



# A Systematic Review of Wearable Sensors and IoT-Based Monitoring Applications for Older Adults – a Focus on Ageing Population and Independent Living

Mirza Mansoor Baig<sup>1</sup> · Shereen Afifi<sup>1</sup> · Hamid GholamHosseini<sup>1</sup> · Farhaan Mirza<sup>1</sup>

Received: 24 February 2019 / Revised: 10 May 2019 / Accepted: 30 May 2019 / Published online: 15 June 2019  
© Springer Science+Business Media, LLC, part of Springer Nature 2019

## Abstract

This review aims to present current advancements in wearable technologies and IoT-based applications to support independent living. The secondary aim was to investigate the barriers and challenges of wearable sensors and Internet-of-Things (IoT) monitoring solutions for older adults. For this work, we considered falls and activity of daily life (ADLs) for the ageing population (older adults). A total of 327 articles were screened, and 14 articles were selected for this review. This review considered recent studies published between 2015 and 2019. The research articles were selected based on the inclusion and exclusion criteria, and studies that support or present a vision to provide advancement to the current space of ADLs, independent living and supporting the ageing population. Most studies focused on the system aspects of wearable sensors and IoT monitoring solutions including advanced sensors, wireless data collection, communication platform and usability. Moderate to low usability/user-friendly approach is reported in most of the studies. Other issues found were inaccurate sensors, battery/ power issues, restricting the users within the monitoring area/ space and lack of interoperability. The advancement of wearable technology and the possibilities of using advanced IoT technology to assist older adults with their ADLs and independent living is the subject of many recent research and investigation.

**Keywords** Ageing population · Independent living · IoT · Wearable devices · Wearable technology · Older adults · Falls

## Introduction

In recent years, there has been an ever-growing need for a sustainable solution/system to support ageing population, independent living, and activities of daily life for older adults. Injuries in older adults are common worldwide, and ageing

further contributes to the severeness such as in case of falls. Therefore, age-related injuries represent one of the most common causes of long-lasting pain, functional impairment, disability and death in older adults [1]. The rate of hospital admission due to falls for people aged 60 and over in Australia, Canada and the United Kingdom ranges from 1.6 to 3.0 per 10,000 population per annum [2–5]. One out of ten falls in older adults results in injuries such as hip fractures, subdural hematomas, deep tissue injuries and head injuries [5]. In addition to physical injury, falls can also have psychological and social consequences. Fear of falling and post-fall anxiety syndrome are well-recognized as negative consequences of falls. The loss of self-confidence that leads to an inability to ambulate safely can result in self-imposed functional limitations.

Moreover, Wearable Sensors (WS) systems are emerging as an effective tool for prevention, early detection and management of Activity of Daily Life (ADLs) and falls among older adults. As WS, smart textiles and body-worn garments become smaller, cheaper and more consumer-accessible, it is expected that they will be used more extensively across a wide variety of contexts. The expansion of wearable/IoT systems

---

This article is part of the Topical Collection on *Mobile & Wireless Health*

✉ Mirza Mansoor Baig  
mirza.baig@aut.ac.nz; mirzamansoor01@gmail.com

Shereen Afifi  
shereen.afifi@aut.ac.nz

Hamid GholamHosseini  
hgholamh@aut.ac.nz

Farhaan Mirza  
farhaan.mirza@aut.ac.nz

<sup>1</sup> School of Engineering, Computer and Mathematical Sciences, Auckland University of Technology, Private Bag 92006, Auckland 1142, New Zealand

for data collection offers the potential for user-engagement and self-management of age-related illness and diseases [6].

Exploiting IoT technologies have been studied for developing ambient assisted living systems for healthcare. However, many challenges exist for achieving reliable and effective systems with high performance [7]. WS have been widely used in various fall detection systems for continuous monitoring, whereas using wearable devices often limits independent ADLs of older adults [8]. IoT and WS technology should be efficiently and widely used to contribute to falls prediction and prevention for the ageing population [9].

We aim to review and analyse the current advancements in the area of wearable technologies and IoT-based monitoring for older adults. Additionally, this review highlights challenges, barriers and opportunities for sustainable adoption of WS and IoT in wider healthcare settings. This review is the continuation of previous literature reviews conducted on WS and IoT systems [2–5, 10–12].

## Methodology

We chose the preferred reporting items for systematic reviews and meta-analyses (PRISMA) as the systematic review methodology [13]. A total of four databases were searched, including PubMed, Scopus, SpringerLink and the IEEE Xplore Digital Library. All databases were searched using keywords “Wearable Sensors” and “Activities of Daily Life” or “Wearable Monitoring” or “Internet of Things” or “IoT for Older Adults” or “ADLs” and “Falls in older adults”. Additionally, we searched the terms ‘elderly’ to avoid excluding paper on older adults and various combinations such as ADLs/ Falls/ Elderly/ IoT/ Sensors/ old age group.

## Articles selection and exclusion criteria

One of the authors conducted an initial screening of the retrieved records. Duplicated articles were eliminated, and additional records were excluded after reviewing individual titles and abstracts. A second author then reviewed the included studies and evaluated the full-text articles or eligibility. The eligibility criteria for inclusion in the review were:

1. Original articles mainly published as a journal article
2. Paper published or reported during 2015 (inclusive) and 2019
3. Wearable sensors/ IoT (hardware integrated with software) for older adult monitoring solution was the primary subject of this study
4. Targeted towards ageing population and independent living only
5. Written and published in English

We excluded articles that were not considered original research, such as letters to the editor, comments or reviews. Because this review paper focused on WS and IoT, we also excluded studies that solely tracked activity, exercise, video surveillance and other generic health and well-being applications.

## Article search results

Initially, 327 studies were identified through database searching. After excluding duplicated records, 234 records were eligible for screening. A total of 193 records did not meet our inclusion criteria based on the initial screening. And 41 studies were included to be evaluated for eligibility. Full-text records were retrieved and reviewed by two authors. After excluding irrelevant studies, 14 articles were selected for the final review. The study selection process is depicted in Fig. 1 and a detail description of the included studies is shown in Table 1.

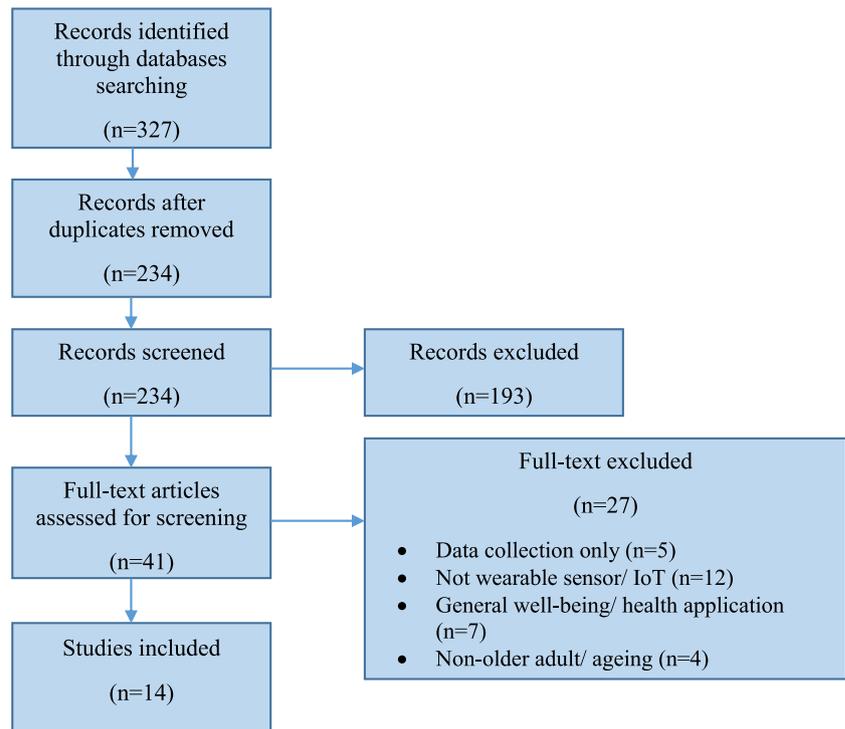
## Overview of wearable sensor and IoT systems for older adults

The subject of advanced WS and IoT technologies for supporting the independent lifestyle of older adults has been an active research area. The selected 14 articles have been analysed in this section and summarised in Table 1.

## Applications on activities of daily life monitoring and independent living

A fully integrated and low power footwear-based wearable system “SmartStep” using insole sensors was presented for activity monitoring [20], while extended and validated for accurate recognition of ADLs [21]. The SmartStep consists of pressure sensors, a 3D accelerometer and a 3D gyroscope integrated on a CC2540 system on chip that is embedded in an insole. A performance comparison was introduced for comparing the SmartStep with a wrist-worn sensor (combining accelerometer and gyroscope), and a combination of both sensors, targeting classification of a broader set of ADLs. The results of the adopted free-living study showed that the SmartStep recorded the best for the perceived comfort, where the overall agreement with ActivPAL was 82.5 and 97% according to the laboratory study.

A modular decision support framework was proposed for improving independent living and aging well based on geriatric depression case study [22]. The proposed decision system consists of three main components, trend analysis, decision support core, and risk prediction and assessment. The proposed system is based on statistical process control for identifying trends and fuzzy cognitive maps learning for depression

**Fig. 1** The study selection process

classification. The presented framework adopted the FCM-DDNHL classification method, where an estimated mean value of 78.66% was achieved for the classification accuracy.

A front-door events classification algorithm was proposed aiming to detect the forget event of older adults in smart houses [23]. A novel brief-return-and-exit (BRE) event classification was introduced targeting non-invasive detection of forgetting event using wireless binary sensors. Results demonstrated a positive correlation between the number of exits, BRE events and BRE percentage, which shows that the proposed forget event detection method could help in evaluating people with dementia.

A data-driven smart home system was introduced, which used web technologies for connecting IoT devices [24]. This study focused on proposing a web-based system targeting the ease of identifying ADLs from sensor data, as well as connecting identified ADLs to controlling actuators. A method of monitoring ADLs was introduced using commercial sensors to record easily distinguished activities while controlling actuators at home by using user-defined rules to show a summary of ADLs. A prototype system was implemented for the proposed design of a data-driven process including log aggregation, activity recognition, and device control steps.

A wrist-wearable accelerometer-based solution was presented for improving fall detection of older adults [25]. A threshold-based peak detection approach was used and extended with an optimization stage for tuning the threshold. The feature extraction stage was also extended to balance the classes of the dataset. Alternative classifiers were analysed

to optimize computation and adaptability, aiming to embed within a smart wristbands/phones. Many different published datasets were applied in this study, in addition to a comprehensive comparison to analyze various solutions for fall detection. Results showed that using SVM model could optimize the specificity and number of false alarms.

A smartphone-based solution was presented for remote and non-invasive monitoring of older adults in smart cities that is based on smartwatch usage [26]. The proposed architecture includes a wearable smartwatch, home sensors and three Android smartphones. The user smartphone handles WS, while the home smartphone/tablet manages home sensors and ambient assisted living's devices. The caregiver smartphone receives data and alerts to allow user monitoring. A framework was adopted for simplifying data collection and management of different external connected devices and sensors in Android applications. The proposed smartphone-based approach (ambient assisted living application) is feasible to achieve non-invasive monitoring and improve the independent living of older adults.

A real-time online assessment and mobility monitoring framework based on a smartwatch was proposed, incorporating a smartwatch application and a remotely-connected server [27]. An infrastructure was designed for sensor and user-reported data collection, transmission, visualization, and analysis for the targeted framework. The smartwatch application collects sensor and user-reported data for processing and transmitting to the remote server, where data is collected and retrieved for remote monitoring as well as data visualization

**Table 1** Summary of the selected papers related to the WS and IoT-based systems

| Author and year                   | Target area or population   | Study aims   | Platform/ sensors used  | Outcomes/ findings   |
|-----------------------------------|---|--|---|--|
| J. Yuan et al. 2015 [14]          | Fall detection and classification of ADLs for eldercare centre  | To develop power-efficient interrupt-driven fall detection and ADLs classification algorithms using a wrist-worn wearable device                                 | Wrist-worn wearable device of a CC2430 chip (8051 MCU with a built-in ZigBee Transceiver from Texas Instruments), a LED, a buzzer and an ADXL345 accelerometer  | The implemented algorithms based on MEMS accelerometer using interrupt-driven approach save power and bandwidth to be implemented efficiently on MCUs  |
| P. Pierleoni et al. 2016 [15, 16] | A waist-worn detector for fall detection of older adults  | To develop a wearable device based on AHRS and barometric sensor to detect all kinds of falls  | Fall detector of ATmega328 MCU with a 3-axis accelerometer, a 3-axis gyroscope, a 3-axis magnetometer, and a barometric sensor  | The developed system is extremely efficient for fall detection with 100% sensitivity   |
| L. Zhu et al. 2017 [17]           | Detecting movements and sudden falling of older adults by using RFID tags   | To implement a novel passive RFID tag-based fall detection system using RSS and Doppler frequency  | A unique 2 × 2 Alien RFID tag was used with a Speedway Revolution R420 RFID reader and an E9208PCRFN antenna  | A prototype monitoring system was implemented with conducted extensive experiments achieving a high accuracy (98%) for behaviour identification  |
| D. Yacchirema et al. 2019 [18]    | Detecting falls and ADLs of older adults in indoor environments using IoT and ensemble-RF classifier                    | To develop a fall detection system exploiting IoT and the ensemble machine learning algorithm for classifying data collected from a wearable device              | The system consists of a wearable device (a 3D-axis accelerometer sensor embedded in a 6LowPAN), a wireless communication network, an IoT gateway, and Cloud services   | The system achieved above 94% for accuracy, precision, sensitivity, and specificity based on the experiment results from collection data, interoperability services, data processing, data analysis, alert emergency service, and cloud services |
| L. Maimoon et al. 2016 [19]       | A smart and connected home health monitoring system for making aging at home easier and safer for senior citizens       | Developing, evaluating, and commercializing a usable smart and connected home monitoring system to extended user functionalities at low cost                     | The system includes 4 object sensors and a WS (3-axis accelerometer-based) with an SOS alarm button and a gateway   | The fall detection system using the WS achieved 0.990 sensitivity and 0.984 specificity and the deep learning model (CNN+ RNN) showed 99.5% accuracy for identifying ADLs  |
| N. Hegde et al. 2018 [20, 21]     | Automatic recognition of ADLs using an insole-based activity monitor designed to be socially acceptable and comfortable | To validate the proposed insole-based activity monitor in recognition of a broad set of ADLs, while comparing to a wrist sensor and testing these in combination | A footwear-based wearable system comprises a 3D accelerometer, a 3D gyroscope and resistive pressure sensors implemented around a CC2540 system-on-chip with an 8051-processor core, BLE connectivity and flash memory buffer | The insole-based activity sensors scored the best on the perceived comfort and may present a compelling alternative or companion to commonly used wrist devices  |
| A.S. Billis et al. 2015 [22]      | Evaluating the progression of depressive symptoms (Geriatric depression case-study)                                     | To develop a modular decision support framework for the promotion of independent living and aging well   | Decision support framework using statistical process control and an FCM-DDNHL method  | The proposed framework will detect elders either suffering from depressive systems or being at high risk in the future.  |
| T.-H. Tan et al. 2017 [23]        | Front-door events classification algorithm to detect the forget event of older adults in smart houses                   | To develop a novel device-free non-invasive front-door events classification algorithm for the forget event detection using wireless binary sensors              | Testbeds with ZigBee wireless module-based binary sensors   | The proposed algorithm is a useful tool for the forget event detection to evaluate people with dementia  |
| D. Seo et al. 2016 [24]           | Monitoring older adults ADLs using a data-driven smart home system  | To develop a data-driven smart home system based on web technologies for connecting IoT devices  | A data-driven smart home system employing an ADLs monitoring method by using commercial sensors and controlling actuators   | The web-based system improved the ease of distinguishing ADLs from sensor data and connecting identified ADLs to controlling actuators aiming to show a summary of ADLs to monitor people  |

**Table 1** (continued)

| Author and year                  | Target area or population   | Study aims  | Platform/ sensors used   | Outcomes/ findings  |
|----------------------------------|---|---|--|---|
| S. B. Khojasteh et al. 2018 [25] | Improving fall detection of older adults using an on-wrist wearable accelerometer   | To develop a wrist wearable solution for improving fall detection by adding optimization stages   | A 3D-axis accelerometer-based wrist-worn on a smart wristband with a peak detection optimization stage, dataset balancing stage and alternative machine learning methods                         | The rule-based systems represent a promising research line similar to neural networks while reducing computational cost. Support vector machine achieved a high specificity   |
| P. Bellagente et al. 2018 [26]   | Remote and non-invasive monitoring older adults in smart cities using a smartphone- and smartwatch-based solution   | To develop an ambient assisted living application (smartphone-based solution) for remotely monitoring older adults in a non-invasive way to improve the lifestyle | The proposed architecture incorporates a wearable smartwatch, home sensors and three Android smartphones with an android app-based framework for integrating connected sensors                   | A versatile and scalable sensory system was presented and simplified with adopting a framework to handle various external devices in Android applications. An ambient assisted living application was achieved for enhancing independent living of older adults |
| M. Kheirkhahan et al. 2019 [27]  | Real-time online assessment and mobility monitoring framework for collecting data simultaneously in domains of physical activity, mobility, EMA, patient-reported outcomes, and intervening health events | To develop a framework for real-time remote monitoring by integrating a smartwatch-based application and a remotely-connected server                              | An infrastructure for sensor and user-reported data collection, transmission, visualization, and analysis, where the workload is distributed among the smartwatch application and server program | The smartwatch-based framework integrating sensor-based and user-reported data collection allows for data visualization and summary statistics in real-time and it meets some of the major requirements for the next generation of IoT-based Health             |

and analysis in real-time. The framework is promising for the next generation of IoT-based mHealth, offering an interactive interface and remote application configuration in addition to server features for flexible online customization. Moreover, the smartwatch accelerometer sensor achieved highly correlated results with a validated and research-grade accelerometer.

### Applications on falls detection and falls prevention

A smart and connected home health monitoring system was presented for senior care at home [28]. The proposed system has both hardware and software components. The hardware components consist of four object sensors, a wearable human sensor with an alarm button and a gateway, while the software components include data collection API, a database, an analytics engine and a web portal. A fall detection system using the WS was proposed, which is based on hidden Markov models with sensor orientation calibration methods. The developed model achieved 0.990 and 0.984 for sensitivity and specificity respectively. In addition, a deep learning-based model (CNN + RNN) was proposed to process accelerometer readings from the wearable and object sensors for recognizing ADLs, showing 99.5% accuracy from the used CNN model.

A fall detection algorithm and ADLs classification algorithm were proposed based on a wrist-worn wearable device to be implemented on microcontrollers units (MCUs) [14]. The proposed algorithms are power-efficient that are capable of implementing on 8-bit MCUs with limited clock speed and memory. Both algorithms employed an interrupt-driven method based on a recent digital Micro-Electro-Mechanical Systems (MEMS) accelerometer that supports interrupts and data buffering. The used approach is more power-efficient and different from conventional algorithms by decreasing time dependency on the host MCU. The proposed classifier achieved 94.97% accuracy as well as saving power and bandwidth.

A waist-worn detector was presented for fall detection of older adults, which utilized an Attitude and Heading Reference System (AHRS) combining a 3-axis accelerometer, a 3-axis gyroscope and a 3-axis magnetometer [15]. A barometer sensor was integrated into the targeting device to improve the efficiency and performance of the system by measuring the altitude variation in a fall [16]. Three different experimental protocols of falls and ADLs were adopted for evaluating the developed fall detection system. The results demonstrated better performance compared to existing conventional fall detection systems exist in the literature through using the four combined sensors with the data fusion algorithms efficiently.

A novel fall detection system was implemented based on simple passive Radio Frequency Identification (RFID) tags and exploiting the Doppler frequency value for fall detection [17]. The RSS was used to detect a static state and the Doppler

effect value was used for identifying a fall action of the older adults. A Wavelet Transform (WT) was applied for pre-processing the RF signal, while a support vector machine classifier was used for fall detection. In addition, a monitoring system's prototype called "TagCare" was introduced and evaluated using extensive experiments, showing a high accuracy for efficient movement and fall detection in real life.

A fall detection system for older adults in indoor environments was presented, which is based on IoT and a Big Data model "Ensemble-Random Forest (RF)", exploiting the machine learning processing algorithms [18]. The proposed system utilized a 3D-axis accelerometer embedded into a 6LoWPAN wearable device for capturing data in real time, to be processed and analysed by the employed ensemble-RF model. For achieving high performance and efficient system, the ensemble-RF classifier was selected based on a comparative study based on testing and analysing other three machine learning algorithms for fall and ADLs detection. The proposed system was evaluated for detecting three types of both falls and ADLs, where a high success rate of above 94% was achieved for accuracy, precision, sensitivity, as well as specificity.

## Challenges and barriers to the wider adoption of WS and IoT applications

The next generation of WS and IoT systems is likely to improve the quality of human life by assuring high comfort while increasing the intelligent use of limited resources. Further improvements in textile sensors design, signal quality, miniaturization and data acquisition techniques are required to fulfil these expectations. Figure 2 shows the overview model of WS/IoT systems and lists four key areas which are currently limiting the wider clinical adoption of wearable technology, especially among older adults. The following sections elaborate on the issues pertaining to these four key areas. Table 2 summaries the issues and challenges related to WS and IoT devices.

### Wearable sensors and IoT devices

The number of biosensors used in current WS is generally large and requires specific on-body placement or body postures to provide reliable measurements [29, 42]. One of the technical barriers when using WS and IoT applications is the obstruction of feature extraction from the signal due to motion artefacts, body movement or respiration and this needs to be resolved in order to collect high-quality data [30]. A study by Etemadi et al. [31] utilized advanced signal processing to collect accurate and reliable seismocardiography (SCG). To increase the quality and accuracy of the SCG, linear filtering, detecting the R-wave peak timings from the ECG, and using

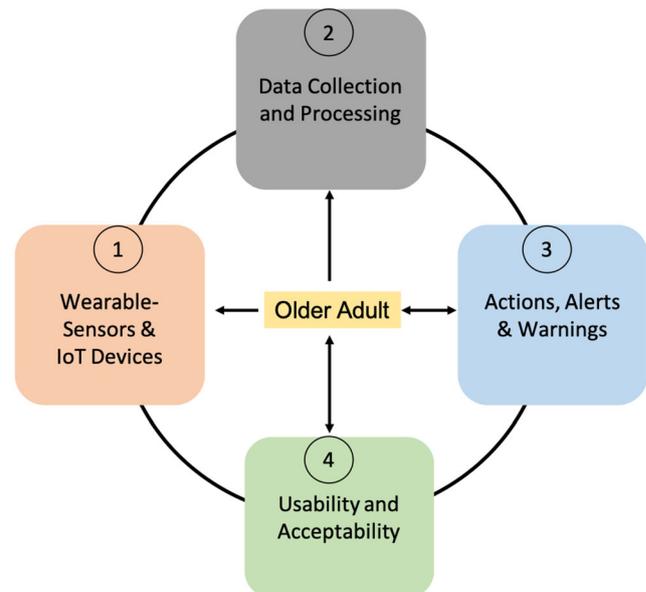


Fig. 2 Overview of WS and IoT-based systems

these timings as a fiduciary for ensemble averaging the SCG were implemented.

In a similar study that investigated biofeedback training for emotion management and patient monitoring [32], the signals collected were unreliable and disturbed by a variety of noises. Most body-worn applications report that the system's accuracy is hampered by noises such as electromagnetic interference of power line, poor quality of contact between the electrode and the skin, baseline wander caused by respiration, electro-surgical instruments and movement of the patient's body. Most of these noises cannot be filtered out completely over the hardware-processing unit due to the processing limitations. Therefore, it is necessary to filter out these noises as much as possible in the software platform. The researchers from this study adopted the Butterworth notch filter and finite impulse response band-pass filter to eliminate power line interference and baseline wander, and a novel multi-scale mathematical morphology (3 M) filter to reduce the impact of the non-linear noises caused by poor electrode contact and motion artefacts.

### Data collection and processing

One of the most common issues with wearable systems is the delay in providing results and generating alerts due to data loss, buffering, network communication, monitoring or processing [33–35]. These systems were developed for specific setup and care settings to assist patients' specific need. Wearable systems using 3G/4G data suffer connectivity issues due to the remote network, low signal strength in remote places, low battery lifetime, low transmission speed, thus resulting in delay or low-quality data for periods of short time [33, 43]. To address these issues, a cross-layer framework has

**Table 2** Issues and challenges on data collection, data processing, usability and acceptability related to WS and IoT devices

| Reference | Application area   | Challenges and gaps   |
|-----------|--|---|
| [29]      | Review of the IoT applications   | Size of the device and accuracy of the collected data   |
| [30]      | Interoperability of the wearable devices   | Poor feature extraction from the signal due to motion artefacts, body movement or respiration           |
| [31]      | Advanced signal processing to collect accurate and reliable seismocardiography (SCG) | Accuracy and reliability of the sensor data   |
| [32]      | Wearable Sensors for ECG monitoring  | Signals collected were unreliable and disturbed by a variety of noises.                                 |
| [30]      | User's posture during rehabilitation exercise  | Usability and accuracy  |
| [33–35]   | Data collection and data processing techniques                                       | Data loss, buffering delay, network/ communication errors, and outcome delays due to complex processing |
| [36, 37]  | Connected network and data security for hospital settings                            | Privacy, security and safety of the transmitted data  |
| [38]      | ECG monitoring   | Poor signal quality, disturbances and noise in the signal   |
| [38, 39]  | Sensor-based WS and IoT applications   | Delays in processing, noise/ signal processing and quality of the collected data                        |
| [40]      | Machine learning for big data in healthcare  | Saleability and big data processing   |
| [41]      | Usability and acceptability performance measurements                                 | Low user acceptability and low usability in other use-cases   |

been developed based on unequal resource allocation to support secure wireless wearable data encryption and transmission [36, 37]. The low battery life issue occurs due to continued connectivity of device/sensor with the Bluetooth, WiFi or 3G/4G networks [38, 44, 45]. Moreover, if the power supply is not an issue, then the mobility of the device may become problematic, especially for older adults.

A portable ECG monitoring device developed by Lee et al. [38] can easily measure the ECG by connecting the measuring module to a patch with a minimized electrode array using a snap button. The measuring module is small (38 mm wide, 38 mm long, and 7 mm thick). The weight of the module including the battery is 10 g. The study reported that an ECG signal was collated using a commercial device that was similar to the conventional Holter monitor. The study reported that even with the wires firmly fixed, the ECG signal quality was often disturbed, as the wires moved depending on the subject's body movements. According to another study, the ratio of motion peaks to normal peaks was estimated as being about 10% when the ECG was taken from a freely moving patient using the Holter monitor [44]. For this reason, ECGs obtained using Holter monitors are limited, and algorithms used to eliminate noise from the data have been actively developed.

The current focus is to detect and exclude the generated noise from the data analysis/ processing phase. However, it is also equally important to reduce the occurrence of noise itself in the first instance, and this is a common issue with almost all sensor-based WS and IoT [38, 39]. In real-time scenarios, wearable data transmission often requires some data processing and therefore network delays. Some systems produced good results when tested offline but reported delay when tested in real-time [33]. Prakash et al. [46] demonstrated an efficient connectivity and communication framework in a

real-time wireless hospital sensor network, which could be adopted for acute care settings.

### Techniques for risk assessment, actions and warnings

Machine learning and artificial intelligence techniques have the potential to transform healthcare services by improving diagnostics and predictive modelling. The utilisation of these techniques in healthcare is still emerging, as it requires considerable analysis to provide reliable results that clinicians would use. The raw data collected from WS would provide a data source that did not exist before. These data would undergo further analysis to be transformed into meaningful and actionable information. This process would be supported by real-time machine learning processing techniques. Advanced signal processing algorithms for faster processing, low power consumption, low cost, and less complexity have been applied to healthcare settings. A medical grade remote monitoring system with reliability exceeding 99% has been developed, but a 2.4-s initial buffering delay, as well as small processing and network delay, were reported [37].

The current state of wearable monitoring systems can be further enhanced with the integration of such techniques into the hardware or in the cloud computing platforms for real-time processing. From a software point-of-view, processing big data is usually linked with programming paradigms [40]. Several open-source frameworks such as Hadoop [47] are being used to set up distributed database environments via a scalable architecture. This provides a basis for further usage via other tools (such as Cascading, Pig, Hive) [47] that enable developing applications to process vast amounts of data (by order of terabytes) on commodity clusters. However, when combined with continuous streams of pervasive health monitoring, this also requires capacities for iterative and low-

latency computations, which depends on sophisticated models of data caching and in-memory computation. Thus, other frameworks such as Storm and Spark have been created to fulfil this gap [47].

An accurate expert/support system could be achieved by utilising the insights gained by taking a machine-learning approach to the data collected via WS and/or wireless medical/IoT devices [48]. A cloud-based clinical decision support system embedded with machine learning techniques could include drug-drug allergies, individualised drug dosing, clinical risk scores/ scales and gaps in care – alerts, reminders, warnings and notifications [49–51].

### Usability and acceptability

We believe that one of the core advantages of WS systems is the patient's (user's) self-engagement with the treatment – which is often missing. There is a shift in wider thinking of WS and IoT systems as 'only data collectors' to viewing them as being self-engaging and motivating systems which allow rich interactions between patients and clinicians [52–54]. User-engagement and user-interaction are some of the important uptake factors among consumers (non-clinical care settings) for wearable technologies [34, 55, 56].

There are very few existing studies that address usability and acceptability challenges for health monitoring. Usability and acceptability performance is evaluated based on different measurements of willingness to use and keep, simplicity, reliability, wearable time, satisfaction level and ADLs interference [41]. The existing WS and IoT devices need modifications in terms of manufacturing and technical capabilities to address critical issues such as battery/power consumption, restricting the user's movements within a confined area/space and high cost. Interoperability is required for IoT applications to support the electronic health record of the user and also to maintain the large health data, especially related to long-term condition or chronic care conditions [57, 58].

A behavioural change of older users is reported with incorporating related information of estimated fall risk to the wearable system, as well as improving the level of user acceptability and awareness [59]. Different processes are identified for facilitating the user-engagement with remote measuring technology. A feedback loop model is proposed to work on identified barriers and facilitators, aiming to moderate a point of disengagement towards a sustainable engagement through a reengagement process [60]. However, specifically designed experimental studies are required for further evaluation of usability and acceptability.

User feedback is one of the essential components for developing an acceptable system that developers should carefully consider. Besides, incorporating behavioural and emotional change models should be considered in the requirements engineering phase, as well as in development, evaluation and

deployment phases. The usability and acceptability challenge for older patients is analysed with a comparative study of using four selected wearable/mobile devices. The study concluded that both hardware/device designers and system developers should cooperate towards ease-of-use and comfort WS and other special needs of older people. Consequently, usability and acceptability of wearable devices should meet the challenging demands and concerns of the older adults, while achieving an efficient and reliable monitoring system [61–63].

### Discussion and conclusions

In this paper, we reviewed 14 WS and IoT-based applications by selecting studies published between 2015 and 2019 to evaluate their technological advancements and their implementation of advanced WS and IoT devices supporting the ageing population and independent living of older adults. We focused on identifying three main challenges regarding data collection and processing; techniques for risk assessment; usability and acceptability of WS and IoT in wider healthcare settings. We analysed design concepts of WS and IoT systems, identified key specifications and parameters such as the position of the sensors and quality of the signals, real-time/ offline data processing, wider system integrations, data quality and user-engagement and user-interaction that requires attention. Also, we have highlighted the potential of such technologies when implemented and tested in the clinical environment [51, 64].

With the ever-growing use of WS and IoT systems, end-user acceptability is an important aspect of the design and development of such systems. The acceptance of any system in the healthcare domain depends on user-awareness, as well as clinician and patient acceptance. Moreover, this review signifies the heavy dependency of wearable monitoring systems on communication technology, sensor connectivity, cost when using mobile data (4G/5G) for data communication for continuous usage and quality of real-time data collection. Data connectivity is one of the main drawbacks of deployed WS and IoT where patients are 'constrained' within fixed spaces fitted with monitoring devices with small Bluetooth range [45, 53, 65–67]. Therefore, further research and development in communication technology, sensor connectivity, and quality of real-time data collection are essential for adoption and use of wearable sensors and IoT-based monitoring applications in senior living.

We also found that majority of WS and IoT applications are struggling with management of battery/power consumption, real-time data processing vs. offline delayed processing, data collection vs. data processing and transmission and quality of the data/ signal. Moreover, end-user acceptability and usability of the application has been neglected in most of the recent research. We believe the usability and acceptability issues

could be addressed by; (1) an early engagement with the wider stakeholders, end-users and clinicians, (2) understanding the issue/ problem and co-designing the solution with end-user (clinical and non-clinical) and (3) adapting the best approach to present the information meaningful and easy to understand.

An advanced wearable application named Hexoskin™ [68] (ClinicalTrials.gov Identifier: NCT02591758) with a smart vest and embedded sensors is available for the consumers. It provides the user with seamless and fully integrated information regarding heart rate, breathing rate, minute ventilation, heart rate maximum, resting heart rate, heart rate recovery, maximal oxygen uptake and cadence. It uses textile-integrated sensors for activity, respiration and heart rate and intelligently makes use of the three-cardiac dry and textile electrodes. The cardiac sensors for ECG uses 1 channel, 256 Hz, heart rate 30–220 beats/min, 1 Hz with QRS event detection, RR intervals and heart rate variability analysis. For breathing monitoring, the system uses two channels, 128 Hz; breathing rate 3–80 breaths per minute, 1 Hz; tidal volume (last inspiration) 80–10,000 mL, 1 Hz; minute ventilation (inductance plethysmography) 2–150 L/min, 1 Hz and inspiration and expiration events: 8 ms resolution. Hexoskin™ provides users with real-time and remote monitoring via secure Bluetooth connected mobile app (iOS and Android), a web dashboard, up to 14 h of battery life (rechargeable), free data storage in cloud and secure access anytime [68, 69]. Hexoskin™ allows users to download the raw data in machine readable format, as well as provide users with processed / meaningful data. The access to the application programming interfaces (APIs) and raw data in machine-readable format enables the healthcare professionals and researchers to mine the data for population health benefits.

A paradigm shift in healthcare delivery is occurring which has been made possible by the technological revolution in WS systems, the IoT, and the potential of employing machine learning, deep learning and artificial intelligence [43]. The treatment of many medical conditions is guaranteed to benefit from the use of wearable and IoT technology [43]. Consequently, WS and IoT applications are showing some potential for low-cost remote monitoring, supporting independent living, reducing falls among older adults, early detection of various long-term conditions and more. However, the presented technical challenges need to be fully understood and resolved before the WS, and IoT-based wearable sensing and IoT-based monitoring applications can be successfully used to support older people at home.

## Compliance with ethical standards

**Conflict of interest** Authors declare no conflict of interest.

**Ethical approval** This article does not contain any studies with human participants performed by any of the authors.

## References

1. Tinetti, M. E., and Kumar, C., The patient who falls. *JAMA* 303(3): 258–266, 2010.
2. Nguyen, H., Mirza, F., Naeem, M. A., and Baig, M. M., Falls management framework for supporting an independent lifestyle for older adults: A systematic review. *Aging Clin. Exp. Res.*:1–12, 2018.
3. Nguyen, H., Mirza, F., Naeem, M. A., and Baig, M. M., Detecting falls using a wearable accelerometer motion sensor. In: *Proceedings of the 14th EAI International Conference on Mobile and Ubiquitous Systems: Computing, Networking and Services*. ACM, 2017, 422–431.
4. Gholamhosseini, H., Baig, M. M., Meintjes, A., Mirza, F., and Lindén, M., Smartphone-based blood pressure monitoring for falls risk assessment: techniques and technologies. In: *Human Monitoring, Smart Health and Assisted Living: Techniques and Technologies*. Vol. 9, 2017, 203.
5. Baig, M. M., Gholamhosseini, H., and Connolly, M. J., Falls risk assessment for hospitalised older adults: A combination of motion data and vital signs. *Aging Clin. Exp. Res.* 28(6):1159–1168, 2016.
6. Sabesan, S., and Sankar, R., Improving long-term management of epilepsy using a wearable multimodal seizure detection system. *Epilepsy Behav.* 46:56–57, 2015.
7. Wan, J., Gu, X., Chen, L., and Wang, J., Internet of things for ambient assisted living: challenges and future opportunities. In: *Cyber-Enabled Distributed Computing and Knowledge Discovery (CyberC), 2017 International Conference on*. IEEE, 2017, 354–357.
8. Vallabh, P., and Malekian, R., Fall detection monitoring systems: A comprehensive review. *J. Ambient. Intell. Humaniz. Comput.* 9(6): 1809–1833, 2018.
9. Nguyen, H., Mirza, F., Naeem, M. A., and Baig, M. M., Falls management framework for supporting an independent lifestyle for older adults: A systematic review. *Aging Clin. Exp. Res.* 30(11):1275–1286, 2018. Journal article.
10. Baig, M. M., Gholamhosseini, H., and Connolly, M. J., A comprehensive survey of wearable and wireless ECG monitoring systems for older adults. *Med. Biol. Eng. Comput.* 51(5):485–495, 2013.
11. Banaee, H., Ahmed, M. U., and Loutfi, A., Data mining for wearable sensors in health monitoring systems: A review of recent trends and challenges. *Sensors* 13(12):17472–17500, 2013.
12. Baig, M. M., and Gholamhosseini, H., Smart health monitoring systems: An overview of design and modeling. *J. Med. Syst.* 37(2):9898, 2013.
13. Moher, D., Liberati, A., Tetzlaff, J., and Altman, D. G., Preferred reporting items for systematic reviews and meta-analyses: The PRISMA statement. *Ann. Intern. Med.* 151(4):264–269, 2009.
14. Yuan, J., Tan, K. K., Lee, T. H., and Koh, G. C. H., Power-efficient interrupt-driven algorithms for fall detection and classification of activities of daily living. *IEEE Sensors J.* 15(3):1377–1387, 2015.
15. Pierleoni, P., Belli, A., Palma, L., Pellegrini, M., Pernini, L., and Valenti, S., A high reliability wearable device for elderly fall detection. *IEEE Sensors J.* 15(8):4544–4553, 2015.
16. Pierleoni, P. et al., A wearable fall detector for elderly people based on AHRs and barometric sensor. *IEEE Sensors J.* 16(17):6733–6744, 2016.
17. Zhu, L., Wang, R., Wang, Z., and Yang, H., TagCare: Using RFIDs to monitor the status of the elderly living alone. *IEEE Access* 5: 11364–11373, 2017.
18. Yacchirema, D., de Puga, J. S., Palau, C., and Esteve, M., Fall detection system for elderly people using IoT and ensemble machine learning algorithm. *Pers. Ubiquit. Comput.*:1–17, 2019.
19. Maimoon, L. et al., SilverLink: developing an international smart and connected home monitoring system for senior care. In: *International Conference on Smart Health*. Springer, 2016, 65–77.

20. Hegde, N., and Sazonov, E., SmartStep: A fully integrated, low-power insole monitor. *Electronics* 3(2):381–397, 2014.
21. Hegde, N., Bries, M., Swibas, T., Melanson, E., and Sazonov, E., Automatic recognition of activities of daily living utilizing insole-based and wrist-worn wearable sensors. *IEEE journal of biomedical and health informatics* 22(4):979–988, 2018.
22. Billis, A. S., Papageorgiou, E. I., Frantzidis, C. A., Tsatali, M. S., Tsolaki, A. C., and Bamidis, P. D., A decision-support framework for promoting independent living and ageing well. *IEEE journal of biomedical and health informatics* 19(1):199–209, 2015.
23. Tan, T.-H., Gochoo, M., Jean, F.-R., Huang, S.-C., and Kuo, S.-Y., Front-door event classification algorithm for elderly people living alone in smart house using wireless binary sensors. *IEEE Access* 5: 10734–10743, 2017.
24. Seo, D., Yoo, B., and Ko, H., *Data-driven smart home system for elderly people based on web technologies*. Cham: Springer International Publishing, 2016, 122–131.
25. Khojasteh, S. B., Villar, J. R., Chira, C., González, V. M., and de la Cal, E., Improving fall detection using an on-wrist wearable accelerometer. *Sensors (Basel, Switzerland)* 18(5):1350, 2018.
26. Bellagente, P. et al., Remote and non-invasive monitoring of elderly in a smart city context. In: *Sensors Applications Symposium (SAS), 2018 IEEE*. IEEE, 2018, 1–6.
27. Kheirkhahan, M. et al., A smartwatch-based framework for real-time and online assessment and mobility monitoring. *J. Biomed. Inform.* 89:29–40, 2019.
28. Maimoon, L. et al., *SilverLink: developing an international smart and connected home monitoring system for senior care*. Cham: Springer International Publishing, 2017, 65–77.
29. Chen, E. T., The internet of things: opportunities, issues, and challenges. In: *The Internet of Things in the Modern Business Environment*. IGI Global, 2017, 167–187.
30. Chen, M., Ma, Y., Song, J., Lai, C.-F., and Hu, B., Smart clothing: Connecting human with clouds and big data for sustainable health monitoring. *Mobile Networks and Applications* 21(5):825–845, 2016.
31. Etemadi, M., Inan, O. T., Heller, J. A., Hersek, S., Klein, L., and Roy, S., A wearable patch to enable long-term monitoring of environmental, activity and hemodynamics variables. *IEEE Transactions on Biomedical Circuits and Systems* 10(2):280–288, 2016.
32. Wu, W., Zhang, H., Pirbhulal, S., Mukhopadhyay, S. C., and Zhang, Y. T., Assessment of biofeedback training for emotion management through wearable textile physiological monitoring system. *IEEE Sensors J.* 15(12):7087–7095, 2015.
33. Rault, T., Bouabdallah, A., Challal, Y., and Marin, F., A survey of energy-efficient context recognition systems using wearable sensors for healthcare applications. *Pervasive and Mobile Computing* 37:23–44, 2017.
34. Wu, J., Li, H., Cheng, S., and Lin, Z., The promising future of healthcare services: When big data analytics meets wearable technology. *Inf. Manag.* 53:1020–1033, 2016.
35. Thomas, S. S., Nathan, V., Zong, C., Soundarapandian, K., Shi, X., and Jafari, R., BioWatch: A noninvasive wrist-based blood pressure monitor that incorporates training techniques for posture and subject variability. *IEEE Journal of Biomedical and Health Informatics* 20(5):1291–1300, 2016.
36. Balamurugan, S., Madhukanth, R., Prabhakaran, V., and Shanker, R. G. K., Internet of health: Applying IoT and big data to manage healthcare systems. *International Research Journal of Engineering and Technology (IRJET)* 310:732–735, 2016.
37. Ghosh, A. M., Halder, D., and Hossain, S. A., Remote health monitoring system through IoT. In: *2016 International Conference on Informatics, Electronics and Vision (ICIEV)*. IEEE, 2016, 921–926.
38. Lee, W., Yoon, H., and Park, K., Smart ECG monitoring patch with built-in R-peak detection for long-term HRV analysis. *Ann. Biomed. Eng.*:1–10, 2016.
39. Kyriazakos, S. et al., eWALL: An intelligent caring home environment offering personalized context-aware applications based on advanced sensing. *Wirel. Pers. Commun.* 87(3):1093–1111, 2016.
40. Araújo, F. H., Santana, A. M., and Neto, P. d. A. S., Using machine learning to support healthcare professionals in making preauthorisation decisions. *Int. J. Med. Inform.* 94:1–7, 2016.
41. Klaassen, B., van Beijnum, B. J., and Hermens, H. J., Usability in telemedicine systems—A literature survey. *Int. J. Med. Inform.* 93: 57–69, 2016.
42. Rajput, D. S., and Gour, R., An IoT framework for healthcare monitoring systems. *International Journal of Computer Science and Information Security (IJCSIS)* 14(5):451, 2016.
43. Ribeiro, J., Wearable technology spending: a strategic approach to decision-making. In: *Wearable Technology and Mobile Innovations for Next-Generation Education*, 2016, 37.
44. Michard, F., A sneak peek into digital innovations and wearable sensors for cardiac monitoring. *J. Clin. Monit. Comput.*:1–7, 2016.
45. Iqbal, M. H., Aydin, A., Brunckhorst, O., Dasgupta, P., and Ahmed, K., A review of wearable technology in medicine. *J. R. Soc. Med.* 109(10):372–380, 2016.
46. Prakash, R., Ganesh, A. B., and Sivabalan, S., Network coded cooperative communication in a real-time wireless hospital sensor network. *J. Med. Syst.* 41(5):72, 2017.
47. Elsebakh, E. et al., Large-scale machine learning based on functional networks for biomedical big data with high performance computing platforms. *Journal of Computational Science* 11:69–81, 2015.
48. Miller, R. A., Diagnostic decision support systems. In: *Clinical Decision Support Systems*. Springer, 2016, 181–208.
49. Berner, E. S., and La Lande, T. J., Overview of clinical decision support systems. In: *Clinical Decision Support Systems*. Springer, 2016, 1–17.
50. Wright, A. et al., Analysis of clinical decision support system malfunctions: A case series and survey. *Journal of the American Medical Informatics Association* 23(6):1068–1076, 2016. <https://doi.org/10.1093/jamia/ocw005>.
51. Baig, M. M., Hosseini, H. G., and Lindén, M., Machine learning-based clinical decision support system for early diagnosis from real-time physiological data. In: *Region 10 Conference (TENCON), 2016 IEEE*. IEEE, 2016, 2943–2946.
52. Price-Haywood, E. G., Harden-Barrios, J., Ulep, R., and Luo, Q., eHealth literacy: Patient engagement in identifying strategies to encourage use of patient portals among older adults. *Population Health Management* 20:486–494, 2017.
53. Davis, S., Roudsari, A., Raworth, R., Courtney, K. L., and MacKay, L., Shared decision-making using personal health record technology: A scoping review at the crossroads. *J. Am. Med. Inform. Assoc.* 24:857–866, 2017.
54. Milani, R. V., and Franklin, N. C., The role of technology in healthy living medicine. *Prog. Cardiovasc. Dis.* 59:487–491, 2017.
55. Park, E., Park, E., Kim, K. J., Kim, K. J., Kwon, S. J., and Kwon, S. J., Understanding the emergence of wearable devices as next-generation tools for health communication. *Inf. Technol. People* 29(4):717–732, 2016.
56. Rupp, M. A., Michaelis, J. R., McConnell, D. S., and Smither, J. A., The impact of technological trust and self-determined motivation on intentions to use wearable fitness technology. In: *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*. Vol. 60, no. 1. SAGE Publications, 2016, 1434–1438.
57. Ullah, F., Habib, M. A., Farhan, M., Khalid, S., Durrani, M. Y., and Jabbar, S., Semantic interoperability for big-data in heterogeneous IoT infrastructure for healthcare. *Sustain. Cities Soc.* 34:90–96, 2017.
58. Kovacs, E., Bauer, M., Kim, J., Yun, J., Le Gall, F., and Zhao, M., Standards-based worldwide semantic interoperability for IoT. *IEEE Commun. Mag.* 54(12):40–46, 2016.

59. Wu, A. Y., and Munteanu, C., Understanding older users' acceptance of wearable interfaces for sensor-based fall risk assessment. In: *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*. ACM, 2018, 119.
60. Simblett, S. et al., Barriers to and facilitators of engagement with remote measurement technology for managing health: Systematic review and content analysis of findings. *J. Med. Internet Res.* 20(7): e10480, 2018.
61. Ahmadi, H., Arji, G., Shahmoradi, L., Safdari, R., Nilashi, M., and Alizadeh, M., The application of internet of things in healthcare: A systematic literature review and classification. *Univ. Access Inf. Soc.*:1–33, 2018.
62. Spanakis, E. G., Psaraki, M., and Sakkalis, V., Congestive heart failure risk assessment monitoring through internet of things and mobile personal health systems. In: *2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. IEEE, 2018, 2925–2928.
63. Malwade, S. et al., Mobile and wearable technologies in healthcare for the ageing population. *Comput. Methods Prog. Biomed.* 161: 233–237, 2018.
64. Yang, Z., Zhou, Q., Lei, L., Zheng, K., and Xiang, W., An IoT-cloud based wearable ECG monitoring system for smart healthcare. *J. Med. Syst.* 40(12):286, 2016.
65. Raja, K., Saravanan, S., Anitha, R., Priya, S. S., and Subhashini, R., Design of a low power ECG signal processor for wearable health system-review and implementation issues. In: *Intelligent Systems and Control (ISCO), 2017 11th International Conference on*. IEEE, 2017, 383–387.
66. Kumari, P., Mathew, L., and Syal, P., Increasing trend of wearables and multimodal interface for human activity monitoring: A review. *Biosens. Bioelectron.* 90:298–307, 2017.
67. Kurien, M., Trott, N., and Sanders, D., Long-term care for patients with coeliac disease in the UK: A review of the literature and future directions. *J. Hum. Nutr. Diet.* 29:617–623, 2016.
68. Jolicoeur, M., *Novel Vitality Indices Derived From the Hexoskin in Patients Affected With Angina Undergoing Coronary Revascularization or Medical Therapy (NOVA-SKIN)* [Clinical Trial]. 2016, 15 October 2016. Available: <https://clinicaltrials.gov/ct2/show/NCT02591758?term=hexoskin&rank=1>.
69. C. T. i. (Hexoskin). *Key Metrics delivered by Hexoskin*. 2016. Available: <http://www.hexoskin.com/pages/key-metrics-delivered-by-hexoskin>.

**Publisher's Note** Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.