RATE

Journal of Rehabilitation and Assistive Technologies Engineering
Volume 6: 1–9
© The Author(s) 2019
Article reuse guidelines:
sagepub.com/journals-permissions
DOI: 10.1177/2055668319839607
journals.sagepub.com/home/jrt
SAGE

Wearable technologies for active living and rehabilitation: Current research challenges and future opportunities

Mary M Rodgers[1], Gad Alon[1], Vinay M Pai[2] and Richard S Conroy[3]

Abstract

This paper presents some recent developments in the field of wearable sensors and systems that are relevant to rehabilitation and provides examples of systems with evidence supporting their effectiveness for rehabilitation. A discussion of current challenges and future developments for selected systems is followed by suggestions for future directions needed to advance towards wider deployment of wearable sensors and systems for rehabilitation.

Keywords

Wearable technology, smart systems (rehabilitation), wearable sensor systems, virtual reality, augmented reality, rehabilitation, interactive feedback, functional electrical stimulation

Date received: 22 July 2017; accepted: 20 February 2019

Introduction

Rapidly changing demographics in the United States and advancements in critical care treatments have led to an increasing need for solutions that promote wellness management and rehabilitation outside of the clinical environment. To be successful, any wellness or rehabilitation interventions need to be multifaceted, from addressing biological function at the cellular level to community support at the personal level. Providing effective rehabilitation is an increasingly complex challenge because of the increased number of individuals with multiple medical conditions and disabilities and the subsequent reduction of access to providers.[1] Recent advances in technology, including wearable sensor systems,[2] may significantly enhance the effectiveness of rehabilitation interventions and help to address health disparities.[3]

Disablement models are helpful for framing how emerging technologies need to fit in a multifaceted solution to be effective in rehabilitation interventions. Several different models define disability and related concepts, including the Disablement Model developed by Nagi,[4] the International Classification of Impairments, Disabilities and Handicaps,[5] and its current revision, International Classification of Functioning, Disability and Health.[6] However, they all view overall disablement as a series of related concepts describing the consequences or impact of a health condition on a person's body, their activities, and on their societal participation.[7] Understanding the context of an individual's disablement is key to optimizing the use of recent advances in technology, including wearable sensor systems, for diagnostic, monitoring and treatment applications.

In this paper, we define wearable technology as "devices that can be worn or mated with human skin to continuously and closely monitor an individual's activities, without interrupting or limiting the user's motions".[8] Wearable technology most commonly refers to electronic technologies, but it can also include products such as smart or advanced materials used in clothing or protective equipment. There are three

[1]Department of Physical Therapy & Rehabilitation Science, University of Maryland School of Medicine, Baltimore, MD, USA
[2]Data Collaboratory, LLC, Potomac, MD, USA
[3]Office of Strategic Coordination, National Institutes of Health, Bethesda, MD, USA

Corresponding author:
Mary M Rodgers, Department of Physical Therapy & Rehabilitation Science, University of Maryland School of Medicine, Baltimore, MD 21021, USA.
Email: mrodgers@som.umaryland.edu

Creative Commons Non Commercial CC BY-NC: This article is distributed under the terms of the Creative Commons Attribution-NonCommercial 4.0 License (http://www.creativecommons.org/licenses/by-nc/4.0/) which permits non-commercial use, reproduction and distribution of the work without further permission provided the original work is attributed as specified on the SAGE and Open Access pages (https://us.sagepub.com/en-us/nam/open-access-at-sage).

general use-cases for wearable devices: (1) prediction of future events, (2) detection of anomalous, critical events, and (3) diagnostic monitoring to improve decision-making.[9] This review focuses primarily on technologies and examples for physical rehabilitation, though this is often only part of an integrated rehabilitation approach that may include cognitive and psychosocial rehabilitation.

There have been tremendous advances in the field of wearable sensors for health monitoring, though theories and evidence for using these sensors widely in rehabilitation[10] and how to best improve outcomes through behavior change[11] are lagging. Other challenges include societal issues such as expectations for privacy and data security, technological issues such as battery lifetime, and cultural barriers such as the consumer's perception of a stigma associated with using medical devices for home-based clinical monitoring.[12] This review aims to summarize some recent developments in the field of wearable sensors and systems relevant to the field of rehabilitation and provide examples of systems with evidence supporting their effectiveness. Current challenges and opportunities for moving these technologies forward for wider-use outside clinical research settings are discussed, highlighting the technologies and evidence needed, and potential future developments that may alter current paradigms.

Current developments in wearable technologies for rehabilitation

In this section, we present some illustrative examples of techniques and applications of wearable technologies and systems for rehabilitation. Virtual reality (VR) systems, functional electrical stimulation (FES), and activity trackers are some of the current wearable technologies being applied to rehabilitation. However, it is important to realize that these advances are in the context of systems. As discussed by Wang et al.,[13] interactive wearable systems facilitating rehabilitation exercise programs are often developed for specific health applications such as patients with neurological conditions, musculoskeletal conditions, chronic pulmonary impairment, or with pain. Most systems are used for monitoring and providing rapid user feedback on posture and extremity movements, and are not networked, smart, or designed for continuous use. Designing these devices as non-obtrusive and intuitive systems for longer-term home-use and connecting these devices to internet services may dramatically widen their range of applications.

Advanced wearable sensors

To date, accelerometers and inertial measurement units are the most frequently used sensors in wearable systems, and provide measurements that can be used to track range of motion and performance.[14] A large number of studies using these sensors have focused on upper body rehabilitation following stroke, and there is some clinical evidence of small improvements, however few randomized clinical trials have been carried out.[13] Increasingly, these systems are interactive and provide more than basic feedback and require less setup and monitoring time by healthcare professionals. Under development are a wider range of wearable sensor systems that may assist in home-based rehabilitation, including body sensor networks, smart clothing, and wearable cameras that provide complementary information to these movement sensors.

Body-worn sensors now come in many shapes and sizes, including chest-worn heart-monitoring straps, headbands for brain-activity measuring electroencephalograms (EEGs), posture-detecting monitors, baby and pregnancy monitors for measuring vitals and movement, and electronic patches.[15] These sensors can provide insights into heart rate, respiratory rate, oxygen saturation and blood pressure, and can detect vital sign abnormalities that provide important contextual information or provide feedback to the wearers. In a study of 16 cardiac rehabilitation patients, a suite of sensors tracking body movement was compared against vital sign measures to track energy expenditure during low-to-moderate intensity daily activities to develop a predictive model for efficacy of beta-blockers.[16] The availability of consumer-grade devices with vital sensors, such as smart watches[17] and chest straps[18] has significantly reduced the barrier to incorporation of these sensors in studies. However, challenges exist with the calibration, accuracy, and sensitivity of these devices for medical applications.

Smart clothing can be considered the ultimate wearable system, as it can integrate into everyday life as part of a garment and/or footwear, and track or measure physiological, contextual or biometric attributes. For example, the Neofect's RAPAEL Smart Glove[19] allows people to rehabilitate their hands by wearing a glove and using accompanying technology. This can be used to recover from injuries, or to help with issues that could arise from adrenoleukodystrophy or other neurological disorders. In a randomized clinical trial using a four-week training program with the Smart Glove, both Fugl–Meyer score and Jebsen–Taylor test scores were improved and retained one month after training completion.

Wearable cameras have been developed for training clinicians and for remote rehabilitation consultation. Chen et al.[20] incorporated wearable cameras and motion sensors in a rehabilitation exercise assessment for knee osteoarthritis that enables the patient to self-manage rehabilitation progress. Accuracy for exercise type classification was 97% and for exercise posture identification was 88%, demonstrating feasibility of the system for rehabilitation assessment. Emerging technologies like 360° vision, VR, artificial intelligence, deep learning, and computer vision will enhance the wearable camera experience, expanding the devices' use cases and applications.

Wearable sensor systems provide the opportunity to not only evaluate rehabilitation as it occurs during daily life activities but also to provide timely, meaningful feedback to patients and their therapists. Such feedback can guide and motivate progressive skills practice aimed at maximizing the recovery of motor function. However, a number of challenges exist related to the accuracy and reproducibility of these sensors, design optimization, system integration, consideration of user experience, the need for user education, and securing reimbursement.[2] Underlying these challenges is the need for stronger evidence on the longer-term effectiveness of these sensor technologies for rehabilitation in both clinical and home settings.

Virtual and augmented reality systems

Augmented reality (AR) headsets like Google Glass and mixed reality systems such as the HoloLens, have been deployed in several industrial and enterprise settings, and there is growing interest in their use for healthcare applications. These systems have become increasingly complex, moving from overlaying digital information towards positional tracking and depth sensors to provide a more immersive experience, and enabling interactions with holographic objects. Increasing numbers of studies have shown positive rehabilitation outcomes using the combination of sensing technology and interactive gaming or VR environments.[21,22] Munroe et al.[23] designed an AR game to provide home-based neurorehabilitation for children with cerebral palsy. The system combines electromyography electrodes and accelerometers in an armband to provide data. A trained classifier determines whether the target neuromotor performance of the arm is achieved and the user moves a virtual object through therapist-prescribed motions. In addition, VR can help patients undergoing physical rehabilitation as they imagine themselves performing slow, simple movements while immersed. VR immersion, coupled with the patient's own visualization, is believed to create brain patterns closer to actual motor skills than visualization alone. This gives the patient a huge advantage in healing. In a blinded randomized controlled trial studying 59 stroke survivors, McEwen et al.[24] found that VR exercise intervention for inpatient stroke rehabilitation improved mobility-related outcomes.

There is significant potential for AR and VR systems to enhance rehabilitation programs and to provide real-time feedback to the patient and to their therapist. However, there is limited evidence so far for the long-term efficacy of these systems and whether they offer sustained improvement over traditional approaches. On the other hand, a recent review by Massetti et al.[25] would suggest that VR interventions yielded improvement in motor functions, greater community participation, and improved psychological and cognitive function. As the technology of AR/VR systems continues to improve, additional clinical studies are needed to generate the evidence base demonstrating the utility and efficacy of such systems for clinical care and research in rehabilitation.[26]

Functional electrical stimulation

Traditionally, functional electrical stimulation (FES) or neuromuscular electrical stimulators have been utilized predominantly for stimulating lower and upper extremity functions. For many years, FES systems included a battery-powered stimulator connected with lead wires to the stimulating electrodes and a wired external trigger to synchronize muscle contraction with the functional activity.[27] More recently, academic researchers and commercial companies are developing wearable, wireless FES systems.[28–31] These systems are self-administered and controlled by the patient. Having low profile, they can be worn comfortably under clothing while functioning in the home and the community.

Current research approaches to improve recovery of connectivity of the brain's motor network include application of iterative algorithms[32–35] and closed-loop control of the desired level of the electrically induced contraction of the target muscles.[36–39] Appropriate closed-loop control design should enable each patient to use their internal sensory-motor control system and add FES only to complete whatever motion the internal control failed to achieve, while walking or using the paretic upper extremity. Examples of research efforts to achieve a reliable, cost-effective, and durable closed-loop control can be found mostly in engineering publications and are still considered "proof of concept" or initial efficacy investigations.[40–42] Attempts to improve the resolution of FES-induced muscle contraction by using multiplexers and arrays of small electrodes[34,43] or manipulation of pulse parameters[44] have yielded some interesting discoveries and electronic innovations. However, these research efforts have failed so far to yield a viable commercial product in rehabilitation medicine.

Using telemedicine and cloud data storage, researchers have successfully demonstrated continuous storage of patients' performance using FES combined with a motorized cycling system, accumulation of training doses, and provision of uninterrupted communication with clinicians.[45] However, so far, most FES systems are configured with very limited storage of performance and compliance. The need to implement FES throughout the continuum of care, from critical-care units to home use, presents another key challenge for both researchers and clinicians. Increasing home-based use will need new algorithms capable of identifying and storing essential data of performance, such as clinical evidence of functional recovery, plateau, or regression, compliance data, and online communication with clinicians. However, with the rapid development of similar wearable systems, such FES systems are likely to be available soon.

Current challenges and opportunities

A generally accepted assumption has been that more data, and in particular data about daily life, will improve the accuracy and reproducibility of healthcare models, and enable more efficient remote monitoring. It is presumed that this will, in turn, improve our ability to delivery cost-efficient and effective care. However, in practice, actionable information from wearable devices is plagued by a number of issues. These include concerns related to quality, battery lifetime, lack of contextual information, privacy and security concerns, as well as variable and proprietary algorithms for annotating data streams. Additionally, many systems are developed for the fitness market, rather than older adults and rehabilitation.

The mix of research prototype devices, consumer-grade, and clinical-grade wearable systems introduces many challenges in determining efficacy. As a result, there are concerns about validation, standardization, and interoperability. When mixed with usability optimized for early-adopters of technology, these concerns provide a significant barrier for widespread adoption and utilization of wearables for active living management and as a routine part of rehabilitation.

This mix also introduces additional barriers such as rapid technology obsolescence, use of proprietary data processing algorithms and formats, and the ability to scale technologies for larger cohorts and longer studies. All these challenges slow progress towards generating a rich evidence base for the effectiveness of these technologies for rehabilitation. Below we discuss three of these challenges, followed by a brief description of three potential areas of opportunity.

Power consumption

While wearable sensor systems can lead to ubiquitous and personalized rehabilitation service for users, the need for size reduction to ensure portability can impose severe restrictions on battery capacity. Energy harvesting or scavenging has been considered as one approach to ensure that the useful features of a wearable sensor are not outweighed by the battery cost, size, and weight. However, energy harvesting generally suffers from low power output, making it a non-ideal proposition to address the power requirement of the wearable sensor components such as the accelerometer. It has been shown that the power requirement of the accelerometer ranges between 0.35 and 5 times the harvested kinetic power for detecting common human activities with high accuracy.[46]

Khalifa et al.[47] have shown that it may be possible to infer human activities directly from the energy-harvesting pattern, which would eliminate the need to use an accelerometer. Their system uses kinetic energy harvesting and leverages the fact that different human activities produce different amount of kinetic energy that can be leveraged for activity recognition. Initial tests have shown that even though the new system (“HARKE or HAR Kinetic Energy”) consumes 72% less energy than the conventional accelerometer-based system, it can classify human activities as accurately as the accelerometer-based human activity recognition (HAR). Advances in energy-harvesting hardware have created an opportunity for realizing battery-free wearables for continuous and pervasive HAR, though these advances have yet to be realized in widely available wearable systems.

Measurement and validation

The calibration and validation of wearable technologies is critical to obtaining accurate data from them.[48] However, the field is still developing a common language for measurement and evaluation of devices to define performance, safety, and durability; this has contributed to the challenges of rigorous calibration and validation. For example, to establish the performance of different devices in step counting, a well-defined and reproducible system that replicates human walking is needed. Additionally, access to the raw and processed data is required to help determine whether variations are due to hardware differences, such as accelerometers, or due to the post-processing algorithms. However, these necessarily narrow approaches to calibration do not capture the complexity of daily life and the variation in gait and mobility. In general, there is reasonable intra-class correlation for wearable devices,[49] though there are limitations that have been highlighted in a number of recent studies. For example, one study noted that readings did not correlate with intensity of exercise,[50] and another noted that recorded steps for some wearables fell to zero for speeds of 0.3–0.5 m/s.[51]

Ethical and privacy issues

A large range of technology companies and start-up ventures have sprung up to exploit data from sensors such as accelerometers, gyroscopes, and pedometers, breath sensing, heart-rate monitors, and calorie trackers for the potential commercial value. However, this raises the delicate question of data ownership and ethical aspects of data usage and interpretation. Another aspect related to privacy is data leakage about non-health-related issues. Spagnolli et al.[52] administered a questionnaire including key dimensions of the Technology Acceptance Model[53,54] to 110 respondents (33 women). This questionnaire referenced three devices (smart shirt, portable EEG system, and eye-tracking glasses) and six usage scenarios (dangerous work, heavy work, sport, home care, research, and retail). The study was able to identify several variables as good predictors of device acceptance, such as perceived usefulness, perceived comfort/pleasantness, facilitating conditions, and attitude towards technology. The study also found that while respondents would share information about their stress level, mental states, and cognitive performance with physician, psychologist, and partner, they were more comfortable sharing their interests and preferences with friends and partner. Additionally, non-experts seemed more concerned about privacy than experts. Li et al.[55] have shown that in the privacy context, people make decisions about adopting healthcare wearable devices based on perceived risk–benefit ratios. Their study of 333 actual users of healthcare wearable devices showed that people use different lenses to evaluate perceived benefits and perceived risks. Thus, while the perceived benefits were determined by perceived informativeness and functional congruence, the perceived privacy risks were informed by health information sensitivity, personal innovativeness, legislative protection, and perceived prestige.

Human-centered design

An area of opportunity is human-centered design. Designing and developing persuasive, seamless technologies that engage users and reinforce positive behavior on a daily basis is very challenging because of the diverse range of user capabilities, motivations, and desired outcomes.[56,57] There is growing interest and published examples of acceptance and usability studies. For example, there are studies of Parkinson's patients,[58] fall detection, and prediction in the home-setting,[59] vibration feedback of gait when using lower limb prosthetics,[60] and feedback on knee habilitation exercises.[61] There is a need for stronger human-centered design approaches, developing interactive systems by focusing on user needs and requirements and applying best practices in usability and ergonomics. If implemented properly, this has the potential to significantly improve satisfaction and sustained use of wearable technologies beyond initial short, incentivized studies.

Personalized models

Human-centered design is focused on developing systems that take into account important factors for definable groups of users. In contrast, personalized models consider the many nuances of the behaviors, needs, and constraints of individual human beings. Personalized systems and models can potentially yield higher rates of adoption of wearable systems, but there are many variables that need to be considered. The rapid rise of a smart and connected health environment including wearable devices, electronic health records, and an integrated care environment has laid the groundwork for having personalized prognostic and predictive models of health to inform wellness and treatment planning. However, development of accurate, personalized forecasting models has been significantly hindered by the degree of inter-individual variability, privacy and security concerns, and inability to efficiently scale these models to a community or national level. Currently, the focus of most personalized models is on understanding and promoting positive health behaviors while retaining patient engagement. The intersection between these behavior changes models and persuasive technology design strategies is particularly of interest for wearable devices.[62] Personalized models may also assist with other aspects of wearable technologies, including a better understanding of intention,[63] and how to implement and scale-up the computational framework.[64]

Collocated interactions

As wearable devices proliferate among groups of individuals, as well as per individual, there has been a growing need to understand interactions, both from a social perspective and from the commercial utilization perspective. Research activities have focused over the last decade on studying scenarios ranging from individual to multiuser experiences and interactions.[65–68] According to Lucero et al.[69] while early research in collocated interactions was centered on device development, the current research has focused more on the experience. They point to multi-player pervasive games such as Blast theory's "Can You See Me Now?"[70] where there is interaction between players in the virtual world and runners in the real world. There is high interactivity with mobile devices, and the gaming platform enables a unique, embedded experience. Lucero et al.[69] have raised the interesting idea of using proxemics, research focused on the culturally dependent use of space and physical measures to mediate and comprehend interpersonal interactions,[71] for supporting mobile collocated interactions. Such a vision would enable wearables to not only be aware of individuals, but also be tuned to interpersonal distances people naturally use in their social interactions.

Future developments

Beyond these expected areas of opportunity, two future developments may disrupt the current paradigm for using wearables for rehabilitation. There is significant interest in developing smart wearables, where the loop is closed and automated feedback is given to the wearer to mitigate risky behavior, reinforce learning, or enable shared decision-making. These systems will require a high degree of sensitivity and specificity for each individual and will need to operate on models with a high degree of predictive power. These systems will need to collect much more information about the local environment, the user's psychological and physiological state and track potentially invasive information such as geolocation and social interactions. The rapid development of integrated data infrastructures and complex algorithms running on multidimensional datasets are enabling tentative exploration of learning healthcare systems. The next decade should show continued development of hybrid closed loop systems providing complex feedback to someone undergoing daily rehabilitation, automatically trigger interventions in an independent living environment, or enable shared decision-making in a managed care facility.

A second area of potential disruption may come through citizen science projects, where communities and individuals hack devices and delve more deeply into their data. Factors influencing this include data portability standards such as the HL7's Fast Healthcare Interoperability Resource, rise of patient-targeted websites on the internet, and the emergence of disease-specific communities where individuals share their experiences and data. All these factors raise the potential for sharing and analysis of wearable data outside the clinical setting. The extent of information sharing on PatientsLikeMe[72] and the emergence of do-it-yourself community projects such as Nightscout and the Open Artificial Pancreas[73] highlight the potential for community-driven research projects to influence future research directions in rehabilitation research.

Conclusions

The evidence base for the efficacy of wearables is expanding. However, this evidence is skewed towards short-term physical rehabilitation training, neurological disorders, and rehabilitation after extremity injuries and focused on secondary endpoints rather than long-term outcomes. This evidence is also skewed towards rehabilitation in a care setting and involving a rehabilitation specialist. There is a need to expand this evidence base by carrying out more efficacy studies to support the longer-term use of wearable sensors in a home-setting using self-guided approaches.

To advance our understanding of the use of these systems in rehabilitation, further research and development is needed to address issues of power consumption, standardization, interoperability, measurement validity, privacy, and confidentiality. There are many prototype research systems tackling these issues, and there is wide availability of clinical-grade, and consumer-grade, wearables. However, the reliability and validity of research and consumer-grade systems needs to be more firmly established to support the conclusions drawn from studies using these devices.

For wider-spread adoption of wearables for rehabilitation, understanding of end-use must go hand-in-hand with technology development. Routine and longer-term use of wearables introduces many challenges that are not addressed in short clinical studies, such as durability, power consumption, comfort and usability. Therefore, to advance the use of wearable systems for rehabilitation outside of the clinical setting, a systematic and integrated approach is needed to develop user-centric systems for a wide range of rehabilitation applications. Such an approach will motivate and maintain engagement within the user community, and demonstrate clear long-term health benefits.

Declaration of conflicting interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) received no financial support for the research, authorship, and/or publication of this article.

Guarantor

MMR

Contributorship

MMR, VMP, and RSC conceived the review. All authors reviewed the literature, wrote the first draft.

MMR reviewed and edited the final version of the manuscript.

ORCID iD

Mary M Rodgers http://orcid.org/0000-0001-6141-1071

References

1. Ma VY, Chan L and Carruthers KJ. Incidence, prevalence, costs, and impact on disability of common conditions requiring rehabilitation in the United States: stroke, spinal cord injury, traumatic brain injury, multiple sclerosis, osteoarthritis, rheumatoid arthritis, limb loss, and back pain. *Arch Phys Med Rehab* 2014; 95: 986–995. e981.
2. Rodgers MM, Pai VM and Conroy RS. Recent advances in wearable sensors for health monitoring. *IEEE Sens J* 2015; 15: 3119–3126.
3. Frontera WR, Bean JF, Damiano D, et al. Rehabilitation research at the National Institutes of Health: moving the field forward (executive summary). *Neurorehabil Neural Repair* 2017; 31: 304–314.
4. Nagi SZ. Some conceptual issues in disability and rehabilitation. In: Sussman M (ed.) *Sociology and rehabilitation*. Washington, DC: American Sociological Society, 1965, p.100.
5. World Health Organization. International classification of impairments, disabilities, and handicaps: a manual of classification relating to the consequences of disease, published in accordance with resolution WHA29. 35 of the Twenty-ninth World Health Assembly, May 1976, 1980.
6. World Health Organization. *International Classification of Functioning,* Disability and Health: ICF. World Health Organization, 2001.
7. Jette AM and Keysor JJ. Disability models: implications for arthritis exercise and physical activity interventions. *Arthritis Care Res* 2003; 49: 114–120.
8. Haghi M, Thurow K and Stoll R. Wearable devices in medical internet of things: scientific research and commercially available devices. *Healthc Inform Res* 2017; 23: 4–15.
9. Banaee H, Ahmed MU and Loutfi A. Data mining for wearable sensors in health monitoring systems: a review of recent trends and challenges. *Sensors* 2013; 13: 17472–17500.
10. Thilarajah S, Clark RA and Williams G. Wearable sensors and mobile health (mHealth) technologies to assess and promote physical activity in stroke: a narrative review. *Brain Impairment* 2016; 17: 34–42.
11. Moller AC, Merchant G, Conroy DE, et al. Applying and advancing behavior change theories and techniques in the context of a digital health revolution: proposals for more effectively realizing untapped potential. *J Behav Med* 2017; 40: 85–98.
12. Knapp M, Barlow J, Comas-Herrera A, et al. *The case for investment in technology to manage the global costs of dementia*. London: PIRU Publication, 2015.
13. Wang Q, Markopoulos P, Yu B, et al. Interactive wearable systems for upper body rehabilitation: a systematic review. *J Neuroeng Rehabil* 2017; 14: 20.
14. Iosa M, Picerno P, Paolucci S, et al. Wearable inertial sensors for human movement analysis. *Expert Rev Med Devices* 2016; 13: 641–659.
15. Iqbal MH, Aydin A, Brunckhorst O, et al. A review of wearable technology in medicine. *J R Soc Med* 2016; 109: 372–380.
16. Kraal JJ, Sartor F, Papini G, et al. Energy expenditure estimation in beta-blocker-medicated cardiac patients by combining heart rate and body movement data. *Eur J Prev Cardiol* 2016; 23: 1734–1742.
17. Reeder B and David A. Health at hand: a systematic review of smart watch uses for health and wellness. *J Biomed Inform* 2016; 63: 269–276.
18. Lim WK, Davila S, Teo JX, et al. Beyond fitness tracking: the use of consumer-grade wearable data from normal volunteers in cardiovascular and lipidomics research. *PLoS Biol* 2018; 16: e2004285.
19. Shin JH, Kim MY, Lee JY, et al. Effects of virtual reality-based rehabilitation on distal upper extremity function and health-related quality of life: a single-blinded, randomized controlled trial. *J Neuroeng Rehabil* 2016; 13: 17.
20. Chen KH, Chen PC, Liu KC, et al. Wearable sensor-based rehabilitation exercise assessment for knee osteoarthritis. *Sensors* 2015; 15: 4193–4211.
21. Laver KE, Lange B, George S, et al. Virtual reality for stroke rehabilitation. *Stroke* 2018; 49: e160–e161.
22. Tieri G, Morone G, Paolucci S, et al. Virtual reality in cognitive and motor rehabilitation: facts, fiction and fallacies. *Expert Rev Med Devices* 2018; 15: 107–117.
23. Munroe C, Meng Y, Yanco H, et al. Augmented reality eyeglasses for promoting home-based rehabilitation for children with cerebral palsy. In: *The eleventh ACM/IEEE international conference on human robot interaction,* Christchurch, NZ, 7–10 March 2016, pp.565–565. New York, NY: IEEE Press.
24. McEwen D, Taillon-Hobson A, Bilodeau M, et al. Virtual reality exercise improves mobility after stroke: an inpatient randomized controlled trial. *Stroke* 2014; 45: 1853–1855.
25. Massetti T, da Silva TD, Crocetta TB, et al. The clinical utility of virtual reality in neurorehabilitation: a systematic review. *J Cent Nerv Syst Dis* 2018; 10: 1179573518813541.
26. Dorsch AK, King CE and Dobkin BH. *Neurorehabilitation technology*. New York, NY: Springer, 2016.
27. Alon G, Embrey DG, Brandsma BA, et al. Comparing four electrical stimulators with different pulses properties and their effect on the discomfort and elicited dorsiflexion. *Int J Physiother Res* 2013; 1: 122–129.
28. Springer S, Vatine JJ, Lipson R, et al. Effects of dual-channel functional electrical stimulation on gait performance in patients with hemiparesis. *Sci World J* 2012; 2012: 530906.
29. Kluding PM, Dunning K, O'Dell MW, et al. Foot drop stimulation versus ankle foot orthosis after stroke: 30-week outcomes. *Stroke* 2013; 44: 1660–1669.

30. Springer S, Vatine JJ, Wolf A, et al. The effects of dual-channel functional electrical stimulation on stance phase sagittal kinematics in patients with hemiparesis. *J Electromyogr Kinesiol* 2013; 23: 476–482.
31. Pool D, Blackmore AM, Bear N, et al. Effects of short-term daily community walk aide use on children with unilateral spastic cerebral palsy. *Pediatr Phys Ther* 2014; 26: 308–317.
32. El-Gohary M and McNames J. Human joint angle estimation with inertial sensors and validation with a robot arm. *IEEE Trans Biomed Eng* 2015; 62: 1759–1767.
33. Freeman C, Exell T, Meadmore K, et al. Computational models of upper-limb motion during functional reaching tasks for application in FES-based stroke rehabilitation. *Biomed Tech* 2015; 60: 179–191.
34. Kutlu M, Freeman CT, Hallewell E, et al. Upper-limb stroke rehabilitation using electrode-array based functional electrical stimulation with sensing and control innovations. *Med Eng Phys* 2016; 38: 366–379.
35. Sampson P, Freeman C, Coote S, et al. Using functional electrical stimulation mediated by iterative learning control and robotics to improve arm movement for people with multiple sclerosis. *IEEE Trans Neural Syst Rehabil Eng* 2016; 24: 235–248.
36. Noma T, Matsumoto S, Shimodozono M, et al. Novel neuromuscular electrical stimulation system for the upper limbs in chronic stroke patients: a feasibility study. *Am J Phys Med Rehabil* 2014; 93: 503–510.
37. Knutson JS, Gunzler DD, Wilson RD, et al. Contralaterally controlled functional electrical stimulation improves hand dexterity in chronic hemiparesis: a randomized trial. *Stroke* 2016; 47: 2596–2602.
38. Wang HP, Bi ZY, Zhou Y, et al. Real-time and wearable functional electrical stimulation system for volitional hand motor function control using the electromyography bridge method. *Neural Regen Res* 2017; 12: 133–142.
39. Kim T, Kim S and Lee B. Effects of action observational training plus brain–computer interface-based functional electrical stimulation on paretic arm motor recovery in patient with stroke: a randomized controlled trial. *Occup Ther Int* 2016; 23: 39–47.
40. Chen YL, Li YC, Kuo TS, et al. The development of a closed-loop controlled functional electrical stimulation (FES) in gait training. *J Med Eng Technol* 2001; 25: 41–48.
41. Jovic J, Fraisse P, Coste CA, et al. Improving valid and deficient body segment coordination to improve FES-assisted sit-to-stand in paraplegic subjects. In: *IEEE international conference on rehabilitation robotics,* June 27–July 1, 2011 Zurich, Switzerland. DOI: 10.1109/ICORR.2011.5975369.
42. Zhang Q, Hayashibe M and Azevedo-Coste C. Evoked electromyography-based closed-loop torque control in functional electrical stimulation. *IEEE Trans Biomed Eng* 2013; 60: 2299–2307.
43. Heller BW, Clarke AJ, Good TR, et al. Automated setup of functional electrical stimulation for drop foot using a novel 64 channel prototype stimulator and electrode array: results from a gait-lab based study. *Med Eng Phys* 2013; 35: 74–81.
44. Wegrzyk J, Ranjeva JP, Foure A, et al. Specific brain activation patterns associated with two neuromuscular electrical stimulation protocols. *Sci Rep* 2017; 7: 2742.
45. Alon G, Conroy VM and Donner TW. Intensive training of subjects with chronic hemiparesis on a motorized cycle combined with functional electrical stimulation (FES): a feasibility and safety study. *Physiother Res Int* 2011; 16: 81–91.
46. Khalifa S, Hassan M, Seneviratne A, et al. Energy-harvesting wearables for activity-aware services. *IEEE Internet Comput* 2015; 19: 8–16.
47. Khalifa S, Hassan M and Seneviratne A. Step detection from power generation pattern in energy-harvesting wearable devices. In: *2015 IEEE international conference on data science and data intensive systems,* Sydney, Australia, 11–13 December 2015, pp.604–610. DOI: 10.1109/Dsdis.2015.102.
48. Bassett DR Jr, Rowlands AV and Trost SG. Calibration and validation of wearable monitors. *Med Sci Sports Exerc* 2012; 44: S32.
49. Evenson KR, Goto MM and Furberg RD. Systematic review of the validity and reliability of consumer-wearable activity trackers. *Int J Behav Nutr Phys Act* 2015; 12: 159.
50. Han KT and Wang PC. Validity of research-grade actigraphy unit for measuring exercise intensity. *Int J Environ Res Public Health* 2017; 14: 511.
51. Simpson LA, Eng JJ, Klassen TD, et al. Capturing step counts at slow walking speeds in older adults: comparison of ankle and waist placement of measuring device. *J Rehabil Med* 2015; 47: 830–835.
52. Spagnolli A, Guardigli E, Orso V, et al. Measuring user acceptance of wearable symbiotic devices: validation study across application scenarios. In: Jacucci G, Gamberini L, Freeman J, et al. (eds.) *Symbiotic interaction*. Third International Workshop, Symbiotic 2014, Helsinki, Finland, 30–31 October 2014, Proceedings, pp.87–98. London: Springer.
53. Davis FD. *A technology acceptance model for empirically testing new end-user information systems: theory and results*. PhD Thesis, Massachusetts Institute of Technology, Cambridge, USA, 1985.
54. Venkatesh V, Morris MG, Davis GB, et al. User acceptance of information technology: toward a unified view. *MIS Q* 2003; 27: 425–478.
55. Li H, Wu J, Gao Y, et al. Examining individuals' adoption of healthcare wearable devices: an empirical study from privacy calculus perspective. *Int J Med Inform* 2016; 88: 8–17.
56. Norman D. *The design of everyday things: revised and expanded edition*. New York, NY: Basic Books (AZ), 2013.
57. Orji R and Moffatt K. Persuasive technology for health and wellness: state-of-the-art and emerging trends. *Health Inform J* 2018; 24: 66–91. DOI: 10.1177/1460458216650979.
58. Cancela J, Pastorino M, Tzallas AT, et al. Wearability assessment of a wearable system for Parkinson's disease remote monitoring based on a body area network of sensors. *Sensors* 2014; 14: 17235–17255.

59. Gövercin M, Költzsch Y, Meis M, et al. Defining the user requirements for wearable and optical fall prediction and fall detection devices for home use. *Inform Health Soc Care* 2010; 35: 177–187.
60. Crea S, Cipriani C, Donati M, et al. Providing time-discrete gait information by wearable feedback apparatus for lower-limb amputees: usability and functional validation. *IEEE Trans Neural Syst Rehabil Eng* 2015; 23: 250–257.
61. Ananthanarayan S, Sheh M, Chien A, et al. Designing wearable interfaces for knee rehabilitation. In: *Proceedings of the 8th international conference on pervasive computing technologies for healthcare,* 2014, pp.101–108. ICST (Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering). May 20–23, 2014 Oldenburg, Germany.
62. Orji R. *Design for behaviour change: a model-driven approach for tailoring persuasive technologies*. Doctoral dissertation, University of Saskatchewan, Canada, 2014.
63. Zhang X, Guo X, Lai K-h, et al. Understanding gender differences in m-health adoption: a modified theory of reasoned action model. *Telemed e-Health* 2014; 20: 39–46.
64. Venčkauskas A, Štuikys V, Toldinas J, et al. A model-driven framework to develop personalized health monitoring. *Symmetry* 2016; 8: 65.
65. Clawson J, Voida A, Patel N, et al. Mobiphos: a collocated-synchronous mobile photo sharing application. In: *Proceedings of the 10th international conference on human computer interaction with mobile devices and services,* Amsterdam, Netherlands, 2–5 September 2008, pp.187–195.
66. Lucero A, Keränen J and Jokela T. Social and spatial interactions: shared co-located mobile phone use. In: *CHI'10 extended abstracts on human factors in computing systems,* 2010, pp.3223–3228. New York, NY: ACM. April 10–15, 2010 Atlanta, GA, USA.
67. Lucero A, Jones M, Jokela T, et al. Mobile collocated interactions: taking an offline break together. *Interactions* 2013; 20: 26–32.
68. Patel NJ and Clawson J. Designing and evaluating mobile systems for collocated group use. In: *Proceedings of the 13th international conference on human computer interaction with mobile devices and services,* 2011, pp.765–768. New York, NY: ACM. August 30–September 2, 2011 Stockholm, Sweden.
69. Lucero A, Clawson J, Fischer J, et al. *Mobile collocated interactions with wearables: past, present, and future*. Berlin: Springer, 2016.
70. Benford S, Crabtree A, Flintham M, et al. Can you see me now? *ACM Trans Comput Hum Interact* 2006; 13: 100–133.
71. Hall ET. A system for the notation of proxemic behavior. *Am Anthropol* 1963; 65: 1003–1026.
72. Wicks P, Massagli M, Frost J, et al. Sharing health data for better outcomes on PatientsLikeMe. *J Med Internet Res* 2010; 12: e19.
73. Lee JM, Hirschfeld E and Wedding J. A patient-designed do-it-yourself mobile technology system for diabetes: promise and challenges for a new era in medicine. *JAMA* 2016; 315: 1447–1448.