mHealth Apps for Older Adults and persons with Parkinson's Disease

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Abstract

Recent years observed massive growth in wearable technology, everything can be smart: phones, watches, glasses, shirts, crutches, etc. These technologies are prevalent in various fields: from wellness, sports, and fitness to the healthcare domain. The spread of this phenomenon led the World Health Organization to define the term 'mHealth' as "medical and public health practice supported by mobile devices, such as mobile phones, patient monitoring devices, personal digital assistants, and other wireless devices". Furthermore, mHealth solutions are suitable to perform real-time wearable biofeedback systems: sensors in the body area network connected to a processing unit (smartphone) and a feedback device (loudspeaker) to measure human functions and return them to the user as (bio)feedback signal.

Considering the COVID-19 pandemic emergency, never as today, we can say that the integration of mHealth systems in our society may contribute to a new era of clinical practice. After reporting a brief description of mHealth system architecture, this chapter explores several opportunities where innovative mHealth solutions could improve assessment and rehabilitation strategies for ageing people and persons with Parkinson's disease. This chapter presents solutions that need a therapist's supervision in a clinical context and others that can be self-administered and require only a smartphone as a stand-alone system. Finally, the Discussion highlights the challenges for future research and development of innovative mHealth systems.

Keywords: Mobile Health applications (mHealth apps), Wearable Inertial Sensors, Assessment, Rehabilitation, IoT, Gait, Biofeedback.

1 Introduction

The evolution of mobile phones and electronic technology leads to continuous miniaturization, making the mobile phone a really wearable device. The use of mobile and wireless technologies to support health objectives can transform the face of health service delivery across the globe [1]. In 2011, the spread of this phenomenon had led The Global Observatory for eHealth of the World Health Organization to define the term 'mHealth' as "medical and public health practice supported by mobile devices, such as mobile phones, patient monitoring devices, personal digital assistants, and other wireless devices" [2]. In 2021, the number of smartphone users worldwide will grow to 3.8 billion, and today 45% of people in the world have smartphones [3]. This figure is up considerably from 2016 when there were 2.5 billion users, 34% of that year's global population [4].

mHealth apps appeared later, and they address a broad array of mHealth applications and the use of mobile phones, e.g., to monitor biological signals or support healthy lifestyles. Thus, mHealth apps allow mobile devices as healthcare systems: for prevention, assessment, therapeutic support, and rehabilitation of motor and non-motor functions [5]–[7]. Importantly, the deployment of mHealth can be achieved using the various sensors available inside smartphones (as a stand-alone system) or in conjunction with external wearable sensors (as an integrated system).

Nowadays, mHealth reality is considered the biggest technological breakthrough, and its potential is increasing together with the utility of mHealth apps [8]. In the context of the on-going COVID-19 pandemic, these technologies have become more relevant than ever, thanks to the advantages they provide [9]. In fact, mHealth platforms, with appropriate information technology (IT) and health literacy, can empower patients to manage their condition better themselves [9]. For example, patients with diabetes can monitor their blood glucose through mobile apps improving both the quality of medical services and their safety [10].

In the following section of this chapter, *Section 2. "mHealth System Architecture connected with apps"*, a generic system architecture to understand mHealth components and workflow better is described. *Section 3. "mHealth apps - Requirements in the Healthcare field"* reports the main requirements related to mHealth systems. *Section 4. "mHealth apps for Clinical Assessment"* and *Section 5. "mHealth apps for Neuromotor Rehabilitation"* present an overview of mHealth solutions for the clinical assessment and rehabilitation of the principal neuromotor dysfunctions experienced by older adults (OA) and persons with Parkinson's disease (PD). Finally, the *Discussion* highlights the challenges for future research and development of innovative mHealth systems.

2 mHealth System Architecture connected with apps

As a result of the growing demand for mHealth system, important research and development efforts have been carried out during the last years both by academia and industry in this area, driving great breakthroughs on enabler technologies, such as wireless communications, micro- and even nano-electronics, or sensing techniques and materials [11], [12]. Advances in microelectronics and wireless communications have made Body Area Networks (BAN), which represent the key functional component in a mHealth systems [5], [13]. BAN are composed of tiny smart sensors deployed in, on, or around a human body. These sensors are distributed on the human body consequently with the different physiological parameters or/and body function to measure. Thus, their location is an important aspect. It is possible to detect brain activity (Electroencephalography - EEG) using a sensor near the scalp. Then, with surface Electromyography (sEMG), it is possible to acquire the myoelectric activity of the specific muscles involved in the execution of selected motor tasks [14]. Besides, wearing on the shoes Inertial Measurement Units (IMUs), which contains tri-axial accelerometer, gyroscope, and (optionally) magnetometer, it is possible to characterize the motor behavior during gait [15]. Lastly, in the management of type 1 diabetes, patients use sensors able to detect blood glucose (BG) in real-time without finger-pricks required [16].
Similarly for other main biosignals, as reported by Dias et al. [5]: Hearth Rate (HR), Skin Perspiration (SP), Respiration Rate (RR), Oxygen Saturation (OS). Importantly, locating the same sensors described above in inappropriate places would not correctly detect the physiological parameters and features reported.
In common, these sensors are connected with a portable processing unit, like a smartphone in mHealth systems connected with apps, to exchange information with clinicians and/or send it as feedback to the patient. A schematic mHealth architecture is designed based on literature review, where the BAN are composed of various sensors properly located in the human body, **Figure 1**.

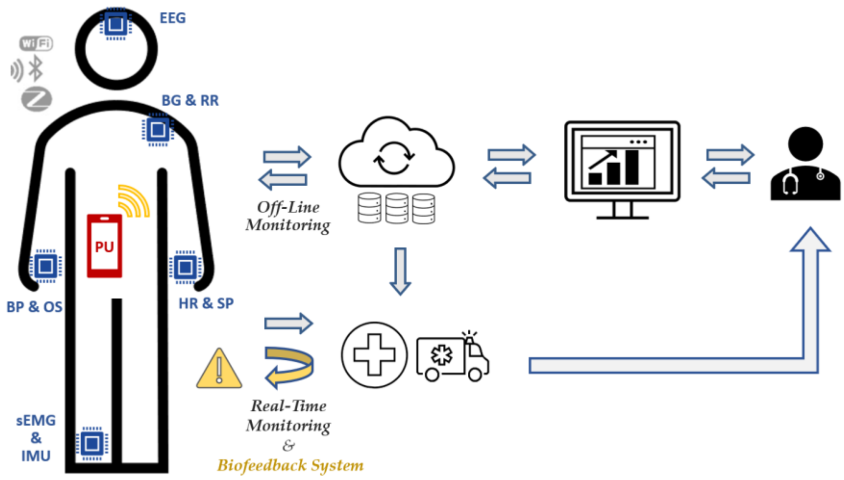

Fig. 1. Schematic mHealth system architecture connected with apps, adapted from [5], [13], [17], [18]. PU (red), Portable Unit (for example a Smartphone). List of sensors node (blue): EEG, Electroencephalography; BG, Blood Glucose; RR, Respiration Rate; HR, Hearth Rate; SP, Skin Perspiration; BP, Blood Pressure; OS, Oxygen Saturation; IMU, Inertial Measurement Unit; sEMG, Surface Electromyography.

2.1 Sensor Node

At first, the sensor architecture or, better, the sensor node is described: a sensor network that is capable of performing some processing, gathering sensory information, and communicating with the data-logger present in the network [19], **Figure 2**.

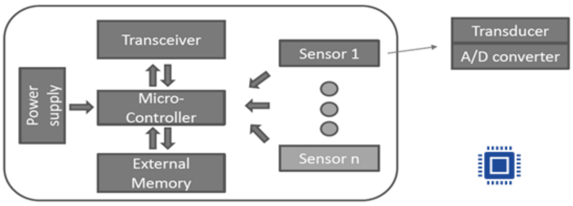

Fig. 2. Schematic overview of a sensor node.

The main components of a sensor node are a microcontroller, transceiver, external memory, power source, one or more sensors, consisting of a transducer and A/D converter:

- **Transducer**: varies its electrical properties to varying environmental conditions. Usually MEMS technology (Micro Electro Mechanical Systems) ensures higher efficiency, lower production costs, and less power consumption than other types of sensors such as piezoelectric. However, depending on the application, a piezoelectric transducer can be more accurate: to analyze human movement in high dynamic tasks, it is common to prefer piezoelectric accelerometers [20], [21].

- **A/D Converter - Analog to Digital Converter**: converts the transducer's voltage value to a digital value. The A/D converter's resolution implies a quantization of the input: this necessarily introduces a small amount of error/noise. Furthermore, an ADC converts the input periodically, sampling the data: this limits the input signal's allowable bandwidth.

- **Micro-controller**: it manages and controls the hardware of the sensor node, can perform local online signal processing (filtering/amplify the signal, data fusion, feature extraction).

- **Transceiver**: it connects the sensor node to the network. It can be an optical or radio-frequency device.
- **External memory**: it is needed to store the program's binary code running on the sensor node.
- **Power supply**: source of power for communication (usually most affecting factor), sensing, and data processing.

2.2 Portable processing Unit (PU)

The portable processing unit (PU), also denominated as data-logger, is where all the information is gathered, containing the outputs and inputs of the mHealth system [5]. The communication between a node sensor and the data-logger is normally made through wireless protocols, avoiding loose wires around the body leading to a higher comfort and movement liberty. As **Figure 1** shows, PU can be a common smartphone with a custom application installed on it. PU can receive data from online monitoring devices and store it in a local memory. This two-way communication allows other devices to establish a wirelessly connection to a main device, which stores the data of several sensors. This system can also be helpful to label the timing of important events using external devices [13], [17], [22]. The wireless protocols most popular in mHealth systems are Radio Frequency Identification (RFID), ANT/ANT+, Bluetooth, Wi-Fi, ZigBee and LoRa (Long Range radio).

RFID is widely used primarily for tracking and identification purposes: a reader or interrogator sends a signal to a tag or label attached to an object to be identified [23]. ANT/ANT+ is a proprietary protocol stack designed for ultra-low-power, short-range wireless communications in sensor networks, especially for health and fitness monitoring systems [23]. It ensures low power consumption by using a low data rate and can operate for more extended periods. Bluetooth is a short-range radio-frequency based connectivity between portables and fixed devices requiring low-power consumption and with a low-cost. It is widely implemented in commercial devices like smartphones and laptops. The new Bluetooth technology named Bluetooth Low-Energy (BLE) has even a lower power consumption with a smaller form factor. Interestingly, in Android devices, the data rate is highly dependent on the model used, with a maximum of around 10 Mbps. Using Bluetooth connectivity, one master device can communicate at a maximum with seven slave nodes, forming a star-type network structure. Wi-Fi protocol lower layers were adopted, allowing higher data throughput for low-power requirements applications, not as low as the Bluetooth technology but can also be a good connection protocol to use, mainly when a higher distance of communication is needed [5]. ZigBee is another technology used for low power and low data rate communication protected using the Advanced Encryption Standard. This feature makes ZigBee ideal for medical applications because it can consume less energy than Bluetooth versions earlier than 4.0, but with a lower data transferring rate [5]. LoRa technology is a long distance coverage, low cost and low power consumption wireless protocol. LoRa network architecture is deployed in a star-of-stars topology where gateways relay messages between end-devices and a central network server. The maximum number of nodes that can communicate with a gateway module depends on its specifications, usually defined by the number of packets it can support [24]. It has the disadvantage of low data rate but a huge advantage of scalability and customization of several parameters such as frequency channel, transmission power, and data rate. In the construction of a wearable device, the communication protocol is crucial to identify the number and the distances of the devices involved. Besides, there is also the need to minimize energy consumption [25] and consider the wireless technologies available in commercial devices (such as smartphones).

Table 1 summarizes some of the main features of these wireless protocols. Mobile telecommunications technologies can also be used to transmit real-time data. However, it is essential to implement strong encryption and authentication technology to ensure a secure transmission channel over the long-range communication medium for the safeguarding of personal medical information [23]. Alternatively, it is also possible to handle sensors node inside the PU: for example, using only a smartphone as a stand-alone system, thus exploiting their built-in sensors [6].

Wireless Protocol	Max Nodes Supported	Range	Max Data Rate	Power Consumption
RFID	1	1-3 m	640 Kbps	200 mW
ANT/ANT+	65 533	30 m	60 Kbps	1 mW
Bluetooth	1 master + 7 slaves	1-100 m	3 Mbps	2.5 - 100 mW
BLE	1 master + 7 slaves	1-100 m	10 Mbps	10 mW
Wi-Fi	255	200 m	54 Mbps	1 W
ZigBee	65 533	100 m	250 Kbps	35 mW
LoRa	HIGH (depends on gateway & single packet)	50 km	700 bps	LOW (customizable)

Tab. 1. Wireless protocols main features. Adapted from Dias et al. [5], Majumder et al. [23].

2.3 Offline Monitoring

All data from vital signs can be stored in a portable unit (micro-SD memory card for example), for future use in medical analysis or just as a personal record. The data can be stored while a real-time monitoring is occurring. The main aim of such monitoring is to record vital data for clinic diagnosis and prediction by clinicians [5]. For example, sleep issues such as apnea, can be analyzed through saved data from the patient: a home sleep monitoring allows to monitor sleep in a familiar environment resulting in reliable data acquisition [22], [26]. Off-line monitoring allows a high level of data processing to give much more information that is valuable to the end-users and clinicians, for example, using data mining techniques to have more in-depth knowledge representation [26].

2.4 Real-Time Monitoring and Biofeedback System

With mHealth systems it is possible to perform clinical monitoring outside a medical environment, alert the patient in case of any physiological problem or monitor himself, and be updated on his vital signs during daily activities [17]. On the other hand, in a medical environment mHealth systems allows the patients monitoring inside the boundaries of a specific area, normally a Hospital, where the patients can move while their vital information is being wirelessly transmitted to a remote monitoring center and thus made available to clinicians [5]. These live systems can also be configured with a set of alarms for each patient helping in the detection of some required anomaly. The vital signs can also be recorded in Medical Information Systems to be later analyzed by clinicians [5], [13], [27]. However, the biggest advantage of mHealth systems in real-time monitoring is the possibility of patient's monitoring at home and outdoors, using internet communications. This feature allows the patient to have a normal life while being monitored, with his vital signs continuously or intermittently transmitted to a remote monitoring center, with health support and, if needed, inform the patient of his medical status [5].

Furthermore, vital signs and physiological parameters can also be transmitted to portable devices, such as smartphones and smartwatches, to visualize and analyze persons' health status, allowing the so-called Biofeedback (BF) process. BF is defined as a process in which a system or agent accurately measures and feeds back, to persons and their therapists, information with educational and reinforcing properties about their physiological processes in the form of analog or binary, auditory, and/or visual feedback signals. The objectives are to help persons develop greater awareness of, confidence in, and an increase in voluntary control over their physiological processes that are otherwise outside awareness and/or under less voluntary control [28]. With BF the information fed back to the patients adds or reinforces their physiological sensory channels: thus, BF was also defined as augmented feedback [29]. With such self-monitoring systems [5], clinicians must carefully teach patients how to use them at home, in particular, how to understand and react to BF alerts [28]. For example, this is what already happens in the treatment of type 1 diabetics' subjects. Several artificial pancreases have been developed to help manage type 1 diabetes [30], [31]. To obtain satisfactory results, the clinician's contribution to patient education is crucial [10], [32]. In the last decades, self-monitoring and BF systems were used in many areas such as instrumental conditioning of autonomic nervous system responses, psychophysiology, behavior therapy, and medicine, stress research and stress management strategies, electromyography, consciousness, electroencephalography, cybernetics, and sports [28]. Nowadays, thanks to mHealth and technological progress, BF systems will become more achievable.

3 mHealth apps – Requirements in the Healthcare field

Healthcare systems have recognized the advantages of using Information and Communication Technologies (ICT), including mHealth app systems, to improve the quality of care, and they are now working, although at a different pace worldwide, to turn traditional into smart healthcare [33]. To meet the increasing demands of an aging population with chronic diseases and comorbidities, technology appears to be to shift from clinic-centric to patient-centric healthcare [34]. Nevertheless, to accelerate the shift toward the brave new world of mHealth, technology must be appropriately designed with the aid of end-users. Many mHealth technologies have failed to innovate the current clinical practice because they ignored the interaction between technology, human characteristics, and socio-economic environment [35]. As an alternative to the technical industrial mindset, User-Centered Design has proven to be an effective tool to realize products and services for the Healthcare sector. User-Centered approach has to be included in the design process since the starting phases to develop a product or system that is effective due to the close relationship with the users' requirements and the high capacity of satisfaction of their needs [36]–[38].

In general, many important factors should be considered when developing a mHealth app [39], [40]. First, the main characteristics related to functionality and adoption of mHealth app are: wearability, monitoring duration, connectivity configuration, and maintainability of the system developed [40]–[42]. Last but not least the user's willingness and motivation: in this aspect, clinicians have a crucial role [42], [43].

Besides, there is the need to identify the key stakeholders. In evaluating a mHealth system, they are clinicians, developers, patients whose management may be affected, and people responsible for purchasing and maintaining the system [44]. Each may have different needs and requests to be satisfied, **Figure 3**.

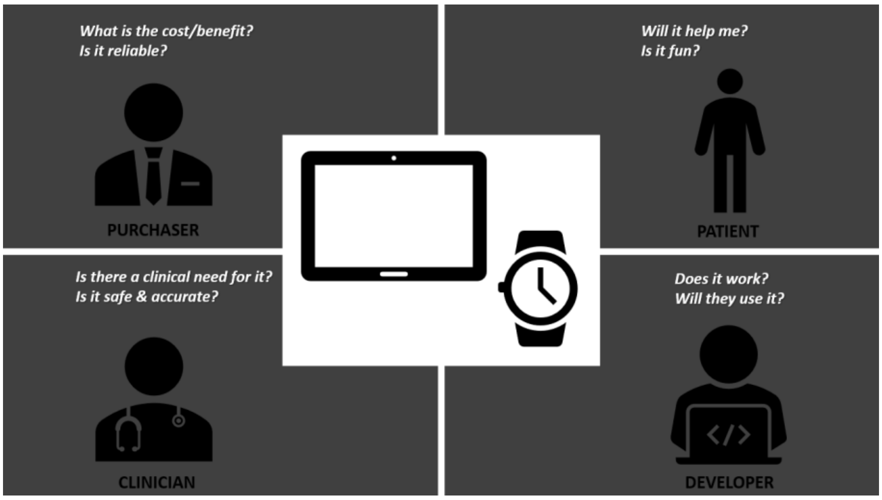

Fig. 3. Different stakeholders may have different needs and requests to be satisfied in the evaluation of a mHealth system. Adapted from Friedman et al. [44].

For example, from the developer's point of view, the algorithms used in the system must be validated, robust and well-written. In general, nobody should use a system or device that elaborated inaccurate measurements: the features implemented should be validated and tested within the proposed usage context [42].

Moreover, as already mentioned, the usability and user-friendliness of the apps are a fundamental determinant for technology adoption, in particular, among older adults [36]–[38], [45], [46]. In particular, usability is defined in the official International Organization for Standardization (ISO) guidelines as "the extent to which a system, product or service can be used by specified users to achieve specified goals with effectiveness, efficiency and satisfaction in a specified context of use" [47]. In addition, perceived usefulness and ease of use causes people to accept or reject information technology [45]. The first is defined as the "degree to which a person believes that using a particular system would enhance his or her functions". The latter, in contrast, refers to "the degree to which a person believes that using a particular system would be free of effort" [45].

Furthermore, when measuring aspects of one's health, the accuracy of the results relies on the correct administration of the test. Thus, any usability problem associated with using a mobile app should be identified and addressed before it is made available to end-users. This is usually done through several iterations of testing with target user groups, ideally until no major usability problems exist with regards to using the apps and administering the test. Usability studies are most often carried out in a lab setting, convenient, and offer a high degree of control instead of field-based usability testing [44]. However, field-based testing, which, in this context, would be a home setting, provides insight into how the system is used under more realistic situations [44]. Depending on the system being tested and the development phase, usability should ideally be tested in both lab and home settings [48].

The use of smartphone apps as stand-alone systems provides a feasible solution in a fully wearable system. They have the significant advantages of pervasiveness, ubiquity, and exploitation of common apps usage experience. Moreover, the choice of off-the-shelf smartphones would also keep the mHealth system costs low, also increasing its compatibility with external commercial devices. On the other hand, there are several challenges associated with the development of mHealth apps:

- Design for all model and system available with the same performance (different smartphones have different capabilities);
- Built-in sensors do not have priority in the mobile operating system, OS (smartphones were born to handle calls and/or messages);
- Safety measures in order to ensure the patients' safety and privacy, developing strategies to ensure data are only accessible to those authorized to access [40];

In particular, to date, there is a lack of standardized regulation methods to evaluate the content and quality of mHealth apps [49]–[51]. The quality assessment of mHealth apps is challenging as it is difficult to identify the core components of quality and appropriate measures to assess them [52]. Besides, the different smartphone models available in the market make this assessment more complicated. For example, smartphone built-in inertial sensors do not have a fixed sample frequency: frequency changes dynamically around a fixed value depending on the OS requests, and it varies across the different smartphone models [53]. Moreover, some features are only available in certain smartphones and not in others (or in other cases, the feature could be limited): BLE connection could be absent in some smartphones or limited to only few megabytes in others, not allowing data exchange with external sensors [54].

On a more general ground and from a healthcare system perspective, introducing guidelines for app development and use may be highly effective in improving the quality standards. In the US, the FDA regulates mHealth within the existing framework for medical devices [55]. Only a limited number of apps meet the definition of medical device and are, as such, subject to the US FDA regulation [55]. In Europe, the new regulations on medical devices (MDR [EU] 2017/745) describe whether mHealth products must be medical devices [56]. As a result, apps that support a medical diagnosis and have medical use must be CE marked as medical devices [57]. While the implementation of the new, more stringent MDR might lead to the development of more high-quality apps and improved patient safety, it might also limit the development and release of new apps and software on the market. Classifying a device as class IIa or higher requires evaluation by a notified body, which can be very costly and, therefore, a barrier to entry for app developers [57].

4 mHealth apps for Clinical Assessment

The health state's measurement is essential in both clinical practice and research to assess and monitoring the severity and progression of a patient's health status, the effect of treatment, and alterations in other relevant factors. The miniaturization of sensing, feedback, and computational devices has opened a new frontier for movement assessment and rehabilitation [58]. Wearable systems are portable and can enable individuals with various movement disorders to benefit from analysis and intervention techniques that have previously been confined to research laboratories and medical clinics [58].

4.1 Older Adults

The clinical assessment of frail older adults (OA) is challenging, as they often have multiple comorbidities and diminished functional and physiological reserves [59]. Besides, the physical illness or adverse effects of drugs are more pronounced resulting in atypical presentation, cognitive decline, delirium or inability to manage routine activities of daily living (ADLs) [60]. ADLs include the fundamental skills typically needed to manage basic physical needs, comprised the following areas: grooming/personal hygiene, dressing, toileting/continence, transferring/ambulating, and eating [61]. Successful ADLs' performance is a significant health indicator that can predict mild cognitive impairments, dementia, and mortality in older adults [62], [63]. Hence, it is crucial to measure ADLs in older adults effectively. Several types of approaches have been used to quantify the level of independence in ADLs. ADLs may be measured by self-report, proxy/caregiver/informant report, and/or direct observation filling ad hoc scale/questionnaire [64]–[66]. These tools obtain a general sense of the level of assistance needed and the most appropriate setting for the patient [61]. Self-report measures are convenient to administer and are frequently used when direct observation is not possible or when individuals are relatively cognitively intact. However, they may be less valid when individuals have poor insight into their functional impairments [67], [68]. Informant-based ratings are commonly completed by caregivers who know the patient well, but how also may be biased by their own burden in caring for the individual or by over or underestimating the patient's true functioning [61]. The use of performance-based measures can provide objective data about ADL functioning and they may be able to detect change over time [69], but generally require more training to administer as compared with self or informant reports [61]. The need to improve these measurements and to objectively quantify how subjects engaged in physical activity (PA) led to the recent spread of wearable-accelerometer devices (or activity trackers) [70]. These devices allow daily monitoring of the behavior of the OA, also enhancing their aptitude for PA [71]. Historically, these accelerometry-based solutions employ summary threshold metrics to assess PA. To date, novel measures, such as fragmentation, allow for a deeper understanding of the quantities and patterns of daily PA, which are most informative for health outcomes [72].

Besides, falls are a major threat to the health and independence of OA. Quantitative methods for assessing fall risk factors are necessary to effectively implement preventative measures and reduce falls' incidence and severity [73]. In the last years, research groups developed different mHealth apps to monitor fall risk factors [73]. In general, mHealth app systems, due to their ubiquitous nature, offer the potential to provide fall risk screening in community settings [73] as an alternative to a qualitative approach.

Moreover, to objectively evaluate specific items of ADLs related to fall risk, in particular gait and balance [73], different instrumented tests can be performed, **Table 1**:

	DESCRIPTION
Turn 180° test [74]	A measure of dynamic postural stability, asking a patient to take few steps and then turn around by 180° to face the opposite direction. Count the number of steps taken to complete a 180° turn
Timed-Up-and-Go test (TUG) [75]	A measurement of mobility. A person is asked to stand up from a seated position, walk for 3 m, turn and walk back to a chair and sit down. Measure the time taken in seconds
Tandem stand test [76]	A measure of balance and ankle strength. A person is asked to stand in a near tandem position with their bare feet separated laterally by 2.5 cm with the heel of the front foot 2.5 cm anterior to the great toe of the back with their eyes closed. A person can hold arms out or move the body to help keep the balance but do not move the feet
Alternate Step test [77]	A measure of strength, balance, coordination, and stair climbing. It provides a measure of mediolateral stability. A person should be asked to place alternate whole left and right barefoot onto a 19 cm high stepper for a total of eight times.
10-Meter Walk test (10MWT) [78]	A measure of walking speed over a short duration. It requires a 20-m path that includes 5 m for acceleration and deceleration. Practically, a full 20-m walkway is not always available, thus there are several shorter distances commonly used to assess walking speed including 3-, 4-, and 6-m assessments
Sit-to-Stand test (StS) [79]	A measurement of functional mobility, balance, and lower limb strength. A person should be able to stand up and sit down five times with crossed arms from a 45-cm straight-backed chair

Table 1. Gait and Balance Assessment Tools. Adapted from Singh et al. [59].

To date, thanks to the great advances in wearable technologies these instrumented tests are feasible not only in clinical, but also continuously at home in a self-administrable way [80]. This is crucial for the prevention of movement dysfunctions in OA. For example, a solution that permits objective evaluation of body posture and gait in OA is the mHealth systems proposed by Bergquist et al. [48]. They developed three smartphone apps for self-administering an instrumented version of the 'Timed Up and Go' test (Self-TUG, **Figure 4**), the 'Standing tandem' test (Self-Tandem), and the 'Five times sit-to-stand' test (Self-

STS). The app uses the inertial sensors of the smartphone and real-time verbal instructions to guide the user during the test (**Figure 4-C**). The usability test of the apps was performed with target elderly groups [48].

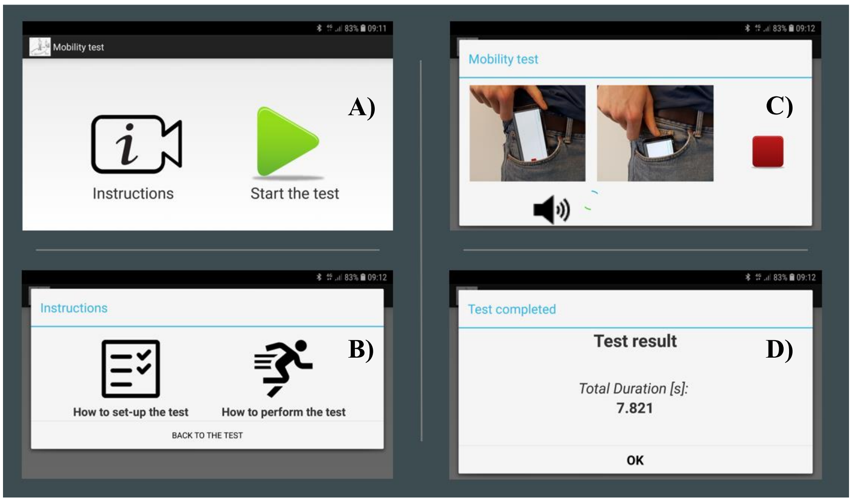

Fig. 4. The Self-TUG app. **A)** Home screen. **B)** Instructions tab to report how to correctly set-up and perform the test. **C)** The inertial sensors of the smartphone and real-time verbal instructions guide the user during the test. **D)** The total duration of the test automatically detect by the app. Adapted from Bergquist et al. [48].

Thus, mHealth solutions also allow pervasive and self-administered systems, feasible in daily life situations [48]. Nevertheless, the usability of the solutions proposed might be critical: it is essential to follow a User-Centered-Design (UCD) approach [37], [38], also considering that fine motor skills issues (such as tremor) in older people may hinder their interaction with these wearable systems [81]. In this perspective, Gabyzon et al. [82] developed and examined the feasibility of a tablet app to assess touchscreen ability in OA. This aspect is crucial for the correct interaction with modern devices. In general, a combination of self-report and performance-based measures of ADL performance may be the best way to fully capture the picture of disability for a given OA [83].

4.2 Persons with Parkinson's disease

Parkinson's disease (PD) is a complex disorder expressed through many motor and nonmotor manifestations, which cause disabilities that can vary both gradually over time or come on suddenly. In addition, there is a wide interpatient variability making the appraisal of the many facets of this disease difficult [84]. Two kinds of measures are used for the evaluation of PD. The first is subjective, inferential, based on rater-based interview and examination or patient self-assessment, and consist of rating scales and questionnaires. These evaluations provide estimations of conceptual, non-observable factors (e.g., symptoms), usually scored on an ordinal scale [84]. The new second type of measure is objective, factual, based on technology-based devices capturing physical characteristics of the pathological phenomena (e.g., sensors to measure the frequency and amplitude of tremor) [84].

Recently, there has been a growing interest in developing an objective assessment of the symptoms in PD, and its health-related outcomes, using new technology-based tools, worn or operated by patients either in a healthcare or domestic environment [84]. The most important new technologies to aid in the treatment monitoring of PD patients are based on the use of inertial measurement units (IMU). Most commercially available IMUs have a triaxial accelerometer and a triaxial gyroscope, although a magnetometer is also commonly included. Over time, sensors have become more sophisticated, and they can be worn unobtrusively and can be attached to almost any body part to measure movement. These wearable devices can record not only the orientation, amplitude, and frequency of movements [85]. These data allow clinicians to assess, for example, the presence and severity of the cardinal features and complications of PD (i.e., tremor, bradykinesia, and dyskinesias) [86]. Kinesia [87], a wireless system for automated assessment of PD tremor, uses an IMU placed on the patient's index finger or the heel and can differentiate between a healthy subject and a patient with bradykinesia. Kinesia system can also record tremor with high reliability and agreement with MDS-UPDRS rest and postural tremor items (one of the most common clinical scale used to provide an overall idea of the motor status of persons with PD) [87], [88]. Objective gait and balance quantification are important for the overall evaluation of the motor status of the PD patient [85]. However, as these symptoms in PD can be both episodic (Freezing of Gait - FOG, hesitation, difficult turning) and continuous (slow gait) associated with variability in performance, clinical examination at a point of time is often inadequate in elucidating the full spectrum of problems [84]. Thanks to the great advances in wearable technologies, various sensor-based and wearable technologies are now being used for the assessment and monitoring of movement patterns during clinical visits and the daily lives of PD patients [84], [85]. In addition, wearable sensors, frequently worn in the lower body segment, have emerged as a novel tool to quantitatively assess FOG during real life with more reliability than clinical measures alone [89], [90]. For example, a solution that permits objective evaluation of body posture and gait in PD subjects is the mTUG/mSWAY system [91], [92]. To date, numerous smartphone applications have been designed specifically for patients with PD. Existing applications include those devised for assessment of motor, cognitive, and psychological symptoms, as well as those intended to adjust and control treatment [93]. For example, Lopane et al. [94] implemented a system that allows optimizing the levodopa therapy in PD subjects according to disease progression to establish the minimum dose required over time, **Figure 5**. Thanks to its integrated technology-based platform composed of a tablet app, a smartphone app, and a digital blood pressure monitor, the protocol can be performed under a physician's supervision, but also self-administer at home [94]. This mHealth system includes the following assessment tests that can be tailored and scheduled into a single assessment protocol:

- alternate finger tapping test (tablet app);
- reaction time test (tablet app);
- actual intake of the levodopa test dose (tablet app);
- measurement of the blood pressure (digital blood pressure monitor);
- measurement of the Timed Up and Go (TUG) test (smartphone app);
- identification of dyskinesia and the measurement of the tremor at rest (smartphone app).

Those two devices automatically connect to the tablet when the assessment protocol starts [94].

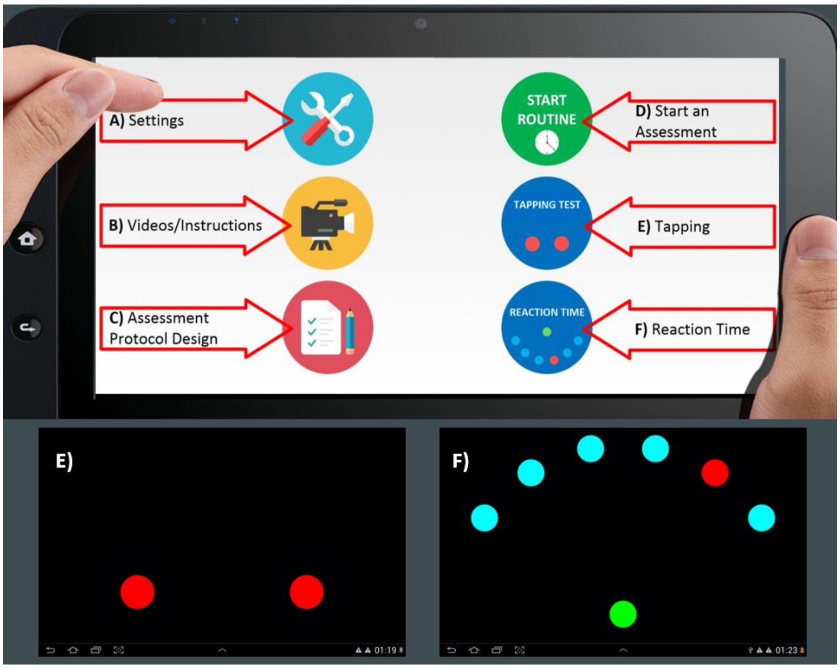

Fig. 5. Menu of the tablet app. **A)** Settings. **B)** Audio/video instructions. **C)** Design the assessment protocol. **D)** Start an assessment protocol. **E)** Demo of the alternate finger tapping test. **F)** Demo of the reaction time test. Adapted from Lopane et al. [94].

Thus, mobile devices seem to be a useful tool for the detection, assessment, and potential care of patients with PD [95]–[97]. However, high-quality studies are lacking, although they are certainly feasible, due to smartphones' accessibility and ease of use [85]. In conclusion, clinical scales are the most widely employed standards for the evaluation of patients with PD [85]. Their limitations include subjectivity and the inability to monitor the disease continuously [85]. New sensors and wearable devices provide objective, accurate, and reproducible measurements that can overcome these barriers and complement the use of traditional methods. However, the use of these new technologies is still limited in practice because most of the studies performed to date were heterogeneous and non-standardized [85].

5 mHealth apps for Neuromotor Rehabilitation

Neurorehabilitation aims to cement patients' existing skills, retrieve any lost skills, and promote the learning of new abilities, allowing people to function at their highest possible level despite their physical impairment. A variety of factors may have a significant effect on neurorehabilitation and influence motor learning processes. These factors include verbal instructions, characteristics, and variability of training sessions, the individual's active participation and motivation, positive and negative learning transfer, posture control, memory, and feedback. All of these factors are clinically applicable, and they provide the basis for emerging or established lines of research having to do with retraining sensorimotor function in neurological patients [98]. The miniaturization of sensing, feedback, and computational devices has opened a new frontier for movement assessment and rehabilitation [58], [99]. Wearable systems are portable and can enable individuals with a variety of movement disorders to benefit from analysis and intervention techniques that have previously been confined to research laboratories and medical clinics [58].

5.1 Older Adults

Rehabilitation can play an essential strategic role to counteract impairments and disability which characterize the aging process. Correct rehabilitative programs must be approached on the functional limitation and residual abilities of older adults (OA). Leading a more active lifestyle and regular physical activity including aerobic and resistance exercises have been demonstrated to improve cardiovascular, respiratory, musculoskeletal, and cognitive wellbeing in OA [100]. Physical activity interventions for people with an intact cognition are well documented and shown to be effective in improving balance and reducing falls [73]. A comprehensive physical activity guideline for all adults, including OA, was published by the American College of Sports Medicine (ACSM) [101]. People with dementia are two to three times more likely to fall and multimodal interventions that combine cognitive, as well as motor therapy, should be performed [102]. Physical activity is beneficial for reducing overall morbidity and mortality in OA [103]. The physical activity recommendations intended for all older adults may need to be modified for particular health conditions and disorders, using specific types of exercise to correct or ameliorate identified impairments and functional limitations [103]. Physical therapists, exercise physiologists, and physicians specializing in rehabilitation can help to tailor the exercise prescription to meet patient needs. In addition, health care providers are perceived as respected sources of health information and should take an active role in promoting physical activity. Primary care clinicians should emphasize the importance of physical activity for health maintenance, ask patients if they are physically active, and advise them to become physically active [103]. Innovatively, a recent European project (www.preventit.eu) developed and tested a personalized mHealth solution aimed at behavioral change in OA, in order to decrease the risk for age-related functional decline.

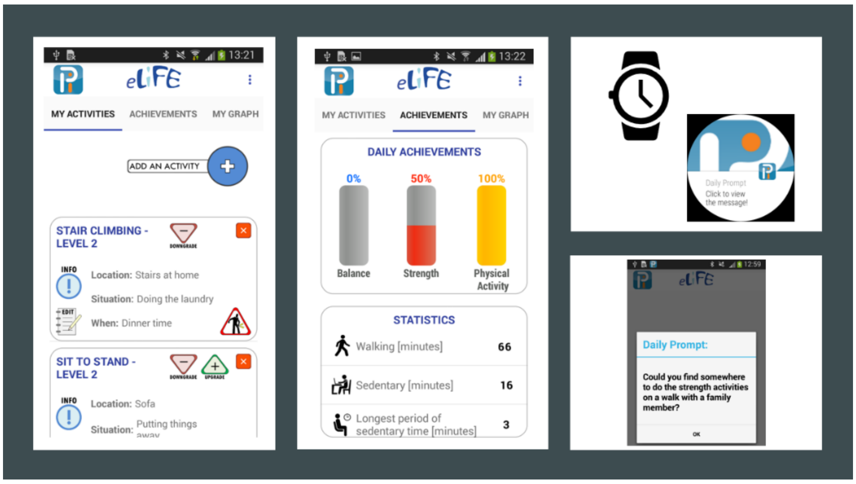

Fig. 6. A beta version of the PreventIT app.

The project consists of a smartphone and smartwatch app to motivate older persons to exercise, and that shows how to integrate mobility exercises in daily living activities, **Figure 6**. This app, created by a multidisciplinary team, was already developed in its final version [104] and a feasibility study was performed [105]. Results indicated that the developed interventions were feasible and safe. Participants liked the concept of lifestyle-integrated activities, managed to change their daily routines towards increased activity, and were positive about the app [105].

5.2 Persons with Parkinson's disease

Despite optimal medical management, most patients with Parkinson's disease (PD) continue to experience a wide range of motor and nonmotor symptoms [106], [107]. All of these influence activities of daily living and affect the patient's quality of life [108], [109]. Examples of motor symptoms that respond insufficiently to medication or surgery include impairments in speech, postural stability, and freezing of gait. Additional disability arises from the presence of nonmotor symptoms (e.g., cognitive impairment, depression, or psychosis), that are sub-optimally controlled with current medical management [106], [110]. This situation creates treatment challenges, not only in advanced disease stages, but even early on in the course of PD [111]. Moreover, although it is recommended to early start rehabilitation, it should be considered that PD is a chronic progressive disorder and the intervention must be adjusted to changing clinical conditions and tailored to the individual patients' needs [112], [113]. A widely held belief holds that nonpharmacological management might offer symptomatic relief of motor or nonmotor symptoms that are otherwise difficult to treat. Hence, a multidisciplinary approach involving non- and pharmacological treatment is the standard nowadays [114].

The use of external sensory cues (e.g., auditory, visual) to reinforce attention toward the task [115] is an effective gait-rehabilitation strategy for persons with PD; the cues stimulate the executive voluntary component of action [116]–[118] by activating the attentional-executive motor control system and bypassing the dysfunctional, habitual, sensorimotor BG network [116], [117], [119]–[122]. This strategy helps people with PD improve gait consistency and rhythmicity.

One of the most innovative developments in the quantitative assessment and management of PD symptoms is the use of wearable technologies during gait [123], which are able to overcome traditional open-loop cue, providing customized cueing: stimuli are triggered when gait deviates from normal, thus providing patients with immediate feedback on their performance. These closed-loop stimuli (audio [124]–[126], visual [127], [128], audio-visual [129] or proprioceptive [130]) are known as intelligent inputs [124]. Closed-loop systems are based on the Knowledge of Performance [29], which is indicated as one of the optimal techniques for motor rehabilitation in PD subjects [131]. In contrast to open-loop systems, in closed-loop systems the external information does not necessarily become part of the participants' movement representation (as explained by the "guidance hypothesis"), thus possibly decreasing the development of cue-dependency [132]. The possibility of real-time biofeedback represents an important step toward the maximum benefit and clinical impact of wearable sensors. Wearable systems also permit data collection in a more naturalistic environment [124], [129]. Casamassima et al. [133] developed a unique mHealth system (CuPiD-system) made of wearable sensors and a smartphone that provides real-time verbal feedback to improve the dynamic balance and gait performance of people with PD [124], [134].

Thanks to advances in technologies, visual feedback is possible through Smart Glasses (SG) [135]. SG represents an ideal modality to provide personalized feedback and assistance to people with PD in daily living situations. Indeed, McNaney et al. [136] reported that participants with PD were generally positive about SG as an everyday assistive device; however, usability issues and social stigma still hinder its general acceptance.

Innovatively, Imbesi et al. [137] proposed a wearable gait rehabilitation solution by integrating the Vuzix Blade SG [138] into the smartphone-based CuPiD-system [133], **Figure 7**.

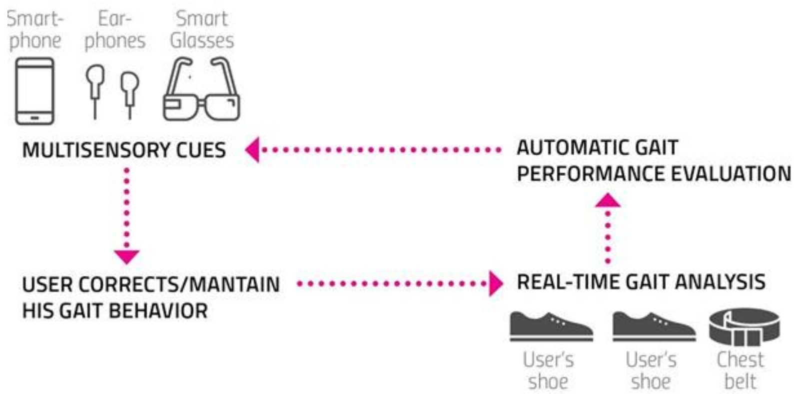

Fig. 7. Schematic representation of the mHealth system. Adapted from Casamassima et al. [133].

Although, the potential of real-time biofeedback in gait rehabilitation through wearable devices is underexploited [85], these new real-time systems seem to increase adherence to treatment, self-management, and quality of life [139], allowing also personalized and tailored rehabilitation on the individual patients' need [124].

6 Discussion and Future scenario

Considering the pandemic emergency, never as of today, we can say that the integration of mHealth apps in our society may contribute to a new era of clinical practice. After reporting a brief description of mHealth system architecture, this chapter explored several different opportunities where innovative mHealth solutions could improve assessment and rehabilitation strategies for ageing people and persons with Parkinson's disease. This chapter reported solutions that need medical support in a clinical context and others that can be self-administered and require only a smartphone as a stand-alone system.

However, the primary aim of a mHealth system is to improve the person's quality of life and increase his autonomy and independence. The huge development of technology in recent years leads to the manufacturing and use of miniature, low-cost sensors and powerful devices that open the way to non-invasive, non-intrusive, and continuous monitoring of an individual's health condition.

There are many challenges for future research and development to improve the performance and acceptance of the mHealth system.

First, to achieve widespread acceptance among the people, the systems need to be affordable, easy-to-use, unobtrusive. Nevertheless, many patients continue to depend on the clinician's support. They would request direct contact with them, and they would reject solutions that might create any distance between them and their clinician. Inclusive design principles might be helpful for designers to collect and elaborate on patients' requirements, next to the technical and technological ones, to improve these aspects.

Second, the new regulations on medical devices in Europe (MDR [EU] 2017/745) might lead to more high-quality mHealth systems, improving patient safety. On the other hand, it might limit the development and release of new solutions and software on the market [49].

Besides, the privacy and security of the sensitive medical information of the user must be guaranteed. More efforts are needed to develop algorithms to ensure highly secured communication.

Third, as we witness a digital transformation of the healthcare system, mHealth technologies are expected to become better integrated into the clinical workflow, especially to provide telemedicine. Thus, thanks to the Internet connection, mHealth systems can increase healthcare access and improve cost-effectiveness. During the COVID-19 pandemic, this transformation of the healthcare system has been dramatically accelerated by new clinical demands, including the need to assure continuity of clinical care services. For example, healthcare professionals could use mHealth systems to monitor patients' conditions remotely and continuously mitigate or prevent hospital surges.

In man's continuous aspiration to improve his well-being, we have to face the exponential growth of technology. Thus, we must deal with unknown challenges, unexpected situations and generate new uncertain solutions. In general, we are used to taking a predictable path, the so-called comfort zone. That is why we are used to choosing the options we already know. The challenge of future research, including the development of mHealth systems, requires a mental shift from linear and predictable to bold and spontaneous, handling the incoming technologies to the best of our abilities.

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