piasetsky E, Rattok J. Relationship between employability and vocational outcome after intensive holistic cognitive rehabilitation. J Head Trauma Rehabil. 1987;35–48.

11. Chan F, Gelman JS, Ditchman N, Kim J-H, Chiu C-Y. The World Health Organization ICF model as a conceptual framework of disability. 2009.

12. Cicerone KD, Goldin Y, Ganci K, Rosenbaum A, Wethe JV, Langenbahn DM, et al. Evidence-based cognitive rehabilitation: systematic review of the literature from 2009 through 2014. Arch Phys Med Rehabil. 2019;100(8):1515–33.

13. Bergquist TF, Jackets MP. Awareness and goal setting with the traumatically brain injured. Brain Inj. 1993;7(3):275–82.

14. Sohlberg MM, Mateer CA. Introduction to cognitive rehabilitation: theory and practice. Guilford Press; 1989.

15. Eberle R, Rosenbaum A. Cognitive rehabilitation manual and textbook: translating evidence-based recommendations into practice. 2nd ed. In ACRM Publishing; In Press.

16. Ramey L, Osborne C, Kasitinon D, Juengst S. Apps and mobile health technology in rehabilitation: the good, the bad, and the unknown. Phys Med Rehabil Clin. 2019;30(2):485–97.

17. Osborne CL, Juengst SB, Smith EE. Identifying user-centered content, design, and features for mobile health apps to support long-term assessment, behavioral intervention, and transitions of care in neurological rehabilitation: an exploratory study. Br J Occup Ther. 2021;84(2):101–10.

18. Heron KE, Smyth JM. Ecological momentary interventions: incorporating mobile technology into psychosocial and health behaviour treatments. Br J Health Psychol. 2010;15(1):1–39.

19. Hay CE, Kinnier RT. Homework in counseling. J Ment Health Couns. 1998;20(2):122.

20. Kazantzis N, L'Abate L. Handbook of homework assignments in psychotherapy. Springer; 2007.

21. Newman MG, Consoli A, Taylor CB. Computers in assessment and cognitive behavioral treatment of clinical disorders: anxiety as a case in point. Behav Ther. 1997;28(2):211–35.

22. Kalichman SC, Kalichman MO, Cherry C, Swetzes C, Amaral CM, White D, et al. Brief behavioral self-regulation counseling for HIV treatment adherence delivered by cell phone: an initial test of concept trial. AIDS Patient Care STDS. 2011;25(5):303–10.

23. Malow RM, West JA, Corrigan SA, Pena JM, Cunningham SC. Outcome of psychoeducation for HIV risk reduction. AIDS Education and Prevention. 1994

24. Baker-Sparr C, Hart T, Bergquist T, Bogner J, Dreer L, Juengst S, et al. Internet and social media use after traumatic brain injury: a traumatic brain injury model systems study. J Head Trauma Rehabil. 2018;33(1):E9-17.

25. Morris JT, Sweatman M, Jones ML. Smartphone use and activities by people with disabilities: user survey 2016. J Technol Pers Disabil. 2017;5:50–66.

26. Pew Research Center. Mobile fact sheet. Pew Research Center. 2018;

27. Juengst SB, Terhorst L, Nabasny A, Wallace T, Weaver JA, Osborne CL, et al. Use of mHealth technology for patient-reported outcomes in community-dwelling adults with acquired brain injuries: a scoping review. Int J Environ Res Public Health. 2021;18(4):2173.

28. mHealth Economics 2017 Report: Status and trends in digital health | R2G [Internet]. research2guidance. [cited 2022 Jan 5]. https://research2guidance.com/product/mhealth-economics-2017-current-status-and-future-trends-in-mobile-health/.

29. Aitken M. Patient adoption of mHealth: use, evidence and remaining barriers to mainstream acceptance. IMS Institute of Healthcare Informatics; 2015 Sep.

30. Constantino T. IMS Health Study: patient options expand as mobile healthcare apps address wellness and chronic disease treatment needs [Internet]. IMS Institute for Healthcare Informatics; 2015 Sep [cited 2022 Jan 5]. https://www.businesswire.com/news/home/20150917005044/en/IMS-Health-Study-Patient-Options-Expand-Mobile.

31. Jones M, Morris J, Deruyter F. Mobile healthcare and people with disabilities: current state and future needs. Int J Environ Res Public Health. 2018;15(3):515.

32. Nussbaum R, Kelly C, Quinby E, Mac A, Parmanto B, Dicianno BE. Systematic review of mobile health applications in rehabilitation. Arch Phys Med Rehabil. 2019;100(1):115–27.

33. Anthes E. Mental health: there's an app for that. Nature News. 2016;532(7597):20.

34. Free C, Phillips G, Galli L, Watson L, Felix L, Edwards P, et al. The effectiveness of mobile-health technology-based health behaviour change or disease management interventions for health care consumers: a systematic review. PLoS Med. 2013;10(1): e1001362.

35. Morris J, Jones M, Thompson N, Wallace T, DeRuyter F. Clinician perspectives on mRehab interventions and technologies for people with disabilities in the United States: a national survey. Int J Environ Res Public Health. 2019;16(21):4220.

36. Plackett R, Thomas S, Thomas S. Professionals' views on the use of smartphone technology to support children and adolescents with memory impairment due to acquired brain injury. Disabil Rehabil Assist Technol. 2017;12(3):236–43.

37. Wong D, Sinclair K, Seabrook E, McKay A, Ponsford J. Smartphones as assistive technology following traumatic brain injury: a preliminary study of what helps and what hinders. Disabil Rehabil. 2017;39(23):2387–94.

38. Nouri R, R Niakan Kalhori S, Ghazisaeedi M, Marchand G, Yasini M. Criteria for assessing the quality of mHealth apps: a systematic review. J Am Med Inform Assoc. 2018;25(8):1089–98.

39. Bedell GM, Wade SL, Turkstra LS, Haarbauer-Krupa J, King JA. Informing design of an app-based coaching intervention to promote social participation of teenagers with traumatic brain injury. Dev Neurorehabil. 2017;20(7):408–17.

40. Lannin N, Carr B, Allaous J, Mackenzie B, Falcon A, Tate R. A randomized controlled trial of the effectiveness of handheld computers for improving everyday memory functioning in patients with memory impairments after acquired brain injury. Clin Rehabil. 2014;28(5):470–81.

41. Narad ME, Bedell G, King JA, Johnson J, Turkstra LS, Haarbauer-Krupa J, et al. Social Participation and Navigation (SPAN): description and usability of app-based coaching intervention for adolescents with TBI. Dev Neurorehabil. 2018;21(7):439–48.

42. Powell LE, Wild MR, Glang A, Ibarra S, Gau JM, Perez A, et al. The development and evaluation of a web-based programme to support problem-solving skills following brain injury. Disabil Rehabil Assist Technol. 2019;14(1):21–32.

43. Ehlhardt LA, Sohlberg MM, Kennedy M, Coelho C, Ylvisaker M, Turkstra L, et al. Evidence-based practice guidelines for instructing individuals with neurogenic memory impairments: What have we learned in the past 20 years? Neuropsychol Rehabil. 2008;18(3):300–42.

44. Templeton JM, Poellabauer C, Schneider S. Enhancement of neurocognitive assessments using smartphone capabilities: systematic review. JMIR Mhealth Uhealth. 2020;8(6): e15517.

45. Sohlberg MM, Kennedy M, Avery J, Coelho C, Turkstra L, Ylvisaker M, et al. Evidence-based practice for the use of external aids as a memory compensation technique. J Med Speech-Lang Pathol. 2007;15(1):xv–xv.

46. Kettlewell J, das Nair R, Radford K. A systematic review of personal smart technologies used to improve outcomes in adults with acquired brain injuries. Clin Rehabil. 2019;33(11):1705–12.

47. Juengst SB, Hart T, Sander AM, Nalder EJ, Pappadis MR. Mobile health interventions for traumatic brain injuries. Curr Phys Med Rehabil Rep. 2019;7(4):341–56.

48. Wright BA. Motivating children in the rehabilitation program. 1983;

49. How T-V, Hwang AS, Green REA, Mihailidis A. Envisioning future cognitive telerehabilitation technologies: a co-design process with clinicians. Disabil Rehabil Assist Technol. 2017;12(3):244–61.

50. Hart T, Dijkers MP, Whyte J, Turkstra LS, Zanca JM, Packel A, et al. A theory-driven system for the specification of rehabilitation treatments. Arch Phys Med Rehabil. 2019;100(1):172–80.

51. Burkow TM, Vognild LK, Johnsen E, Bratvold A, Risberg MJ. Promoting exercise training and physical activity in daily life: a feasibility study of a virtual group intervention for behaviour change in COPD. BMC Med Inform Decis Mak. 2018;18(1):136.

52. Rajani NB, Weth D, Mastellos N, Filippidis FT. Use of gamification strategies and tactics in mobile applications for smoking cessation: a review of the UK mobile app market. BMJ Open. 2019;9(6): e027883.

53. Timpel P, Cesena FHY, da Silva CC, Soldatelli MD, Gois E, Castrillon E, et al. Efficacy of gamification-based smartphone application for weight loss in overweight and obese adolescents: study protocol for a phase II randomized controlled trial. Ther Adv Endocrinol Metab. 2018;9(6):167–76.

54. Worthen-Chaudhari L, McGonigal J, Logan K, Bockbrader MA, Yeates KO, Mysiw WJ. Reducing concussion symptoms among teenage youth: Evaluation of a mobile health app. Brain Inj. 2017;31 (10):1279–86.

Telerehabilitation Technology

25

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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.

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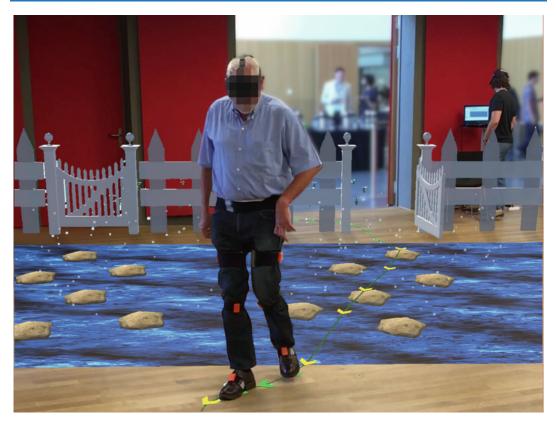
Fig. 25.2 A client after stroke performing a mixed reality gait training parkour with a holographic head-mounted display. Obstacles that require specific gait adaptations are placed throughout a given physical environment, transforming the space into a virtual rehabilitation gym (from [240])

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.

References

1. Appleby E, et al. Effectiveness of telerehabilitation in the management of adults with stroke: a systematic review. PLoS ONE. 2019;14: e0225150.
2. Brennan DM, Mawson S, Brownsell S. Telerehabilitation: enabling the remote delivery of healthcare, rehabilitation, and self management. Stud Health Technol. 2009;145:231–48.
3. Richmond T, et al. American telemedicine association's principles for delivering telerehabilitation services. Int J Telerehabilitation 2017; 9:63–68.
4. Katz RC. Application of computers to the treatment of US veterans with aphasia. Aphasiology. 2009;23:1116–26.
5. Vaughn GR. Tel-communicology: health-care delivery system for persons with communicative disorders. ASHA. 1976;18:13–7.

6. Shinar D, et al. Reliability of the activities of daily living scale and its use in telephone interview. Arch Phys Med Rehab. 1987;68:723–8.

7. Mayo NE. Stroke Rehabilitation at Home. Stroke. 2018;47:1685–91.

8. Danzl MM, Etter NM, Andreatta RD, Kitzman PH. Facilitating neurorehabilitation through principles of engagement. J Allied Heal. 2012;41:35–41.

9. Isernia S, et al. Efficiency and patient-reported outcome measures from clinic to home: the human empowerment aging and disability program for digital-health rehabilitation. Front Neurol. 2019;10:1206.

10. Vickery DM, et al. Effect of a Self-care Education Program on Medical Visits. JAMA. 1983;250:2952–6.

11. Coulter A, Ellins J. Client-focused interventions: a review of the evidence, vol 1. London: Health Foundation; 2006.

12. Laver KE, et al. Telerehabilitation services for stroke. Cochrane Database Syst Rev. 2020;1: CD010255

13. Deng H, et al. Complex versus simple ankle movement training in stroke using telerehabilitation: a randomized controlled trial. Phys Ther. 2012;92:197–209.

14. Baur K, Rohrbach N, Hermsdörfer J, Riener R, Klamroth-Marganska V. The "Beam-Me-In Strategy"–remote haptic therapist-patient interaction with two exoskeletons for stroke therapy. J Neuroeng Rehabil. 2019;16:85.

15. Mutalib SA, et al. Modernising the dynamometer for grip assessment: comparison between gripable and jamar. 2021. https://doi.org/10.21203/rs.3.rs-720982/v1.

16. Laver KE, et al. Virtual reality for stroke rehabilitation. Cochrane Database Syst Rev. 2017. https://doi.org/10.1002/14651858.cd008349.pub4.

17. Annaswamy TM, et al. Using biometric technology for telehealth and telerehabilitation. Phys Med Rehabil Cli. 2021;32:437–49.

18. Weiss PL, Kizony R, Feintuch U, Katz N. Textbook of neural repair and rehabilitation 2006;182–197. https://doi.org/10.1017/cbo9780511545078.015.

19. Rinne P, et al. Democratizing neurorehabilitation: how accessible are low-cost mobile-gaming technologies for self-rehabilitation of arm disability in stroke? PLoS ONE. 2016;11: e0163413.

20. Klamroth-Marganska V, et al. Does therapy always need touch? A cross-sectional study among Switzerland-based occupational therapists and midwives regarding their experience with health care at a distance during the COVID-19 pandemic in spring 2020. Bmc Health Serv Res. 2021;21:578.

21. Seifert A. Die Nutzung des Internets durch Personen ab 65 Jahren und ihr subjektives Gefühl der Exklusion. Blätter Der Wohlfahrtspflege. 2021;168:149–51.

22. Ballmer T. et al. Behandlungen auf Distanz während des Lockdowns. Ergotherapie. 2021:22–27.

23. Almathami HKY, Win KT, Vlahu-Gjorgievska E. Barriers and facilitators that influence telemedicine-based, real-time, online consultation at patients' homes: systematic literature review. J Med Internet Res. 2020;22: e16407.

24. Bahari M, Jafni TI, Miskon S, Ismail W. A review of success/failure factors influencing healthcare personnel for telerehabilitation. In: 2019 6th International conference res innovation information syst icriis; 2019. p. 1–7.

25. Jafni TI, Bahari M, Ismail W, Radman A. Understanding the implementation of telerehabilitation at pre-implementation stage: a systematic literature review. Procedia Comput Sci. 2017;124:452–60.

26. Yusof M. Mohd. A case study evaluation of a Critical Care Information System adoption using the socio-technical and fit approach. Int J Med Inform. 2015;84:486–499.

27. Creagh AP, et al. Smartphone-based remote assessment of upper extremity function for multiple sclerosis using the Draw a Shape Test. Physiol Meas. 2020;41: 054002.

28. Donkor ES. Stroke in the 21st century: a snapshot of the burden, epidemiology, and quality of life. Stroke Res Treat. 2018;2018:3238165.

29. Feigin VL, et al. Global and regional burden of stroke during 1990–2010: findings from the Global Burden of Disease Study 2010. Lancet. 2014;383:245–55.

30. Broeks JG, Lankhorst GJ, Rumping K, Prevo AJH. The long-term outcome of arm function after stroke: results of a follow-up study. Disabil Rehabil. 2009;21:357–64.

31. Nijland RHM, van Wegen EEH, der Wel BCH, Kwakkel G. Presence of finger extension and shoulder abduction within 72 hours after stroke predicts functional recovery. Stroke. 2010;41:745–50.

32. Kwakkel G, Kollen BJ, van der Grond J, Prevo AJH. Probability of regaining dexterity in the flaccid upper limb. Stroke. 2003;34:2181–6.

33. van Lieshout ECC, van de Port IG, Dijkhuizen RM, Visser-Meily JMA. Does upper limb strength play a prominent role in health-related quality of life in stroke patients discharged from inpatient rehabilitation? Top Stroke Rehabil. 2020;27:1–9.

34. Ytterberg C, et al. A qualitative study of cognitive behavioural therapy in multiple sclerosis: experiences of psychotherapists. Int J Qual Stud Heal. 2017;12:1325673.

35. Bernhardt J, et al. Agreed definitions and a shared vision for new standards in stroke recovery research: The Stroke Recovery and Rehabilitation Roundtable taskforce. Int J Stroke. 2017;12:444–50.

36. Levin MF, Kleim JA, Wolf SL. What do motor "recovery" and "compensation" mean in patients following stroke? Neurorehab Neural Re. 2009;23:313–9.

37. Roby-Brami A, et al. Motor compensation and recovery for reaching in stroke patients. Acta Neurol Scand. 2003;107:369–81.

38. Cirstea MC, Levin MF. Compensatory strategies for reaching in stroke. Brain. 2000;123:940–53.

39. Prange-Lasonder GB, et al. European evidence-based recommendations for clinical assessment of upper limb in neurorehabilitation (CAULIN): data synthesis from systematic reviews, clinical practice guidelines and expert consensus. J Neuroeng Rehabil. 2021;18:162.

40. Burridge J, et al. A systematic review of international clinical guidelines for rehabilitation of people with neurological conditions: what recommendations are made for upper limb assessment? Front Neurol. 2019;10:567.

41. Hughes A-M, et al. Evaluation of upper extremity neurorehabilitation using technology: a European Delphi consensus study within the EU COST Action Network on Robotics for Neurorehabilitation. J Neuroeng Rehabil. 2016;13:86.

42. Schwarz A, Kanzler CM, Lambercy O, Luft AR, Veerbeek JM. Systematic review on kinematic assessments of upper limb movements after stroke. Stroke. 50:718–727.

43. Pohl J, et al. Consensus-based core set of outcome measures for clinical motor rehabilitation after stroke—a Delphi study. Front Neurol. 2020;11:875.

44. Kwakkel G, et al. Standardized measurement of sensorimotor recovery in stroke trials: consensus-based core recommendations from the stroke recovery and rehabilitation roundtable. Int J Stroke. 2017;12:451–61.

45. Kwakkel G, et al. Standardized measurement of quality of upper limb movement after stroke: consensus-based core recommendations from the second stroke recovery and rehabilitation roundtable. Neurorehab Neural Re. 2019;33:951–8.

46. Organization WH. International classification of functioning, disability and health (ICF). 2001.

47. Waddell KJ, Strube MJ, Tabak RG, Haire-Joshu D, Lang CE. Upper limb performance in daily life improves over the first 12 weeks poststroke. Neurorehab Neural Re. 2019;33:836–47.

48. Lee SI, et al. A novel upper-limb function measure derived from finger-worn sensor data collected in a free-living setting. PLoS ONE. 2019;14: e0212484.

49. Fugl-Meyer AR, Jääskö L, Leyman I, Olsson S, Steglind S. The post-stroke hemiplegic patient. 1. a method for evaluation of physical performance. Scand J Rehabil Med. 1975;7:13–31.

50. Sullivan KJ, et al. Fugl-Meyer assessment of sensorimotor function after stroke. Stroke. 2011;42:427–32.

51. Lyle RC. A performance test for assessment of upper limb function in physical rehabilitation treatment and research. Int J Rehabil Res. 1981;4:483–92.

52. Yozbatiran N, Der-Yeghiaian L, Cramer SC. A standardized approach to performing the action research arm test. Neurorehab Neural Re. 2008;22:78–90.

53. Singer B, Garcia-Vega J. The Fugl-Meyer upper extremity scale. j Physiother. 2017;63:53.

54. van der Lee JH, Roorda LD, Beckerman H, Lankhorst GJ, Bouter LM. Improving the action research arm test: a unidimensional hierarchical scale. Clin Rehabil. 2002;16:646–53.

55. Amano S. et al. Reliability of remote evaluation for the Fugl–Meyer assessment and the action research arm test in hemiparetic patients after stroke. Top Stroke Rehabil. 2018:1–6. https://doi.org/10.1080/10749357.2018.1481569.

56. Murphy MA, Häger CK. Kinematic analysis of the upper extremity after stroke–how far have we reached and what have we grasped? Phys Ther Rev. 2015;20:137–55.

57. Thrane G, Sunnerhagen KS, Murphy MA. Upper limb kinematics during the first year after stroke: the stroke arm longitudinal study at the University of Gothenburg (SALGOT). J Neuroeng Rehabil. 2020;17:76.

58. Subramanian SK, Yamanaka J, Chilingaryan G, Levin MF. Validity of movement pattern kinematics as measures of arm motor impairment poststroke. Stroke. 2010;41:2303–8.

59. Ellis MD, Lan Y, Yao J, Dewald JPA. Robotic quantification of upper extremity loss of independent joint control or flexion synergy in individuals with hemiparetic stroke: a review of paradigms addressing the effects of shoulder abduction loading. J Neuroeng Rehabil. 2016;13:95.

60. Milosevic B, Leardini A, Farella E. Kinect and wearable inertial sensors for motor rehabilitation programs at home: state of the art and an experimental comparison. Biomed Eng Online. 2020;19:25.

61. Merriaux P, Dupuis Y, Boutteau R, Vasseur P, Savatier X. A study of vicon system positioning performance. Sensors Basel Switz. 2017;17:1591.

62. Mavor MP, Ross GB, Clouthier AL, Karakolis T, Graham RB. Validation of an IMU suit for military-based tasks. Sensors Basel Switz. 2020;20:4280.

63. Kanko RM, Laende EK, Davis EM, Selbie WS, Deluzio KJ. Concurrent assessment of gait kinematics using marker-based and markerless motion capture. J Biomech. 2021;127: 110665.

64. Mathiowetz V, et al. Grip and pinch strength: normative data for adults. Arch Phys Med Rehab. 1985;66:69–74.

65. Xu J. et al. Separable systems for recovery of finger strength and control after stroke. J Neurophysiol. 2017. https://doi.org/10.1152/jn.00123.2017.

66. Subramanian SK, Cross MK, Hirschhauser CS, Johnson VB, Reistetter TA. Post-stroke upper limb rehabilitation using virtual reality interventions: Do outcome measures assess extent or type of motor improvement? In: 2019 Int Conf Virtual Rehabilitation Icvr. 2019. p. 1–6.

67. Stinear CM, Smith M-C, Byblow WD. Prediction tools for stroke rehabilitation. Stroke. 2019;50:3314–22.

68. Murphy MA, Sunnerhagen KS, Johnels B, Willén C. Three-dimensional kinematic motion analysis of a daily activity drinking from a glass: a pilot study. J Neuroeng Rehabil. 2006;3:18.

69. Murphy MA, Willén C, Sunnerhagen KS. Kinematic variables quantifying upper-extremity performance after stroke during reaching and drinking from a glass. Neurorehab Neural Re. 2011;25:71–80.

70. Frykberg GE, Grip H, Murphy MA. How many trials are needed in kinematic analysis of reach-to-grasp?—A study of the drinking task in persons with stroke and non-disabled controls. J Neuroeng Rehabil. 2021;18:101.

71. David A, Subash T, Varadhan SKM, Melendez-Calderon A, Balasubramanian S. A framework for sensor-based assessment of upper-limb functioning in hemiparesis. Front Hum Neurosci. 2021;15:667509.

72. Thrane G, Emaus N, Askim T, Anke A. Arm use in patients with subacute stroke monitored by accelerometry: association with motor impairment and influence on self-dependence. J Rehabil Med. 2011;43:299–304.

73. Kim GJ, Parnandi A, Eva S, Schambra H. The use of wearable sensors to assess and treat the upper extremity after stroke: a scoping review. Disabil Rehabil. 2021:1–20. https://doi.org/10.1080/09638288.2021.1957027.

74. Wang Q, Markopoulos P, Yu B, Chen W, Timmermans A. Interactive wearable systems for upper body rehabilitation: a systematic review. J Neuroeng Rehabil. 2017;14:20.

75. Iosa M, Picerno P, Paolucci S, Morone G. Wearable inertial sensors for human movement analysis. Expert Rev Med Devic. 2016;13:1–19.

76. Yang L, Zhang L, Dong H, Alelaiwi A, Saddik AE. Evaluating and improving the depth accuracy of kinect for windows v2. IEEE Sens J. 2015;15:4275–85.

77. Yeung L-F, Yang Z, Cheng KC-C, Du D, Tong RK-Y. Effects of camera viewing angles on tracking kinematic gait patterns using Azure Kinect, Kinect v2 and Orbbec Astra Pro v2. Gait Posture. 2021;87:19–26.

78. Wang J, et al. Deep 3D human pose estimation: a review. Comput Vis Image Und. 2021;210:103225.

79. Mathis A, Schneider S, Lauer J, Mathis MW. A primer on motion capture with deep learning: principles, pitfalls, and perspectives. Neuron. 2020;108:44–65.

80. Needham L, et al. The accuracy of several pose estimation methods for 3D joint centre localisation. Sci Rep-UK. 2021;11:20673.

81. Arac A. Machine learning for 3D kinematic analysis of movements in neurorehabilitation. Curr Neurol Neurosci. 2020;20:29.

82. Din SD, Patel S, Cobelli C, Bonato P. Estimating Fugl-Meyer clinical scores in stroke survivors using wearable sensors. In: 2011 Annu Int Conf Ieee Eng Medicine Biology Soc. 2011. p. 5839–5842.

83. Kim W-S, Cho S, Baek D, Bang H, Paik N-J. Upper extremity functional evaluation by Fugl-Meyer assessment scoring using depth-sensing camera in hemiplegic stroke patients. PLoS ONE. 2016;11:e0158640.

84. Yu L, Xiong D, Guo L, Wang J. A remote quantitative Fugl-Meyer assessment framework for stroke patients based on wearable sensor networks. Comput Meth Prog Bio. 2016;128:100–10.

85. Adans-Dester C, et al. Enabling precision rehabilitation interventions using wearable sensors and machine learning to track motor recovery. Npj Digital Med. 2020;3:121.

86. Chin LF, Hayward KS, Brauer S. Upper limb use differs among people with varied upper limb impairment levels early post-stroke: a single-site, cross-sectional, observational study. Top Stroke Rehabil. 2019;27:1–12.

87. Strømmen AM, Christensen T, Jensen K. Quantitative measurement of physical activity in acute ischemic stroke and transient ischemic attack. Stroke. 2014;45:3649–55.

88. Schambra HM, et al. A taxonomy of functional upper extremity motion. Front Neurol. 2019;10:857.

89. Lemmens RJM, Janssen-Potten YJM, Timmermans AAA, Smeets RJEM, Seelen HAM. Recognizing complex upper extremity activities using body worn sensors. PLoS ONE. 2015;10:e0118642.

90. Panwar M, et al. Rehab-net: deep learning framework for arm movement classification using wearable sensors for stroke rehabilitation. IEEE T Biomed Eng. 2018;66:3026–37.

91. Biswas D, et al. Recognition of elementary arm movements using orientation of a tri-axial accelerometer located near the wrist. Physiol Meas. 2014;35:1751–68.

92. Ward NS, Brander F, Kelly K. Intensive upper limb neurorehabilitation in chronic stroke: outcomes from the Queen Square programme. J Neurology Neurosurg Psychiatry. 2019;90:498.

93. Ballester BR. et al. Relationship between intensity and recovery in post-stroke rehabilitation: a retrospective analysis. J Neurology Neurosurg Psychiatry jnnp. 2021. https://doi.org/10.1136/jnnp-2021-326948.

94. Krakauer JW, Carmichael ST, Corbett D, Wittenberg GF. Getting neurorehabilitation right. Neurorehab Neural Re. 2012;26:923–31.

95. Maier M, Ballester BR, Verschure PFMJ. Principles of neurorehabilitation after stroke based on motor learning and brain plasticity mechanisms. Front Syst Neurosci. 2019;13:74.

96. Gittler M, Davis AM. Guidelines for adult stroke rehabilitation and recovery. JAMA. 2018;319:820–1.

97. Foundation S. Clinical guidelines for stroke management. 2017. https://informme.org.au/en/Guidelines/Clinical-Guidelines-for-Stroke-Management.

98. Lambercy O, et al. Neurorehabilitation from a distance: can intelligent technology support decentralized access to quality therapy? Front Robot AI. 2021;8:612415.

99. Lee SH, et al. Comparisons between end-effector and exoskeleton rehabilitation robots regarding upper extremity function among chronic stroke patients with moderate-to-severe upper limb impairment. Sci Rep-UK. 2020;10:1806.

100. Chen Y, et al. Home-based technologies for stroke rehabilitation: a systematic review. Int J Med Inform. 2018;123:11–22.

101. Sigrist R, Rauter G, Riener R, Wolf P. Augmented visual, auditory, haptic, and multimodal feedback in motor learning: a review. Psychon B Rev. 2013;20:21–53.

102. Riener R. Virtual reality for neurorehabilitation. In: Dietz V, Ward N (eds) Oxford textbook of neurorehabilitation. Oxford Medicine Online; 2016. https://doi.org/10.1093/med/9780199673711. 003.0034.

103. Amorim P, Santos BS, Dias P, Silva S, Martins H. Serious games for stroke telerehabilitation of upper limb - a review for future research. Int J Telerehabilitation. 2020;12:65–76.

104. Kim W-S, et al. Clinical application of virtual reality for upper limb motor rehabilitation in stroke: review of technologies and clinical evidence. J Clin Medicine. 2020;9:3369.

105. Da-Silva RH, et al. Prompting arm activity after stroke: A clinical proof of concept study of wrist-worn accelerometers with a vibrating alert function. J Rehabil Assistive Technol Eng. 2018;5:2055 668318761524.

106. Da-Silva RH, et al. Wristband Accelerometers to motiVate arm Exercises after Stroke (WAVES): a pilot randomized controlled trial. Clin Rehabil. 2019;33:1391–403.

107. Chae SH, Kim Y, Lee K-S, Park H-S. Development and clinical evaluation of a web-based upper limb home rehabilitation system using a smartwatch and machine learning model for chronic stroke survivors: prospective comparative study. Jmir Mhealth Uhealth. 2020;8: e17216.

108. Lee SI, et al. Enabling stroke rehabilitation in home and community settings: a wearable sensor-based approach for upper-limb motor training. IEEE J Transl Eng Heal Med. 2018;6:2100411.

109. Whitford M, Schearer E, Rowlett M. Effects of in home high dose accelerometer-based feedback on perceived and actual use in participants chronic post-stroke. Physiother Theor Pr. 2018;36:1–11.

110. Parker J, Powell L, Mawson S. Effectiveness of upper limb wearable technology for improving activity and participation in adult stroke survivors: systematic review. J Med Internet Res. 2020;22: e15981.

111. Merians AS, et al. Virtual reality–augmented rehabilitation for patients following stroke. Phys Ther. 2002;82:898–915.

112. Subramanian SK, Cross MK, Hirschhauser CS. Virtual reality interventions to enhance upper limb motor improvement after a stroke: commonly used types of platform and outcomes. Disabil Rehabil

Assistive Technol. 2020:1–9. https://doi.org/10. 1080/17483107.2020.1765422.

113. Slater M, Wilbur S. A framework for immersive virtual environments (FIVE): speculations on the role of presence in virtual environments. Presence Teleoperators Virtual Environ. 1997;6:603–16.

114. Voinescu A, Sui J, Fraser DS. Virtual reality in neurorehabilitation: an umbrella review of meta-analyses. J Clin Med. 2021;10:1478.

115. Morel M, Bideau B, Lardy J, Kulpa R. Advantages and limitations of virtual reality for balance assessment and rehabilitation. Neurophysiol Clinique Clin Neurophys. 2015;45:315–26.

116. Levac DE, Huber ME, Sternad D. Learning and transfer of complex motor skills in virtual reality: a perspective review. J Neuroeng Rehabil. 2019;16:121.

117. Perrochon A, Borel B, Istrate D, Compagnat M, Daviet J-C. Exercise-based games interventions at home in individuals with a neurological disease: a systematic review and meta-analysis. Ann Phys Rehabil Med. 2019;62:366–78.

118. Cramer SC, et al. Efficacy of home-based telerehabilitation vs in-clinic therapy for adults after stroke: a randomized clinical trial. Jama Neurol. 2019;76:1079.

119. Akbari A, Haghverd F, Behbahani S. Robotic home-based rehabilitation systems design: from a literature review to a conceptual framework for community-based remote therapy during COVID-19 pandemic. Front Robot AI. 2021;8: 612331.

120. Gassert R, Dietz V. Rehabilitation robots for the treatment of sensorimotor deficits: a neurophysiological perspective. J Neuroeng Rehabil. 2018;15:46.

121. Noronha B, Accoto D. Exoskeletal devices for hand assistance and rehabilitation: a comprehensive analysis of state-of-the-art technologies. IEEE Trans Med Robot Bionics. 2021;3:525–38.

122. Ranzani R. Towards minimally-supervised robot-assisted therapy of hand function to increase therapy dose after stroke. 2021.

123. Mehrholz J, Pohl M, Platz T, Kugler J, Elsner B. Electromechanical and robot-assisted arm training for improving activities of daily living, arm function, and arm muscle strength after stroke. Cochrane Db Syst Rev. 2018;2018:CD006876

124. Veerbeek JM, Langbroek-Amersfoort AC, van Wegen EEH, Meskers CGM, Kwakkel G. Effects of robot-assisted therapy for the upper limb after stroke. Neurorehab Neural Re. 2017;31:107–21.

125. Wu J, Cheng H, Zhang J, Yang S, Cai S. Robot-assisted therapy for upper extremity motor impairment after stroke: a systematic review and meta-analysis. Phys Ther. 2021;101.

126. Mehrholz J, Pollock A, Pohl M, Kugler J, Elsner B. Systematic review with network meta-analysis of randomized controlled trials of robotic-assisted arm training for improving activities of daily living and upper limb function after stroke. J Neuroeng Rehabil. 2020;17:83.

127. Linder SM. et al. Improving quality of life and depression after stroke through telerehabilitation. Am J Occup Ther. 2015;69:6902290020p1–6902290020p10.

128. Manjunatha H, et al. Upper limb home-based robotic rehabilitation during covid-19 outbreak. Front Robot AI. 2021;8: 612834.

129. Babič J. et al. Challenges and solutions for application and wider adoption of wearable robots. Wearable Technol. 2021;2.

130. Proulx CE, et al. Review of the effects of soft robotic gloves for activity-based rehabilitation in individuals with reduced hand function and manual dexterity following a neurological event. J Rehabil Assistive Technol Eng. 2020;7:2055668320 918130.

131. Duncan PW, et al. Management of adult stroke rehabilitation care. Stroke. 2005;36:e100–43.

132. Wade DT, Wood VA, Heller A, Maggs J, Hewer RL. Walking after stroke. measurement and recovery over the first 3 months. Scand J Rehabil Med. 1987;19:25–30.

133. Combs SA, et al. Is walking faster or walking farther more important to persons with chronic stroke? Disabil Rehabil. 2012;35:860–7.

134. Blennerhassett JM, Levy CE, Mackintosh A, Yong A, McGinley JL. One-quarter of people leave inpatient stroke rehabilitation with physical capacity for community ambulation. J Stroke Cerebrovasc Dis. 2018;27:3404–10.

135. de Graaf JA, et al. Long-term restrictions in participation in stroke survivors under and over 70 years of age. Disabil Rehabil. 2017;40:1–9.

136. Portelli R, et al. Institutionalization after stroke. Clin Rehabil. 2005;19:97–108.

137. Newman AB, et al. Association of long-distance corridor walk performance with mortality, cardiovascular disease, mobility limitation, and disability. JAMA. 2006;295:2018–26.

138. Wade DT, Skilbeck CE, Wood VA, Hewer RL. Long-term survival after stroke. Age Ageing. 1984;13:76–82.

139. Grau-Pellicer M, Chamarro-Lusar A, Medina-Casanovas J, Ferrer B-CS. Walking speed as a predictor of community mobility and quality of life after stroke. Top Stroke Rehabil. 2019;26:349–58.

140. Zahuranec DB, Skolarus LE, Feng C, Freedman VA, Burke JF. Activity limitations and subjective well-being after stroke. Neurology. 2017;89:944–50.

141. Harris JE, Eng JJ. Goal priorities Identified through client-centred measurement in individuals with chronic stroke. Physiother Can. 2004;56:171.

142. Wade DT. Measurement in neurological rehabilitation. Curr Opin Neurol Neu. 1992;5:682–6.

143. Butland RJ, Pang J, Gross ER, Woodcock AA, Geddes DM. Two-, six-, and 12-minute walking tests in respiratory disease. Br Med J Clin Res Ed. 1982;284:1607.

144. Podsiadlo D, Richardson S. The timed "Up & Go": a test of basic functional mobility for frail elderly persons. J Am Geriatr Soc. 1991;39:142–8.

145. Cheng DK-Y, et al. Distance-limited walk tests post-stroke: A systematic review of measurement properties. NeuroRehabilitation. 2021;48:413–39.

146. Cheng DK, Nelson M, Brooks D, Salbach NM. Validation of stroke-specific protocols for the 10-meter walk test and 6-minute walk test conducted using 15-meter and 30-meter walkways. Top Stroke Rehabil. 2019;27:1–11.

147. Lexell J, Flansbjer U-B, Holmbäck AM, Downham D, Patten C. Reliability of gait performance tests in men and women with hemiparesis after stroke. J Rehabil Med. 2005;37:75–82.

148. Tilson JK, et al. Meaningful gait speed improvement during the first 60 days poststroke: minimal clinically important difference. Phys Ther. 2010;90:196–208.

149. Fulk GD, Echternach JL, Nof L, O'Sullivan S. Clinometric properties of the six-minute walk test in individuals undergoing rehabilitation poststroke. Physiother Theor Pr. 2009;24:195–204.

150. Salbach NM, et al. Considerations for the selection of time-limited walk tests poststroke. J Neurol Phys Ther. 2017;41:3–17.

151. Morris S, Morris ME, Iansek R. Reliability of measurements obtained with the timed "Up & Go" test in people with Parkinson Disease. Phys Ther. 2001;81:810–8.

152. Hafsteinsdóttir TB, Rensink M, Schuurmans M. Clinimetric properties of the timed up and go test for patients with stroke: a systematic review. Top Stroke Rehabil. 2014;21:197–210.

153. Chan PP, Tou JIS, Tse MM, Ng SS. Reliability and validity of the timed up and go test with a motor task in people with chronic stroke. Arch Phys Med Rehab. 2017;98:2213–20.

154. Coutts F. Gait analysis in the therapeutic environment. Manual Ther. 1999;4:2–10.

155. Mohan DM, et al. Assessment methods of post-stroke gait: a scoping review of technology-driven approaches to gait characterization and analysis. Front Neurol. 2021;12: 650024.

156. Burridge JH, Hughes A-M. Potential for new technologies in clinical practice. Curr Opin Neurol. 2010;23:671–7.

157. Parks MT, Wang Z, Siu K-C. Current low-cost video-based motion analysis options for clinical rehabilitation: a systematic review. Phys Ther. 2019;99:1405–25.

158. Kirtley C. Clinical gait analysis: theory and practice. 2006.

159. Perry J, Burnfield J. Gait analysis: normal and pathological function. 2010.

160. Simon SR. Quantification of human motion: gait analysis—benefits and limitations to its application to clinical problems. J Biomech. 2004;37:1869–80.

161. Muro-de-la-Herran A, Garcia-Zapirain B, Mendez-Zorrilla A. Gait analysis methods: an overview of wearable and non-wearable systems highlighting clinical applications. Sensors. 2014;14:3362–94.

162. Colyer SL, Evans M, Cosker DP, Salo AIT. A review of the evolution of vision-based motion analysis and the integration of advanced computer vision methods towards developing a markerless system. Sports Med Open. 2018;4:24.

163. Balta D. et al. A two-dimensional clinical gait analysis protocol based on markerless recordings from a single RGB-Depth camera. In: 2020 IEEE Int symposium medical meas appl memea. 2020. p. 1–6.

164. Mehta D, et al. VNect. Acm Trans Graph Tog. 2017;36:1–14.

165. Bartol K, Bojanic D, Petkovic T, D'Apuzzo N, Pribanic T. A review of 3D human pose estimation from 2D images. In: 11th International conference and exhibition on 3D body scanning and processing technologies. 2020.

166. Sarafianos N, Boteanu B, Ionescu B, Kakadiaris IA. 3D Human pose estimation: a review of the literature and analysis of covariates. Comput Vis Image Und. 2016;152:1–20.

167. Stamm O, Heimann-Steinert A. Accuracy of monocular two-dimensional pose estimation compared with a reference standard for kinematic multiview analysis: validation study. Jmir Mhealth Uhealth. 2020;8: e19608.

168. Guzik A, et al. Establishing the minimal clinically important differences for sagittal hip range of motion in chronic stroke patients. Front Neurol. 2021;12: 700190.

169. Guzik A, Drużbicki M, Wolan-Nieroda A, Turolla A, Kiper P. Estimating minimal clinically important differences for knee range of motion after stroke. J Clin Medicine. 2020;9:3305.

170. Calabrese E. et al. DHP19: dynamic vision sensor 3D human pose dataset. In: 2019 IEEE Cvf conf comput vis pattern recognit work cvprw. 2019. p. 1695–1704.

171. Yoon S, et al. Development and validation of 2D-LiDAR-based gait analysis instrument and algorithm. Sensors. 2021;21:414.

172. Sakdarakse S, Somboon P. Development of LIDAR based gait training system with gait assessment. In: 2020 17th Int conf electr eng electron comput telecommun information technology ecti-con. 2020. p. 263–266.

173. Glandon A. et al. 3D skeleton estimation and human identity recognition using lidar full motion video. In: 2019 Int Jt Conf Neural Networks Ijcnn. 2019. p. 1–8.

174. von Marcard T, Henschel R, Black MJ, Rosenhahn B, Pons-Moll G. Recovering accurate 3D human pose in the wild using IMUs and a moving camera. In: Computer vision–ECCV 2018, 15th European conference. 2018. p. 614–631. https://doi.org/10.1007/978-3-030-01249-6_37.

175. Basu CK, Deacon F, Hutchinson JR, Wilson AM. The running kinematics of free-roaming giraffes, measured using a low cost unmanned aerial vehicle (UAV). PeerJ. 2019;7: e6312.

176. Lafferty L. et al. Clinical indoor running gait analysis may not approximate outdoor running gait based on novel drone technology. Sports Heal Multidiscip Approach. 2021:194173812110509. https://doi.org/10.1177/19417381211050931.

177. Poitras I, et al. Validity and reliability of wearable sensors for joint angle estimation: a systematic review. Sensors Basel Switz. 2019;19:1555.

178. Petraglia F. et al. Inertial sensors versus standard systems in gait analysis: a systematic review and meta-analysis. Eur J Phys Rehab Med. 2019:55.

179. Soulard J, Vaillant J, Balaguier R, Vuillerme N. Spatio-temporal gait parameters obtained from foot-worn inertial sensors are reliable in healthy adults in single- and dual-task conditions. Sci Rep-UK. 2021;11:10229.

180. Lefeber N, Degelaen M, Truyers C, Safin I, Beckwée D. Validity and reproducibility of inertial physilog sensors for spatiotemporal gait analysis in patients with stroke. IEEE T Neur Sys Reh. 2019;27:1865–74.

181. Wüest S, Massé F, Aminian K, Gonzenbach R, de Bruin ED. Reliability and validity of the inertial sensor-based Timed "Up and Go" test in individuals affected by stroke. J Rehabil Res Dev. 2016;53:599–610.

182. Yang S, Zhang J-T, Novak AC, Brouwer B, Li Q. Estimation of spatio-temporal parameters for post-stroke hemiparetic gait using inertial sensors. Gait Posture. 2013;37:354–8.

183. Zhang W, et al. Gait symmetry assessment with a low back 3D accelerometer in post-stroke patients. Sensors. 2018;18:3322.

184. Peters DM, et al. Utilization of wearable technology to assess gait and mobility post-stroke: a systematic review. J Neuroeng Rehabil. 2021;18:67.

185. Ferraris C, et al. Monitoring of gait parameters in post-stroke individuals: a feasibility study using RGB-D sensors. Sensors. 2021;21:5945.

186. Cao Z, Simon T, Wei SE, Sheikh Y. Realtime multi-person 2D pose estimation using part affinity fields. In: 2017 IEEE Conf comput vis pattern recognit cvpr. 2017. p. 1302–1310. https://doi.org/10.1109/cvpr.2017.143.

187. Pedersen JCL. et al. Improving the accuracy of intelligent pose estimation systems through low level image processing operations. In: International conference on digital image & signal processing (DISP'19). 2019.

188. Routhier F, et al. Clinicians' perspectives on inertial measurement units in clinical practice. PLoS ONE. 2020;15: e0241922.

189. Block VAJ, et al. Remote physical activity monitoring in neurological disease: a systematic review. PLoS ONE. 2016;11: e0154335.

190. Wu J, et al. An intelligent in-shoe system for gait monitoring and analysis with optimized sampling and real-time visualization capabilities. Sensors. 2021;21:2869.

191. MacLellan MJ, Patla AE. Adaptations of walking pattern on a compliant surface to regulate dynamic stability. Exp Brain Res. 2006;173:521–30.

192. Truong PH, Lee J, Kwon A-R, Jeong G-M. Stride counting in human walking and walking distance estimation using insole sensors. Sensors. 2016;16:823.

193. van de Port I, Wevers L, Kwakkel G. Is outdoor use of the six-minute walk test with a global positioning system in stroke patients' own neighbourhoods reproducible and valid? J Rehabil Med. 2011;43:1027–31.

194. Wing MG, Eklund A, Kellogg LD. Consumer-grade global positioning system (GPS) accuracy and reliability. J Forest. 2005;103:169–73.

195. Ullrich M, et al. Detection of unsupervised standardized gait tests from real-world inertial sensor data in Parkinson's Disease. IEEE T Neur Sys Reh. 2021;29:2103–11.

196. Kawai H, et al. Association between daily living walking speed and walking speed in laboratory settings in healthy older adults. Int J Environ Res Pu. 2020;17:2707.

197. Takayanagi N, et al. Relationship between daily and in-laboratory gait speed among healthy community-dwelling older adults. Sci Rep-uk. 2019;9:3496.

198. Toosizadeh N, et al. Motor performance assessment in Parkinson's Disease: association between objective in-clinic, objective in-home, and subjective/semi-objective measures. PLoS ONE. 2015;10: e0124763.

199. Polhemus A, et al. Walking on common ground: a cross-disciplinary scoping review on the clinical utility of digital mobility outcomes. Npj Digital Med. 2021;4:149.

200. Warmerdam E, et al. Long-term unsupervised mobility assessment in movement disorders. Lancet Neurol. 2020;19:462–70.

201. Atrsaei A, et al. Gait speed in clinical and daily living assessments in Parkinson's disease patients: performance versus capacity. Npj Park Dis. 2021;7:24.

202. Martindale CF, Christlein V, Klumpp P, Eskofier BM. Wearables-based multi-task gait and activity segmentation using recurrent neural networks. Neurocomputing. 2021;432:250–61.

203. Dehzangi O, Taherisadr M, ChangalVala R. IMU-based gait recognition using convolutional neural networks and multi-sensor fusion. Sensors. 2017;17:2735.

204. Rast FM, Labruyère R. Systematic review on the application of wearable inertial sensors to quantify everyday life motor activity in people with mobility impairments. J Neuroeng Rehabil. 2020;17:148.

205. Jourdan T, Debs N, Frindel C. The contribution of machine learning in the validation of commercial wearable sensors for gait monitoring in patients: a systematic review. Sensors. 2021;21:4808.

206. Porciuncula F, et al. Wearable movement sensors for rehabilitation: a focused review of technological and clinical advances. Pm&r. 2018;10:S220–32.

207. Chen S, Lach J, Lo B, Yang G-Z. Toward pervasive gait analysis with wearable sensors: a systematic review. IEEE J Biomed Health. 2016;20:1521–37.

208. Werner C, Easthope CA, Curt A, Demkó L. Towards a mobile gait analysis for patients with a spinal cord injury: a robust algorithm validated for slow walking speeds. Sensors. 2021;21:7381.

209. Tietsch M, et al. Robust step detection from different waist-worn sensor positions: implications for clinical studies. Digital Biomarkers. 2020;4:50–8.

210. Dorsey ER, Glidden AM, Holloway MR, Birbeck GL, Schwamm LH. Teleneurology and mobile technologies: the future of neurological care. Nat Rev Neurol. 2018;14:285–97.

211. Bravata DM, et al. Using pedometers to increase physical activity and improve health: a systematic review. JAMA. 2007;298:2296–304.

212. Rozanski GM, Aqui A, Sivakumaran S, Mansfield A. Consumer wearable devices for activity monitoring among individuals after a stroke: a prospective comparison. Jmir Cardio. 2018;2: e1.

213. Degroote L, Bourdeaudhuij ID, Verloigne M, Poppe L, Crombez G. The accuracy of smart devices for measuring physical activity in daily life: validation study. Jmir Mhealth Uhealth. 2018;6: e10972.

214. Tedesco S, et al. Accuracy of consumer-level and research-grade activity trackers in ambulatory settings in older adults. PLoS ONE. 2019;14: e0216891.

215. Henriksen A, et al. Using fitness trackers and smartwatches to measure physical activity in research: analysis of consumer wrist-worn wearables. J Med Internet Res. 2018;20: e110.

216. Huang Y, Xu J, Yu B, Shull PB. Validity of FitBit, Jawbone UP, Nike+ and other wearable devices for level and stair walking. Gait Posture. 2016;48:36–41.

217. Altilio R, Liparulo L, Panella M, Proietti A, Paoloni M. Multimedia and gaming technologies for telerehabilitation of motor disabilities [Leading Edge]. IEEE Technol Soc Mag. 2015;34:23–30.

218. Held JP, et al. Autonomous rehabilitation at stroke patients home for balance and gait: safety, usability and compliance of a virtual reality system. Eur J Phys Rehab Med. 2017. https://doi.org/10.23736/s1973-9087.17.04802-x.

219. Cikajlo I, Rudolf M, Goljar N, Matjačić Z. Virtual reality task for telerehabilitation dynamic balance training in stroke subjects. In: 2009 Virtual rehabilitation international conference. 2009. p.121–125. https://doi.org/10.1109/icvr.2009.5174217.

220. Trombetta M, et al. Motion rehab AVE 3D: a VR-based exergame for post-stroke rehabilitation. Comput Meth Prog Bio. 2017;151:15–20.

221. Henrique PPB, Colussi EL, Marchi ACBD. Effects of exergame on patients' balance and upper limb motor function after stroke: a randomized controlled trial. J Stroke Cerebrovasc Dis. 2019;28:2351–7.

222. Kannan L, Vora J, Bhatt T, Hughes SL. Cognitive-motor exergaming for reducing fall risk in people with chronic stroke: a randomized controlled trial. NeuroRehabilitation. 2019;44:493–510.

223. Lupo A, et al. Effects on balance skills and patient compliance of biofeedback training with inertial measurement units and exergaming in subacute stroke: a pilot randomized controlled trial. Funct Neurol. 2018;33:131–6.

224. Huber SK, Held JPO, de Bruin ED, Knols RH. Personalized motor-cognitive exergame training in chronic stroke patients—a feasibility study. Front Aging Neurosci. 2021;13: 730801.

225. Shull PB, Damian DD. Haptic wearables as sensory replacement, sensory augmentation and trainer–a review. J Neuroeng Rehabil. 2015;12:59.

226. Shull PB, Jirattigalachote W, Zhu X. An overview of wearable sensing and wearable feedback for gait retraining. In: Proceedings of the 6th international conference, Intelligent Robotics and Applications, ICIRA 2013, Busan, South Korea, 25–28 September 2013, p. 434–443. https://doi.org/10.1007/978-3-642-40852-6_44.

227. van Meulen FB, et al. Objective evaluation of the quality of movement in daily life after stroke. Front Bioeng Biotechnol. 2016;3:210.

228. Schließmann D, et al. Trainer in a pocket - proof-of-concept of mobile, real-time, foot kinematics feedback for gait pattern normalization in individuals after stroke, incomplete spinal cord injury and elderly patients. J Neuroeng Rehabil. 2018;15:44.

229. Mikolajczyk T, et al. Advanced technology for gait rehabilitation: an overview. Adv Mech Eng. 2018;10:1687814018783627.

230. Genthe K, et al. Effects of real-time gait biofeedback on paretic propulsion and gait biomechanics in individuals post-stroke. Top Stroke Rehabil. 2018;25:1–8.

231. Massé F, et al. Improving activity recognition using a wearable barometric pressure sensor in mobility-impaired stroke patients. J Neuroeng Rehabil. 2015;12:1–15.

232. Tate JJ, Milner CE. Real-time kinematic, temporospatial, and kinetic biofeedback during gait retraining in patients: a systematic review. Phys Ther. 2010;90:1123–34.

233. van Gelder LMA, Barnes A, Wheat JS, Heller BW. The use of biofeedback for gait retraining: a mapping review. Clin Biomech. 2018;59:159–66.

234. Spencer J, Wolf SL, Kesar TM. Biofeedback for post-stroke gait retraining: a review of current evidence and future research directions in the context of emerging technologies. Front Neurol. 2021;12: 637199.

235. Xu J, et al. Configurable, wearable sensing and vibrotactile feedback system for real-time postural balance and gait training: proof-of-concept. J Neuroeng Rehabil. 2017;14:102.

236. Biesmans S, Markopoulos P. Design and evaluation of SONIS, a wearable biofeedback system for gait retraining. Multimodal Technol Interact. 2020;4:60.

237. Ma CZ-H, Zheng Y-P, Lee WC-C. Changes in gait and plantar foot loading upon using vibrotactile wearable biofeedback system in patients with stroke. Top Stroke Rehabil. 2017;25:20–7.

238. Zhang H, et al. Wearable biofeedback system to induce desired walking speed in overground gait training. Sensors. 2020;20:4002.

239. Afzal MR, Pyo S, Oh M-K, Park YS, Yoon J. Evaluating the effects of delivering integrated kinesthetic and tactile cues to individuals with unilateral hemiparetic stroke during overground walking. J Neuroeng Rehabil. 2018;15:33.

240. Held JPO, et al. Augmented reality-based rehabilitation of gait impairments: case report. Jmir Mhealth Uhealth. 2020;8: e17804.

241. Massetti T, et al. The clinical utility of virtual reality in neurorehabilitation: a systematic review. J Central Nerv Syst Dis. 2018;10:1179573518813541.

242. Brewster S. et al. What is mixed reality? In: Proceedings of the 2019 Chi conf hum factors comput syst. 2019, p. 1–15. https://doi.org/10.1145/3290605.3300767.

243. Morishima S. et al. Effects of head-display lag on presence in the oculus rift. In: Proceedings of the 24th Acm symposium virtual real softw technology 83. 2018. https://doi.org/10.1145/3281505.3281607.

244. Chan ZYS, et al. Walking with head-mounted virtual and augmented reality devices: effects on position control and gait biomechanics. PLoS ONE. 2019;14: e0225972.

245. Kolivand H, Sunar MS. Realistic real-time outdoor rendering in augmented reality. PLoS ONE. 2014;9: e108334.

246. Kress BC, Cummings WJ. Optical architecture of HoloLens mixed reality headset. Digital Opt Technol 2017;2017:103350K-1–103350K-10. https://doi.org/10.1117/12.2270017.

247. Tuena C, et al. Usability issues of clinical and research applications of virtual reality in older people: a systematic review. Front Hum Neurosci. 2020;14:93.

248. Lloréns R, Noé E, Colomer C, Alcañiz M. Effectiveness, usability, and cost-benefit of a virtual reality-based telerehabilitation program for balance recovery after stroke: a randomized controlled trial. Arch Phys Med Rehab. 2015;96:418-425.e2.

249. Vaquero-Melchor D, Bernardos AM. Enhancing interaction with augmented reality through mid-air haptic feedback: architecture design and user feedback. Appl Sci. 2019;9:5123.

250. Ott R, Thalmann D, Vexo F. Haptic feedback in mixed-reality environment. Vis Comput. 2007;23:843–9.

251. Corbetta D, Imeri F, Gatti R. Rehabilitation that incorporates virtual reality is more effective than

standard rehabilitation for improving walking speed, balance and mobility after stroke: a systematic review. J Physiother. 2015;61:117–24.

252. de Rooij IJM, van de Port IGL, Meijer J-WG. Effect of virtual reality training on balance and gait ability in patients with stroke: systematic review and meta-analysis. Phys Ther. 2016;96:1905–18.

253. Berthier ML. Poststroke aphasia. Drug Aging. 2005;22:163–82.

254. Duffy J. Motor speech disorders. (2019).

255. Flowers HL, Silver FL, Fang J, Rochon E, Martino R. The incidence, co-occurrence, and predictors of dysphagia, dysarthria, and aphasia after first-ever acute ischemic stroke. J Commun Disord. 2013;46:238–48.

256. Wray F, Clarke D. Longer-term needs of stroke survivors with communication difficulties living in the community: a systematic review and thematic synthesis of qualitative studies. BMJ Open. 2017;7: e017944.

257. Cock ED, et al. Dysphagia, dysarthria and aphasia following a first acute ischaemic stroke: incidence and associated factors. Eur J Neurol. 2020;27:2014–21.

258. Ruben RJ. Redefining the survival of the fittest: communication disorders in the 21st century. Laryngoscope. 2000;110:241–241.

259. Worrall L, et al. What people with aphasia want: Their goals according to the ICF. Aphasiology. 2011;25:309–22.

260. Puyvelde MV, Neyt X, McGlone F, Pattyn N. Voice stress analysis: a new framework for voice and effort in human performance. Front Psychol. 2018;09:1994.

261. Themistocleous C, Eckerström M, Kokkinakis D. Voice quality and speech fluency distinguish individuals with mild cognitive impairment from healthy controls. PLoS ONE. 2020;15: e0236009.

262. Chiaramonte R, Vecchio M. A systematic review of measures of dysarthria severity in stroke patients. Pm&r. 2021;13:314–24.

263. Wallace SJ. et al. Many ways of measuring: a scoping review of measurement instruments for use with people with aphasia. Aphasiology. 2020:1–66. https://doi.org/10.1080/02687038.2020.1836318.

264. Ziegler W, Staiger A, Schölderle T, Vogel M. Gauging the auditory dimensions of dysarthric impairment: reliability and construct validity of the Bogenhausen Dysarthria Scales (BoDyS). J Speech Lang Hear Res. 2017;60:1516–34.

265. Kertesz A, Raven JC. The Western Aphasia Battery-Revised (WAB-R). (PsychCorp, 2007).

266. Huber W, Poeck K, Weniger D, Willmes K. Der Aachener Aphasie Test (AAT). (Hogrefe, 1983).

267. Brandenburg C, Worrall L, Rodriguez A, Bagraith K. Crosswalk of participation self-report measures for aphasia to the ICF: what content is being measured? Disabil Rehabil. 2014;37:1113–24.

268. Armstrong E. The challenges of consensus and validity in establishing core outcome sets. Aphasiology. 2017:1–4. https://doi.org/10.1080/02687038.2017.1398804.

269. Patel RR, et al. Recommended protocols for instrumental assessment of voice: american speech-language-hearing association expert panel to develop a protocol for instrumental assessment of vocal function. Am J Speech-Lang Pat. 2018;27:887–905.

270. Maryn Y, Roy N, Bodt MD, Cauwenberge PV, Corthals P. Acoustic measurement of overall voice quality: a meta-analysisa). J Acoust Soc Am. 2009;126:2619–34.

271. Reetz S, Bohlender JE, Brockmann-Bauser M. Do standard instrumental acoustic, perceptual, and subjective voice outcomes indicate therapy success in patients with functional dysphonia? J Voice. 2019;33:317–24.

272. Brockmann-Bauser M, Bohlender JE, Mehta DD. Acoustic perturbation measures improve with increasing vocal intensity in individuals with and without voice disorders. J Voice. 2018;32:162–8.

273. Bogert B, Healy MJR, Tukey JW. The quefrency alanysis of time series for echoes ; Cepstrum, pseudo-autocovariance, cross-cepstrum and saphe cracking. In: Rosenblatt M (ed) Proceedings of the symposium on time series analysis. p. 209–243 (Wiley; 1963).

274. Fraile R, Godino-Llorente JI. Cepstral peak prominence: a comprehensive analysis. Biomed Signal Proces. 2014;14:42–54.

275. Murton O, Hillman R, Mehta D. Cepstral peak prominence values for clinical voice evaluation. Am J Speech-Lang Pat. 2020;29:1596–607.

276. de Jong NH, Wempe T. Praat script to detect syllable nuclei and measure speech rate automatically. Behav Res Methods. 2009;41:385–90.

277. de Jong NH, Pacilly J, Heeren W. PRAAT scripts to measure speed fluency and breakdown fluency in speech automatically. Assess Educ Princ Policy Pract. 2021:1–21. https://doi.org/10.1080/0969594x.2021.1951162.

278. Grande M, et al. Basic parameters of spontaneous speech as a sensitive method for measuring change during the course of aphasia. Int J Lang Comm Dis. 2008;43:408–26.

279. Hussmann K, et al. Computer-assisted analysis of spontaneous speech: quantification of basic parameters in aphasic and unimpaired language. Clin Linguist Phonet. 2012;26:661–80.

280. Barthel G, Djundja D, Meinzer M, Rockstroh B, Eulitz C. Aachener Sprachanalyse (ASPA): evaluation bei Patienten mit chronischer Aphasie. Sprache Stimme Gehoer. 2006;30:103–10.

281. Grande M, Springer L, Huber W. Richtlinien fuer die Transkription mit dem Programm ASPA (Aachener Sprachanalyse). Sprache Stimme Geh R. 2006;30:179–85.

282. MacWhinney B. The Childes Project. 2000. https://doi.org/10.4324/9781315805641.

283. Brown C, Snodgrass T, Kemper SJ, Herman R, Covington MA. Automatic measurement of propositional idea density from part-of-speech tagging. Behav Res Methods. 2008;40:540–5.

284. Ferguson A, Spencer E, Craig H, Colyvas K. Propositional idea density in women's written language over the lifespan: computerized analysis. Cortex. 2014;55:107–21.

285. MacWhinney B, Fromm D. AphasiaBank as big-data. Semin Speech Lang. 2016;37:010–22.

286. MacWhinney B, Fromm D, Forbes M, Holland A. AphasiaBank: Methods for studying discourse. Aphasiology. 2011;25:1286–307.

287. Fromm D, et al. Discourse characteristics in aphasia beyond the western aphasia battery cutoff. Am J Speech-Lang Pat. 2017;26:762–8.

288. Carrier M. Automated speech recognition in language learning: potential models, benefits and impact. Train Lang Cult. 2017;1:46–61.

289. Jacks A, Haley KL, Bishop G, Harmon TG. Automated speech recognition in adult stroke survivors: comparing human and computer transcriptions. Folia Phoniatr Logo. 2019;71:286–96.

290. Dekhtyar M, Braun EJ, Billot A, Foo L, Kiran S. Videoconference administration of the western aphasia battery–revised: feasibility and validity. Am J Speech-Lang Pat. 2020;29:673–87.

291. Wood E, Bhalloo I, McCaig B, Feraru C, Molnar M. Towards development of guidelines for virtual administration of paediatric standardized language and literacy assessments: considerations for clinicians and researchers. Sage Open Med. 2021;9:205031212110505.

292. Grillo EU, Wolfberg J. An assessment of different praat versions for acoustic measures analyzed automatically by voice value and manually by two raters. J Voice. 2020. https://doi.org/10.1016/j.jvoice.2020.12.003.

293. Mueller A, et al. Digital endpoints for self-administered home-based functional assessment in pediatric Friedreich's ataxia. Ann Clin Transl Neur. 2021;8:1845–56.

294. Brandenburg C, Worrall L, Copland D, Rodriguez A. An exploratory investigation of the daily talk time of people with non-fluent aphasia and non-aphasic peers. Int J Speech-lang Pa. 2016;19:1–12.

295. Hillman RE, Heaton JT, Masaki A, Zeitels SM, Cheyne HA. Ambulatory monitoring of disordered voices. Ann Otology Rhinol Laryngol. 2006;115:795–801.

296. Mehta DD, Stan JHV, Hillman RE. Relationships between vocal function measures derived from an acoustic microphone and a subglottal neck-surface accelerometer. IEEE ACM Trans Audio Speech Lang Process. 2016;24:659–68.

297. Mehta DD, et al. Using ambulatory voice monitoring to investigate common voice disorders: research update. Front Bioeng Biotechnol. 2015;3:155.

298. Association ASLH. Telepractice: overview. https://www.asha.org/PRPSpecificTopic.aspx?folderid=8589934956&section=Overview (2018).

299. Association ASLH. Scope of practice in audiology. https://www.asha.org/policy/sp2018-00353/ (2018).

300. Association ASLH. Scope of practice in speech-language pathology. https://www.asha.org/policy/sp2016-00343/ (2016).

301. Grillo EU. Building a successful voice telepractice program. Perspect Asha Spec Interest Groups. 2019;4:100–10.

302. Grillo EU. Results of a survey offering clinical insights into speech-language pathology telepractice methods. Int J Telerehabil. 2017;9:25–30.

303. Pitt R, Theodoros D, Hill AJ, Rodriguez AD, Russell T. The feasibility of delivering constraint-induced language therapy via the Internet. Digital Heal. 2017;3:2055207617718767.

304. Weidner K, Lowman J. Telepractice for adult speech-language pathology services: a systematic review. Perspect Asha Spec Interest Groups. 2020;5:326–38.

305. Walker JP, Price K, Watson J. Promoting social connections in a synchronous telepractice, aphasia communication group. Perspect Asha Spec Interest Groups. 2018;3:32–42.

306. Pitt R, Theodoros D, Hill AJ, Russell T. The impact of the telerehabilitation group aphasia intervention and networking programme on communication, participation, and quality of life in people with aphasia. Int J Speech-lang. 2018:1–11. https://doi.org/10.1080/17549507.2018.1488990.

307. Marshall J, et al. A randomised trial of social support group intervention for people with aphasia: a Novel application of virtual reality. PLoS ONE. 2020;15: e0239715.

308. Hinckley JJ, Patterson JP, Carr TH. Differential effects of context- and skill-based treatment approaches: preliminary findings. Aphasiology. 2001;15:463–76.

309. Jamal N, Shanta S, Mahmud F, Sha'abani M. Automatic speech recognition (ASR) based approach for speech therapy of aphasic patients: a review. Aip Conf Proc. 2017;1883:020028.

310. Maryn Y, Bodt MD, Cauwenberge PV. Effects of biofeedback in phonatory disorders and phonatory performance: a systematic literature review. Appl Psychophys Biof. 2006;31:65–83.

311. Stan JHV, Mehta DD, Hillman RE. The effect of voice ambulatory biofeedback on the daily performance and retention of a modified vocal motor behavior in participants with normal voices. J Speech Lang Hear Res. 2015;58:713–21.

312. Stan JHV, Mehta DD, Sternad D, Petit R, Hillman RE. Ambulatory voice biofeedback: relative frequency and summary feedback effects on performance and retention of reduced vocal intensity in the daily lives of participants with normal voices. J Speech Lang Hear Res. 2017;60:853–64.

313. Palmer R, et al. Self-managed, computerised speech and language therapy for patients with chronic aphasia post-stroke compared with usual care or attention control (Big CACTUS): a multicentre, single-blinded, randomised controlled trial. Lancet Neurol. 2019;18:821–33.

314. Zheng C, Lynch L, Taylor N. Effect of computer therapy in aphasia: a systematic review. Aphasiology. 2015:1–34. https://doi.org/10.1080/02687038.2014.996521.

315. Tjoa E, Guan C. A survey on explainable artificial intelligence (XAI): toward medical XAI. IEEE T Neur Net Lear. 2021;32:4793–813.

316. Willems EMG, Vermeulen J, van Haastregt JCM, Zijlstra GAR. Technologies to improve the participation of stroke patients in their home environment. Disabil Rehabil. 2021:1–11. https://doi.org/10.1080/09638288.2021.1983041.

317. Cities P. The city as a digital playground. Gaming Media Soc Eff. 2017. https://doi.org/10.1007/978-981-10-1962-3.