IoT Wearable Sensors and Devices in Elderly Care: A Literature Review

Thanos G. Stavropoulos *, Asterios Papastergiou, Lampros Mpaltadoros, Spiros Nikolopoulos and Ioannis Kompatsiaris

Centre for Research & Technology Hellas, Information Technologies Institute, 6th Km Charilaou-Thermi, 57001 Thessaloniki, Greece; astepapa@iti.gr (A.P.); lamprosm@iti.gr (L.M.); nikolopo@iti.gr (S.N.); ikom@iti.gr (I.K.)

* Correspondence: athstavr@iti.gr; Tel.: +30-2311-257-738

Received: 15 April 2020; Accepted: 13 May 2020; Published: 16 May 2020

Abstract: The increasing ageing global population is causing an upsurge in ailments related to old age, primarily dementia and Alzheimer’s disease, frailty, Parkinson’s, and cardiovascular disease, but also a general need for general eldercare as well as active and healthy ageing. In turn, there is a need for constant monitoring and assistance, intervention, and support, causing a considerable financial and human burden on individuals and their caregivers. Interconnected sensing technology, such as IoT wearables and devices, present a promising solution for objective, reliable, and remote monitoring, assessment, and support through ambient assisted living. This paper presents a review of such solutions including both earlier review studies and individual case studies, rapidly evolving in the last decade. In doing so, it examines and categorizes them according to common aspects of interest such as health focus, from specific ailments to general eldercare; IoT technologies, from wearables to smart home sensors; aims, from assessment to fall detection and indoor positioning to intervention; and experimental evaluation participants duration and outcome measures, from acceptability to accuracy. Statistics drawn from this categorization aim to outline the current state-of-the-art, as well as trends and effective practices for the future of effective, accessible, and acceptable eldercare with technology.

Keywords: IoT; wearables; sensors; devices; elders; old age; AAL; Alzheimer’s; dementia

1. Introduction

The world’s population is increasingly aging [1]. People aged above 65 years old amount to 702.9 million in 2019, projected to reach 1548.9 million in 2050, marking a 120% increase. Likewise, people aged above 80 years old amount to 53.9 million in 2019, projected to reach 109.1 million in 2050, marking a 102.6% increase. This is causing a similar shift in terms of lifestyle and, naturally, healthcare needs, towards ailments associated primarily (but not exclusively) with elders. The most prominent of those is dementia, in its early and progressed forms, from mild cognitive impairment (MCI) to Alzheimer’s disease (AD), a neurodegenerative disorder with several cognitive and functional limitations. People living with dementia globally amount to 50 million in 2019 and are expected to triple to 150 million by 2050 [2]. Most of them (around 80%) are elders over 75 [3]. Seventy percent of them cannot live independently without assistance from a caregiver [4]. Yet, there is no solution for reversing cognitive-related challenges in the patient population. Holistic and objective information to clinicians about patient health status can drive tailored interventions to alleviate the ailments and slow down the progression of the disease. However, this imposes a huge burden to informal caregivers and healthcare professionals. The same burden is imposed by physical frailty, inability to conduct daily activities independently, and cardiovascular disease (CVD) associated with old age [5].
In this light, the Internet of Things (IoT) is a promising solution to offer continuous, objective, and holistic monitoring, alleviating the burden of human caregiver effort and supporting clinical decision making. IoT is a generally new concept, providing the possibility of healthcare monitoring with the use of wearable devices. IoT can be defined as a network of physical objects with embedded technology for sensing, interacting with the environment, and offering autonomous communication. Wearable devices with sensors are a popular application of IoT that attracted much attention in the last decade, to the point of affordable fitness applications in the retail market. Such wristbands or smartwatches can monitor an individual’s activities through day and night, without much interruption and discomfort [6]. The range of wearables is widening from watches to smart textiles, electronics in clothes, belt-worn PCs, and smart glasses. Analytics and artificial intelligence (AI) techniques are often coupled with wearables and IoT to extract intelligence, patterns, trends, user profiles, outliers for deeper assessment, and care [7].

As an emerging area of research, assistive technologies for elders present much room for a comprehensive, systematic review to identify current practices and future trends and opportunities. Current literature reviews have surveyed a limited number of papers and have yet to produce wider set of indexes, aspects, and features that such technologies offer for the care of dementia, as well as other elderly-associated ailments such as frailty and CVD [8].

This paper presents such a systematic literature review of IoT sensors and devices in elderly care. It targets both existing review studies and case studies, and identifies common parameters—both technological, such as the type of devices, as well as clinical, such as their healthcare focus from AD to frailty and CVD, clinical trial duration, and cohort size. Of the immense amount of work in technology for elderly care, recent individual studies in the past decade (2010 to 2019) were identified. From those, review studies are examined first, presenting their aspects in terms of health focus, device types, and criteria examined. Then, the review goes into deeper detail of individual case studies, identified through citations of the aforementioned earlier reviews and a wider literature search. It presents common aspects among them, such as health focus, aims, device types, experimental evaluation duration, participants (cohort), and outcome measures. Through the common aspects, statistics are drawn outlining current state-of-the-art in the field, as well as future trends and effective practices to invest in the future of eldercare with technology.

The paper is structured as follows. Section 2 presents earlier review studies and their aspects. Section 3 reviews individual case studies, examining common aspects such as health focus, IoT technology, aim, and evaluation. Section 3 presents outcomes and statistics from the review. Section 5 reports limitations and challenges, and Section 6 presents conclusions.

2. Related Review Studies in IoT Wearable Sensors and Devices for Eldercare

In this section, we present related work in the form of literature reviews in the area of IoT device and sensor technology for the care of elders. The work in this area is segmented into several categories in multiple aspects. We identify those aspects to be mainly three aspects: “health focus”, “IoT technology”, and “review criteria”, represented graphically in Figure 1.

Table 1 shows an evaluation of review studies according to those aspects, always following a distinct set of values for each aspect. The following subsections present each aspect and how current review studies perform in them.
Figure 1. Review study classification taxonomy. IoT, Internet of Things; CVD, cardiovascular disease.

Table 1. Review studies and their aspects: health focus, Internet of Things (IoT) technology, and review criteria.

| Review Study       | Year | Health Focus                  | IoT Technology                          | Review Criteria                                                                 |
|--------------------|------|-------------------------------|----------------------------------------|--------------------------------------------------------------------------------|
| Talboom & Huentelman [9] | 2018 | Alzheimer’s, Parkinson’s      | Wearables, Biometric Sensors           | Ease of Use, Efficacy, Invasiveness, Esthetics                                 |
| Ienca et al. [8]   | 2017 | Dementia, Alzheimer’s         | Wearables, Smartphones, Applications,  | Efficacy, Performance, Clinical Value                                         |
|                    |      |                               | Robotics                               |                                                                                  |
| Li et al. [4]      | 2015 | Dementia, Chronic Disease     | Smart Home                             | Networking, Social Inclusion, Ontologies                                       |
|                    |      |                               |                                        |                                                                                  |
| Al-Shaqi et al. [10] | 2016 | Dementia, Alzheimer’s         | Biometric Sensors, Environmental Sensors, Indoor Positioning, Smart Home | Networking, Ease of Use, Cost, Efficacy                                       |
| Patel et al. [11]  | 2012 | Dementia, Alzheimer’s, Parkinson’s, CVD | Wearables, Biometric Sensors, Indoor Positioning, Microphone | Cost, Energy Consumption                                                       |
### Table 1. Cont.

| Review Study                  | Year | Health Focus                                      | IoT Technology                                         | Review Criteria                  |
|-------------------------------|------|--------------------------------------------------|--------------------------------------------------------|-----------------------------------|
| Banaee et al. [12]            | 2013 | Dementia, Alzheimer’s, Parkinson’s, CVD          | Wearables                                              | Sensor Types, Networking          |
| Salih et al. [13]             | 2013 | Dementia, Alzheimer’s, CVD                      | Microphone, Environmental Sensors, Biometric Sensors, Smart Home | Networking, Security              |
| Rashidi & Mihailidis [14]     | 2013 | Dementia                                         | Wearables, Wearable Cameras, Environmental Sensors, Indoor Positioning | Sensor Types, Data Format         |
| Surendran et al. [15]         | 2018 | Alzheimer’s                                      | Wearables, Wearable Cameras                           | Networking, Accuracy              |
| Spasova & I. Iliev [16]       | 2014 | Frailty and Falls, Dementia, Alzheimer’s         | Wearables, Cameras, Environmental Sensors, Indoor Positioning | Networking, Sensor Types, Efficacy |
| Wang et al. [17]              | 2017 | Frailty and Falls, CVD                          | Indoor Positioning                                     | Accuracy, Security, Networking, Range, Cost, Ease of Use |
| Piwek et al. [18]             | 2016 | Anxiety, Obesity, Sleep Disorders               | Wearables, Smartphones, Applications                  | Robustness, Security              |
| Dimitrov [19]                 | 2016 | Orthopedics, Robotic Surgery, CVD               | Wearables                                              | Ease of Usage, Networking         |
| Scarpato et al. [20]          | 2017 | Pulmonary, CVD                                   | Wearables, Biometric Sensors                          | Energy Consumption, Size          |
| Haghi et al. [6]              | 2017 | Healthcare                                       | Wearables, Biometric Sensors                          | Cost, Size, Energy Consumption    |
| Lee et al. [21]               | 2016 | Healthcare                                       | Wearables                                              | Robustness, Cost, Size, Energy Consumption |
| Cedillo et al. [22]           | 2018 | Eldercare                                        | Wearables, Applications                               | Sensor Types, Networking          |
| Baig et al. [23]              | 2019 | Eldercare                                        | Wearables                                              | Ease of Use, Energy               |
| Seneviratne et al. [24]       | 2017 | Eldercare                                        | Wearables                                              | Energy Consumption                |
| Blackman et al. [25]          | 2016 | Eldercare                                        | Wearables, Environmental Sensors, Indoor Positioning  | Safety, Ease of Use               |
| Peetoom et al. [26]           | 2015 | Eldercare, Frailty and Falls                     | Wearables, Smart Home, Cameras, Microphone             | Sensor Types, Efficacy            |

2.1. Health Focus

The health focus aspect represents the healthcare-related, medical, or clinical aims the studies examine. Some of them are ailments and disease types or general “healthcare” and “eldercare”. In the former category, we find “dementia” in all its forms and pre-stages, including subjective cognitive impairment (SCI) and mild cognitive impairment (MCI) [27], and “Alzheimer’s” (AD) as a special...
Sensors 2020, 20, 2826

case of severe dementia, “Parkinson’s” disease (PD), “CVD”, “frailty and falls”, “orthopedics”, “robotic surgery”, “pulmonary” disease, “anxiety”, “obesity”, “sleep disorders”, or “chronic disease” in general. To begin with, eldercare refers to care of elders with no specific ailment in mind, but rather monitoring and maintaining an active and healthy lifestyle in old age, prolonging independent living (so-called living in place), also referred to as active and healthy ageing (AHA) and often achieved through ambient, smart home, unobtrusive assistive technology—the so-called ambient assisted living (AAL) [23–25]. Beyond general healthcare and into specific ailments, AD and dementia are the most prominent of them. Although AD is a subtype, or a severe, progressed stage of dementia, some studies focus especially on that, such as Surendran et al. [15]. Others refer to the general spectra of dementia and AD alike, such as [8,10]. Dementia is sometimes presented as a sole health focus [14] or examined along other chronic disease in general [4] or frailty and falls [16]. PD is a popular health focus [9] combined with AD and dementia, and even CVD [11,12]. The study in [26] considers general eldercare, that is, prolonged independent living, as well as falls related to frailty.

In the less popular application areas, a lot of wearable devices can detect parameters such as blood pressure [20] and oxygen levels in blood [17], and thus constitute a very useful tool in the hands of persons with diabetes in CVD [19], arthritis, and orthopedics [13]. These devices measure sleep and asthma, related to anxiety and sleep disorders [18], as well as general eldercare [22]. Some reviews consider general healthcare provision, which includes eldercare [6,21], and focus on the more technical aspects such as encryption and data safety [28], examined in the next sections.

2.2. IoT Technology

The IoT technology aspect considers the various IoT wearable sensors and devices found in earlier review studies, mainly categorized in “wearables”, “smartphones”, “robotics”, “smart home”, “environmental sensors”, “indoor positioning”, “biometric sensors”, (fixed) “cameras”, “wearable cameras”, “microphone”, and “applications”. While all categories refer to specific hardware, the latter refers to any type of software and AI algorithm on local PCs or the cloud, which does not require a hardware IoT component of the former categories.

The study in [26] considers five types of devices: PIR motion sensors, body-worn sensors, pressure sensors, video monitoring, and sound recognition. Our review generalizes further to include more device types that are not considered there; for example, PIR motion sensors and pressure sensors are included in “smart home” sensors along with other possible types such as door-window sensors, appliance and object usage sensors, and so on. Body-worn sensors are essentially “wearables”, and video monitoring and sound recognition are mapped to “cameras” and “microphones”, respectively, in our review.

To begin with, “wearables” are dominant in the literature, owing to their increasing popularity and affordability. Cedillo et al. [22] selected the most relevant devices to an AAL context, combining “wearables” and “applications” that contribute to the wellbeing of elders. Piwek et al. [18] includes various types of wearables, such as headbands, sociometric badges, camera clips, smartwatches, and sensors embedded in clothing, while Haghi et al. [6] deal with nine different motion trackers and four commercially available wrist-worn devices in the market for vital signs measurement, that is, FitBit, Jawbone, Withings, and Misfit. Another study [24] complements this list of commercial wrist-worn devices with Apple iWatch, Samsung Gear S2, Pebble Time, UP4 by Jawbone, Empatica, and Fitbit Flex, among others, through head-mounted devices and other accessories, such as smart jewelry, e-textiles, skin patches, and even an e-tattoo. In addition to both commercial devices and research prototypes, this review also examines pertaining potential security threats and confidentiality issues. Surendran et al. [15] explores smart wearable locator band, smart socks, the CleverCare Smart watch, iTraq, MedicAlert Safely Home, PocketFinder, Trax, and wearable cameras.

Biometric sensors are a special type of wearable or non-wearable devices that are used for both continuous and on-demand measurement of physiological and medical data. While they are often applied to security, for example, through fingerprint scanning, they are also used in
healthcare, for example, measuring body temperature, electrocardiogram (ECG), pulse oxygen saturation, blood pressure, blood glucose, and so on [29]. Patel et al. [11] examines both smart home sensors for in-house positioning and microphones to record audio and voice, as well as a wide range of biometric sensors for glucose, pH, and O2 measurements. Another study [9] deals with what IoT offers to the neurological aspects of health disorders, examining devices that can be classified as both “wearables” and “biometric sensors”, such as the Basis Health Tracker, Misfit Shine, Fitbit Flex, Withings Pulse O2, Activwatch Spectrum, FitBit, Empatica 4, Bittium Faros, and PhysioCam. It also mentions an in-ear sensor for EEG (electroencephalogram). The study in [19] examines four wearables from a medical point of view, namely, Myo, Zyo patch, MyDario, and SleepBot. Along those lines, the study of [20] examines wearables and biometric sensors for diabetes, heart monitoring, and pulmonary disease, including radio-frequency identification (RFID) and wireless sensor networks (WSN) parameters.

Smart home devices are usually ambient and inobtrusive in an AAL context. A study from Wang [17] reviews indoor positioning systems, emphasizing on human activity recognition, as well as biometric sensors (vital sign monitoring, blood pressure, and glucose). Blackman et al. [25] consider three generations of AAL, gathering 64 studies, and consider parameters such as social support, interface, and health monitoring capabilities. They include wearables and smart home sensors (AiperCare, Aladdin, bed occupancy sensor, and so on), as well as environmental sensors such as gas detectors. The review in [14] deals with most types of “smart home” ambient sensors, “wearables” and “wearable cameras”, e-textiles, and “indoor positioning” systems, especially oriented around AAL projects.

Fall detection, prevention, and risk assessment mainly involve wrist-worn sensors, RFID sensors, and a footwear, as reviewed in Baig et al. [23]. The researchers in [16] also review AAL platforms, with wearables and smart home sensors to enable multimodal fall detection. Related to that, lencA et al. [8] cover a wide area of intelligent assistive technologies around mobility and rehabilitation aid.

2.3. Review Criteria

Review criteria are used in earlier studies to evaluate, examine, and classify solutions offered in the surveyed case studies. In this paper, they are classified as follows: “sensor types”, “data format”, “ease of use”, “efficacy”, “invasiveness”, “esthetics”, “performance”, “networking”, “ontologies”, “safety”, “security”, “robustness”, “cost”, “energy consumption”, “accuracy”, “range”, “social inclusion”, and “clinical value”.

The first set of criteria considers IoT technology and infrastructure parameters such as sensor types, networking architecture, and communication protocols. Salih et al. [13] refer to sensor types in wireless sensor networks (WSNs) for various sensing modalities, while also reviewing algorithms and intelligence applications of artificial neural networks (ANNs), activity prediction, and decision making. Similarly, the study in [10] reviews sensor characteristics, existing AAL platforms that stem from collaborative projects, and activity recognition systems.

Sensor types and networking are also considered in Banaee et al. [12], who additionally examine data mining from wearables to provide valuable information. Li et al. [4] review smart home and health care solutions, while emphasizing healthcare, rehabilitation, and AAL infrastructure with mobility assistance applications of robotic service platforms, multi-agent systems, and other human machine interfaces. Lee et al. [21] explores the field of sustainable wearables, while Surendran et al. [15] explores the networking and accuracy of several wearables and cameras. The study in [26] considers the types of sensors in five categories and especially their efficacy in various short studies (non-longitudinal).

Networking also entails communications and, many times, the data acquisition techniques. The study in [10] considers the various types of communication between devices and gateways, usually smartphones or PCs. Transmitter and receiver size is mentioned in [11], where a smaller size may be beneficial to weight, but reduces performance in transmission bandwidth. Banaee et al. [12] consider
data acquisition for training algorithms as a criterion. Moreover, Li et al. [4] examine communications between devices as well as software agents in multi-agent systems. Some other technological aspects taken into consideration in some reviews are data format and data rate [14]; networks, data sets, models, and ANNs [12], update rate, data output, and algorithms [17]; or CPU, connectivity, memory, GPS, RAM, display, design, and communication capabilities [24].

When considering infrastructure, performance, and sustainability, energy consumption is also considered [11,21]. This plays an important role in portables and wearables as it attributes to comfort, but increases size [20]. Referring to elders, long battery life—and thus low power consumption—is all the more critical [23], as they are not familiar with consistently charging their devices. Thus, battery issues need to be minimal, or ideally, not exist at all [24]. Battery size and comfort usually relate to cost, but wearables become increasingly more portable, long-lasting, and affordable in retail, but maybe less durable and accurate [10].

Regarding security, Azzawi et al. [28] review data acquisition, processing, and analyzing parameters of body wearable sensors. They identify the need for secure infrastructure, in terms of new authentication mechanisms tailored to IoT devices. Network architecture [4] and strong authentication and encryption [28] can be different aspects of each device. Data security, in general, is a very important parameter [13]—the study of [18] and other reviews categorize devices with this criterion quite often.

Important criteria when it comes to healthcare and the elderly revolve around ease of use, size, and invasiveness, which ultimately shape the acceptance factors of the technology. This criterion is a fundamental concern for several studies [9,10]. The latter study also considers “easy installation”, which is an important parameter as well. More aspects relate to ease of use, such as compactness in [11,21], connectivity and easy device management [19], weight [6], and whether the user needs to operate a device or not [17]. Piwek et al. [18] also include the criterion of “behavioral effect”, which examines whether a device alters the user’s behavior in their everyday life. Blackman et al. [25] review the importance of a specialized user interface, as every user has different technological competence and literacy. Moreover, an emergency button is examined as a useful functionality of wearables for elders. Finally, esthetics also play a role in elderly users, many times with respect to stigma [9].

Some studies go into clinical validation, such as Ienca et al. [8], which takes into consideration the evidence of clinical validation for each device and the direct applicability to their health focus. Moreover, in [9], the wearables’ efficacy in the current health focus was reviewed. Lastly, two important criteria are safety [21,25] and daily tasks evaluation—two aspects of elders’ everyday life, which is the primary focus.

3. Review of Case Studies

This section presents a detailed review of case studies of IoT wearable sensors and devices for eldercare. In this paper, we use the general term “case study” to refer to any published study related to the topic, of any type. Some of them might be observational, interventional, or usability studies. These can be discriminated in this review through their “aims”, which are usually “monitoring” and “intervention” for observational and interventional studies, respectively. Usability studies can be discriminated through their evaluation outcome measures, which are mostly “acceptance”, “user satisfaction”, and “feedback”. All those aspects and categories are explained below.

First, we present our proposed aspects and classification criteria of case studies, shown graphically in Figure 2. All studies share the same aspects, “health focus” and “IoT technology”, similar to review studies in the previous section, as well as more detailed information per-case, that is, “aim”, “description” and “evaluation”. Furthermore, we classify case studies to those with and those without an experiment for evaluation. Studies with evaluation are also examined for the aspects of “duration”, “participants”, and “outcome measures” related to it.
Some studies go into clinical validation, such as Ienca et al. [8], which takes into consideration the evidence of clinical validation for each device and the direct applicability to their health focus. Moreover, in [9], the wearables’ efficacy in the current health focus was reviewed. Lastly, two important criteria are safety [21,25] and daily tasks evaluation—two aspects of elders’ everyday life, which is the primary focus.

3. Review of Case Studies

This section presents a detailed review of case studies of IoT wearable sensors and devices for eldercare. In this paper, we use the general term “case study” to refer to any published study related to the topic, of any type. Some of them might be observational, interventional, or usability studies. These can be discriminated in this review through their “aims”, which are usually “monitoring” and “intervention” for observational and interventional studies, respectively. Usability studies can be discriminated through their evaluation outcome measures, which are mostly “acceptance”, “user satisfaction”, and “feedback”. All those aspects and categories are explained below.

First, we present our proposed aspects and classification criteria of case studies, shown graphically in Figure 2. All studies share the same aspects, “health focus” and “IoT technology”, similar to review studies in the previous section, as well as more detailed information per-case, that is, “aim”, “description” and “evaluation”. Furthermore, we classify case studies to those with and those without an experiment for evaluation. Studies with evaluation are also examined for the aspects of “duration”, “participants”, and “outcome measures” related to it.

Figure 2. Case study classification taxonomy.

Table 2 presents what we have identified as recent and representative works according to the previous classification. The following subsection presents how the studies consider each aspect. Studies with an evaluation experiment are examined at the end as they entail even more aspects pertaining to evaluation duration, participants (cohort), and outcome measures.

| Case Study          | Year | Health Focus                | IoT Technology                | Aim                                      | Description                                                                 | Evaluation |
|---------------------|------|----------------------------|------------------------------|------------------------------------------|----------------------------------------------------------------------------|------------|
| Rodrigues et al.    | 2018 | Alzheimer’s, Fall Detection | Wearables, Smartphones       | Fall Detection, Wandering Detection, Emergency | Fall and wandering detection for emergency alerts | -          |
| Ehrl er & Lovis     | 2014 | Eldercare                   | Wearables                    | Comparison                               | Smartwatches for elderly support                                          | -          |
| Sharma & Kaur       | 2017 | Alzheimer’s, Telemedicine   | Smartphones, Applications    | Monitoring, Symptom Detection            | Android app to monitor AD symptoms and contact doctors                    | -          |
| Aljehani et al.     | 2018 | Alzheimer’s                 | Wearables, Applications      | GPS Tracking, Biometric Sensors          | GPS and heart rate logging                                                 | -          |
| Bose [34]           | 2013 | Dementia, Alzheimer’s       | Biometric Sensors            | Emergency                                | Detect emergency and send alerts                                           | -          |
| Karakaya et al.     | 2017 | Fall Detection              | Wearables, Applications      | Fall Prediction                          | Predictive model for falls                                                 | -          |
| Khojasteh et al.    | 2018 | Fall Detection              | Wearables                    | Development                              | Fall detection from wrist-worn sensors                                    | -          |
| Algase et al.       | 2018 | Dementia                    | Wearables                    | Wandering Detection                      | Four devices for wandering detection                                       | -          |
| Hao et al.          | 2017 | Alzheimer’s                 | Indoor Positioning Sensors   | Pattern Detection                        | Detect indoor movement patterns of AD                                      | √          |
| Thorpe et al.       | 2016 | Dementia                    | Wearables, Applications      | User-centered AAL                        | User-centered approach to develop AAL                                      | √          |
| Ellis et al.        | 2015 | Fall Detection, Parkinson’s | Wearables, Applications      | GAIT Analysis                            | GAIT analysis from two devices                                             | √          |
| Weiss et al.        | 2019 | Parkinson’s                 | Wearables                    | Movement Analysis                        | Movement analysis (turn and sit) for PD                                     | √          |
| Mc Ardle et al.     | 2018 | Alzheimer’s                 | Wearables                    | GAIT Analysis                             | GAIT analysis, acceptability, and feasibility                              | √          |
| Silva et al.        | 2017 | Alzheimer’s                 | Wearable Cameras             | Intervention                             | Camera intervention for improvement                                         | √          |
Table 2. Cont.

| Case Study            | Year | Health Focus | IoT Technology | Aim                                           | Description                                                                 | Evaluation |
|-----------------------|------|--------------|----------------|-----------------------------------------------|-----------------------------------------------------------------------------|------------|
| Costa et al. [44]     | 2016 | Alzheimer’s  | Wearables      | Fall Prediction, Fall Prediction, Assessment  | Fall prediction and AD assessment                                          | ✓          |
| Zhou et al. [45]      | 2016 | Alzheimer’s  | Wearables      | Assessment                                    | Motor-cognitive assessment                                                  | ✓          |
| Hsu et al. [46]       | 2014 | Alzheimer’s  | Wearables      | Assessment                                    | Indicators for AD assessment                                               | ✓          |
| Abbate et al. [47]    | 2014 | Alzheimer’s  | Wearables, Indoor Positioning | Fall Detection, Monitoring | Fall prediction and AD assessment                                          | ✓          |
| Woodberry et al. [48] | 2015 | Alzheimer’s  | Wearable Cameras | Intervention   | External memory aid to promote recall of episodic memories                   | ✓          |
| Leuty et al. [49]     | 2013 | Dementia     | Wearables      | Intervention                                    | Promote engagement, art creation                                            | ✓          |
| Lancioni et al. [50]  | 2013 | Alzheimer’s  | Indoor Positioning | AAL, Intervention | Indoor activity and travel support                                            | ✓          |
| Aloulou et al. [51]   | 2013 | Dementia     | Indoor Positioning | AAL | AAL in nursing homes                                                            | ✓          |
| Pot et al. [52]       | 2012 | Alzheimer’s  | Indoor Positioning | Monitoring | GPS for indoor tracking                                                        | ✓          |
| Jelicic et al. [53]   | 2014 | Alzheimer’s  | Telemedicine    | Assessment, Intervention                      | Lexical-semantic stimulation through Telecommunication                     | ✓          |

3.1. Health Focus

Most case studies found present a device, or more, that measures different parameters of a disease. Alzheimer’s disease (AD) is the most common disease included in our study. There are some studies that focus on devices for the general elder population [31], dementia [37,39,49,51], Parkinson’s disease [41], and fall detection [35,36], or even combining some, or all, of the above mentioned [30,34,40,47].

3.2. IoT Technology

The devices presented here are mostly Wearables. Other types of sensors include smartphone Android apps [32]; all types of smart home ambient sensors [38], for example, a wireless doorbell system presented by Lancioni et al. [50]; rehab devices applications [53]; and so on. The various types follow those classified previously in related review studies.

3.3. Aim

This category is very general for the studies examined. Some of the reviews presented the aim of the detection of specific symptoms or behaviors arising from a person that has a known disease. Such review studies are [30,38,41–43]. The aim of [35,40,44–46,50] is prediction, which refers to predicting a disease of a healthy subject, via symptoms, repetitive behavior, and so on. When studying [30,34], it is easily outlined that there is an interest for emergency situations. Another focus of this category is monitoring [32,47]. These studies refer to a monitoring system for patients with a specific disease. Furthermore, another aim found in [36,39,51] is development. These reviews focus on developing an algorithm or a specific architecture for a system, so it measures specific characteristics. Two studies [31,37] focus on comparing the reviewed subjects, while two others’ [33,52] aim is tracking the patient, so the caregiver can be more comfortable or even the subject himself can be more independent. Finally, there are also aims such as biometric measurements [33], recall of some memories [48], patients’ improvement [49], and rehabilitation [53].
3.4. Description

Rodrigues et al. [30] used a smartphone and a smartwatch, which had simple interaction with the user, a fall alert, and an OK button to tap if the elder was well after falling or if he/she was lost and wandering. Ehrler & Lovis [31] present the advantages and disadvantages of smartwatches in the current study field, such as ubiquity, activity sensors, user adoption and safety, personalization, price, continuous medical surveillance, and appropriate ground to implement a platform with multiple services for elders, as well as considering disadvantages such as physical constraints like tiny screen size, small connectors, and limited power autonomy. Sharma and Kaur [32] developed an Android app that can access the disease’s symptoms data. Each user can find out if he suffers from the disease or not, as well as contact the doctor directly via messages and calls. They also propose a framework reducing communication cost.

A novel feature in the app’s language was presented by Aljehani et al. [33], who constructed an app for Apple smartwatch that supports the Arabic language. The app measures heart rate and locates the patient, who showed over 94% satisfaction using it. Bose et al. [34] constructed a sensor that measures heartbeat, acceleration, blood pressure, and body temperature. Its data is safely transferred to the remote control station via a developed wireless mesh network architecture. Some of its advantages are wireless signal detection, reliable data collection and transmission, low power, and efficient channel allocation. Karakaya et al. [35] used a smart watch (with an accelerometer and gyroscope) with a mobile app as a system to collect sensory data for the elderly people’s activities prediction. The app reads the outputs of the sensors in a smart watch continuously and uploads them to a web service, which initiates a classifier program to predict the activity and can communicate with the smart watch to warn or check the user condition. Finally, Khojasteh et al. [36] developed a dataset and an artificial neural network, using a smartwatch for data collection. Their method, however, needs to be validated with more datasets, specifically from real fall events. Some of its features are usability, ergonomic solutions to problems, users’ comfort, less communications, and more battery life.

3.5. Evaluation

The "evaluation" column in Table 2 categorizes the case studies found according to having tested the presented device with a study group. This section dives further into studies with evaluation and examines their pertaining aspects, namely, “study duration”, “participants” (study cohort size, demographics, health condition, and so on), and “outcome measures”, as shown on Table 3.

| Case Study         | Year | Study Duration | Participants | Outcome Measures                           |
|--------------------|------|----------------|--------------|--------------------------------------------|
| Algase et al. [37]  | 2018 | 1 Week         | 178 (mean age 85.3 y/o) | Acceptance, Accuracy of Wandering Detection |
| Hao et al. [38]    | 2017 | 6 Months       | 20           | Accuracy of Assessment by Pattern Detection |
| Thorpe et al. [39] | 2016 | 7 Days         | 10 (61–73 y/o) | Acceptance, Feedback                      |
| Ellis et al. [40]  | 2015 | 1–2 h          | 24: 12 PD & 12 HC (40–85 y/o) | Accuracy of Assessment by GAIT Analysis |
| Weiss et al. [41]  | 2019 | Less than 1 h  | 96 PD        | Accuracy of PD Assessment by Movement Analysis |
| Mc Ardle et al. [42]| 2018 | 7 Days         | 20 (55–80 y/o) | Acceptance, Accuracy of Assessment by GAIT Analysis |
| Silva et al. [43]  | 2017 | 6-Week Trial, 6-Month Follow-up | 51 AD (60–80 y/o) | Cognitive State Improvement through Intervention |
| Costa et al. [44]  | 2016 | 2–3 h          | 72: 36 AD (76 ± 7 y/o), 36 HC (70 ± 8 y/o) | Accuracy of Fall Detection and Assessment |
| Zhou et al. [45]   | 2016 | 5 Min Session | 30: 11 HC, 10 aMCI, 9 AD (71–93 y/o) | Reliability, Accuracy of Motor-cognitive Assessment |

Table 3. Review of case studies with evaluation and their aspects. MCI, mild cognitive impairment.
Table 3. Cont.

| Case Study      | Year  | Study Duration | Participants | Outcome Measures                          |
|-----------------|-------|----------------|--------------|-------------------------------------------|
| Hsu et al. [46] | 2014  | A Few h        | 71: 21 AD & 50 HC | Accuracy of Assessment                    |
| Abbate et al. [47] | 2014  | 2–4 Days       | 4 AD (75–92 y/o) | Acceptance, User Satisfaction, Accuracy of Fall Detection |
| Woodberry et al. [48] | 2015  | 3.5 Months     | 6 (64–84 y/o)  | User Satisfaction, Cognitive State Improvement through Intervention |
| Leuty et al. [49] | 2013  | Five 1-Hour Trials | 6 (mean age 89.2 y/o) | User Satisfaction, Feedback |
| Lancioni et al. [50] | 2013  | Ten 1-Minute Trials | 6 (75–89 y/o) | Cognitive State Improvement through Intervention |
| Aloulou et al. [51] | 2013  | 14 Months      | 10: 8 AD, 2 Carers | Feedback, Accuracy of Indoor Positioning |
| Pot et al. [52] | 2012  | 3 Months       | 56 Patient-Carer pairs | User Satisfaction, Acceptance, Feedback, Accuracy of Indoor Positioning |
| Jelcic et al. [53] | 2014  | 3 Months       | 27            | Cognitive State Improvement through Intervention, Accuracy of Assessment |

3.5.1. Duration

Study durations can vary. Studies [41,45,50] are minute-long trials, while the studies in [40,44,46,49] last for a couple of hours. Longer studies lasts from a couple of days to a whole week [37,39,42,47]. Several studies may last from a couple of months or case studies [38,48,52,53], while only one study lasts more than a year [51]. Statistics of their distribution are presented further in Section 4.

3.5.2. Participants

The demographics of participants in each study are one of their most characteristic aspects. Several studies involve small groups of ten participants [39,47,49,51] or less [48,50]. Fewer studies fall into the range of ten to twenty [38,42] and twenty to thirty [40,53]. Even less studies involve more participants, from thirty to seventy [43,45,52] and from seventy to a hundred [41,44,46]. Only one study involves more than a hundred participants, with 178 subjects [37].

Another demographic is the age and gender of the participants and the presence of caregivers in the study. Thorpe et al. [39] examine pairs of subjects (two female and three male) and caregivers. Ellis et al. [40] study 12 patients (five female) and 12 health subjects (four female). Weiss et al. [41] has 96 patients with a 22% percentage of female subjects in it. Costa et al. [44] studied 36 AD patients (24 females, 12 males) with a mean age of 76 ± 7 years and 36 healthy subjects (15 females-21 males), with a mean age of 70 ± 8 years. Zhou et al. [45] have a 43.3% percentage of female subjects in their trial, while Woodberry et al. [48] deal with four female and two male subjects. Lancioni et al. [50] had six subjects and two studies. The first study had three participants from 75 to 89 years old and the second study had the same three plus one more, whose age is 71 years old. Jelcic et al. [53] examined 27 patients divided into three groups: seven of them followed the LSS-tele treatment, 10 of them followed the LSS-standard direct intervention, and 10 were the control condition. Lastly, Algase et al. [37] studied 178 patients, of which 75.3% are females.

Regarding drop-outs and attrition, unfortunately, not all papers clearly mention them nor the underlying reasons. One study does mention drop-outs due to adherence problems (n = 2) and technical problems (n = 1) [42]. The study in [40] mentions data loss, owing to connectivity issues; faults in file transfer; and equipment failure, resulting in dropping data of six participants from the study. However, those cannot be classified as drop-outs owing to the participant choice or circumstance. As a result, drop-outs cannot always be interpreted as adherence problems, but also technical ones, and even so, are not always mentioned. Therefore, they are left out of the survey in order to avoid misleading the reader.
3.5.3. Outcome Measures

In accordance to evaluation aims, the outcome measures aim to assess mainly parameters of comfort or efficacy and effectiveness to either assess a condition, or to improve it, through monitoring and intervention. This section provides details on each evaluation and reports on their results.

Algase et al. [37] tested the four wearables Actillume, StepWatch, Step Sensor, and TriTrac-R3D. While Step Sensor was the staff’s preferred device, its performance was least acceptable for research purposes. StepWatch and Actillume were able to yield the largest amount of meaningful data. There were benefits such as appearance, comfort, ease of application and cleaning, location, safety, size, and weight. Hao et al. [38] applied in-house IoT sensors and targeted excessive active levels, abnormal sleeping patterns, and repetitive behavior, all indicating potential AD. Limitations faced were sensor quality, assumptions, and data combination with qualitative information. Thorpe et al. [39] tested a smartwatch and a mobile phone with various applications, and there was promise for user adoption overall, with scheduling as most successful and navigation as least successful in terms of usability and usefulness. Some of their recommendations for future work are using the smartwatch as output only, personalizing the solution to users’ individual needs, and making it as familiar to them as possible.

Moreover, Ellis et al. [40] examine gait with the iPod Touch in combination with two foot sensors and a mobile app, and found that, relatively to healthy (HE) subjects, patients with Parkinson’s disease (PD) walked with slower and took shorter steps, as well as increased step time and step length variability. Weiss et al. [41] issue a small, light-weight sensor attached to a Velcro elastic belt on the patient’s lower back to examine strategies that older adults take when they turn to sit. During testing without medication, about two-thirds of the participants performed the turn using the overlapping-strategy. Patients with PD were almost twice as likely to choose the overlapping strategy (part of the turning and sitting take place concurrently, in an overlapping manner) compared with the distinct strategy (turning is first completed and only then sitting begins). A single wearable is presented by Mc Ardle et al. [42], who demonstrate that gait could be a useful clinical biomarker to prevent dementia, as changes can occur up to 12 years prior to diagnosis of cognitive impairment. They found that people with mild AD walked more slowly and were more asymmetrical with impaired variability and postural control of gait compared with this reference control group. Silva et al. [43] examined three cognitive training groups, stating that the one with the wearable camera had significantly reduced depressive symptoms, and highlight that SenseCam is useful to stimulate not only cognitive function, but also overall function (affective, functional), even in a neurodegenerative condition such as AD.

In the meantime, Woodberry et al. [48] also use SenseCam and view images to patients and tested in parallel groups with diaries. SenseCam outperformed the diary method and showed improvement over time. The patients remembered more images from the SenseCam trial. Costa et al. [44] examined a triaxial accelerometer and gyroscope. Participants were exposed to seven increasingly difficult postural tasks and found high intercorrelation between the different proposed kinematic variables and substantial overlap between healthy subjects and AD patients. Zhou et al. [45] present a wearable sensor (triaxial accelerometer, gyroscope, and magnetometer) combined with a human-machine interface. Three tests between the subject and the PC were held and all subjects were able to complete all tests without any support from the study administrator. None of the participants were stopped or overtaxed during the test, indicating its feasibility for older adults, including those with MCI and dementia. Number-letter is the most sensitive test to identify motor-cognitive impairment among older adults. Excellent test-retest reliability was achieved, when alteration between numbers and letters was used. Hsu et al. [46] dealt with an inertial-sensor-based wearable device (a triaxial accelerometer and two gyroscopes) mounted on participants’ feet and waist. The participants were demanded to walk along two straight lines of 40 m, one for single-task walking and the other for dual-task walking, and another trial had eight balance ability tests. For the dual-task test, the AD group differed significantly from the HC group on number of strides, walking time, stride length, stride speed, stance time, stance period, swing period, CV of stand period, and CV of swing period under the dual-task condition. In single task walking, no significant differences in gait were observed. This indicated that the countdown
motion is related to the cognitive function and attention, so the AD patients performed worse in those gait parameters than the HCs in dual-task walking. For the balance test, AD patients presented larger average sway speed in all of the rest parameters.

Finally, Abbate et al. [47] developed a four-component-system with two wearable sensors (waist and head), an in-house sensor, and a camera. The waist sensor achieved higher usability than the head sensor, so there had to be modifications to the latter. Leuty et al. [49] used ePAD (Engaging Platform for Art Development) in a small trial to engage persons with dementia in creative art occupations and users were highly satisfied. Lancioni et al. [38] developed a wireless doorbell system and examined two aspects: two activities requiring 20 steps by the patients, and then to reach five rooms to deliver some material. The results were improved after the intervention, but different outcomes may result from the small patient groups and from characteristics of the patients and/or of the travel routes. Aloulou et al. [51] developed a set of sensors and devices controlled by a software platform. The study had three phases, of which, during the first two, the interaction is only with the caregivers. They found that the majority of the patients’ unsupervised time was spent in their bedroom or washroom. Pot et al. [52] developed a tracking device combining GPS and GPRS, track and trace function, and telephone contact. Both carers and patients were less worried when being alone, were more often outside independently, and received more freedom from their caregivers. Jelcic et al. [53] developed a rehab protocol based on two applications run on two PCs (via Skype) that contained lexical tasks aimed at enhancing semantic verbal processing, and found that the use of telecommunication technologies could have influenced the profile of cognitive changes after rehabilitation.

4. Results and Statistics

In this section, the review outcomes are aggregated and presented visually. Starting with the review/survey studies utilized in this publication, Figure 3 presents graphically their health focus in categories. Alzheimer’s and dementia are the most reviewed, with eight studies each. Moreover, some of the studies reviewed combinations and not only a single health focus. Review studies referring to Alzheimer’s disease combine with Parkinson’s disease and dementia, while the latter combines with Alzheimer, cardiovascular diseases, and fall detection. Cardiovascular disease is the next most reviewed, with six studies (one of them combining with Fall Detection), and eldercare with five studies. Moreover, frailty and falls and Parkinson’s disease are represented in three studies each.
Review studies are also classified according to the IoT technology devices they are demonstrating (Figure 4). Wearables are reviewed in the majority of review studies, sixteen in number, which identifies their popularity in this scientific field. Biometric devices measure parameters such as blood glucose, blood oxygen, and so on, and are reviewed in six studies. Environmental sensors and indoor positioning sensors are reviewed in five studies each. Smart home and smartphone devices are reviewed in three studies each. Finally, camera, wearable camera, and microphone are featured in one study each.

![Review studies – IoT technology](image)

**Figure 4.** Review studies according to Internet of Things (IoT) technology devices are presented.

Overall, another classification extracted from all criteria examined in past review studies is shown on (Figure 5). Four larger categories can be discriminated: (1) criteria affecting the amount of impact in a patient’s health, which can be health focus, aims, system functionality for the patient, clinical validation, and evaluation outcomes; (2) acceptance and usability parameters, which include esthetics, ease of use, invasiveness, and size of the devices, as well the system’s user interface; (3) cost-effectiveness, which regards accuracy, energy consumption, efficacy, cost, and speed parameters (latency, bandwidth, and so on); and (4) infrastructure, related to security and transport protocols, data models and ontologies, computing capabilities, and network architecture. Categories of parameters affect one another, for example, more capable infrastructure relates to cost-effectiveness or more acceptance and usability owing to decreased delay.

Case studies are also separated according to their health focus. In Figure 6, the allocation of studies is presented. Alzheimer’s disease is once again the leading health focus with fifteen studies. Two of them are combined with fall detection and one with dementia. Dementia and fall detection are represented in five studies each. Finally, Parkinson’s disease appears in two studies, and the general categories of eldercare and telemedicine in one study each.
Figure 5. Categories of criteria examined in review studies.

Case studies are also separated according to their health focus. In Figure 6, the allocation of studies is presented. Alzheimer’s disease is once again the leading health focus with fifteen studies. Two of them are combined with fall detection and one with dementia. Dementia and fall detection are represented in five studies each. Finally, Parkinson’s disease appears in two studies, and the general categories of eldercare and telemedicine in one study each.

Figure 6. Case study papers according to their health focus.

Another criterion is the IoT technology devices presented in each case study, which is demonstrated in Figure 7. The category of wearables, such as in the review studies, is represented by the majority of studies, fifteen in number. Moreover, in this category, the combination of wearables and applications is represented in five studies. Indoor positioning sensors are represented in five studies, and wearable cameras, smartphones and telemedicine in two studies each. Finally, biometric sensors and telemedicine are represented in one study each.

Studies classified by different “aims” are shown in Figure 8. There are five studies aiming for intervention, assessment comes second with four case studies, and monitoring third with three. Aims that were represented in two of the case studies each were fall detection, wandering detection, emergency, fall prediction, and AAL. The rest of the aims identified appear in one case study each and include comparison, symptom detection, GPS tracking, biometric sensors, development, pattern detection, user-centered AAL, gait analysis, and movement analysis.
Studies classified by different “aims” are shown in Figure 8. There are five studies aiming for intervention, assessment comes second with four case studies, and monitoring third with three. Aims that were represented in two of the case studies each were fall detection, wandering detection, emergency, fall prediction, and AAL. The rest of the aims identified appear in one case study each and include comparison, symptom detection, GPS tracking, biometric sensors, development, pattern detection, user-centered AAL, gait analysis, and movement analysis.

Figure 8. Case study papers according to their aim. AAL, ambient assisted living.

When considering case studies involving patients (i.e., studies with an evaluation), there are differences in their duration. It can be from some minutes to several months, as shown in Figure 9. Three studies examined last less than one hour; four of them last for some hours less than five; four of them for some days less than one week; four of them for several weeks or months, but less than a year; and only one study lasted for more than one year. The results can be explained from the fact that many studies need baseline periods, so it is sometimes inevitable to have a trial last for less than a week and so it might come to last for several months. On the contrary, there are some studies with very short trial periods, such as short gait examinations, that last from several minutes each or a couple to some hours long.
of them for some days less than one week; four of them for several weeks or months, but less than a year; and only one study lasted for more than one year. The results can be explained from the fact that many studies need baseline periods, so it is sometimes inevitable to have a trial last for less than a week and so it might come to last for several months. On the contrary, there are some studies with very short trial periods, such as short gait examinations, that last from several minutes each or a couple to some hours long.

**Figure 9.** Case studies with evaluation according to their duration.

Remaining in the field of clinical trials involving patients, there is another aspect that is worth considering. The number of persons included in each evaluation is a very important parameter and accordingly classifies the trial (Figure 10). The results suggest that a trial usually involves less than forty participants. More specifically, six studies involved 1 to 19 participants and five studies involved 20 to 39. Moreover, two studies involved 40 to 59 participants and the same number of studies involved 60 to 79 participants. As the number of participants increases, fewer studies are addressed. Additionally, a case study with more patients has a baseline period before and after the trial, so it is outlined that it will last longer. Consequently, one study involved 80 to 99 participants and, finally, more than 100 participants were involved in only one study.

**Figure 10.** Case studies with evaluation according to their participant number.

Finally, outcome measures are featuring important aspects of the evaluation and are shown in Figure 11. The most common outcome measure categories, with six studies, are patients’ feedback and recognition of mental state. How patients value these studies is very important, and the researchers aim for patient approval and high quality results, considering all the parameters of the trial.
Finally, outcome measures are featuring important aspects of the evaluation and are shown in Figure 11. The most common outcome measure categories, with six studies, are patients’ feedback and recognition of mental state. How patients value these studies is very important, and the researchers aim for patient approval and high quality results, considering all the parameters of the trial.

Most of the studies (eight) measure accuracy of assessment. Acceptance was evaluated in five and user satisfaction and cognitive state improvement were addressed in four studies each. Considering user acceptance, for some technologies, patients recognized that it was positively affecting their lives, but they were not comfortable enough to accept them. Patient feedback results also appear in four studies and no negative feedback was identified in general. Accuracy of indoor positioning and fall detection was demonstrated in two studies and reliability was analyzed in one study.

5. Limitations and Challenges

Both market penetration and literature research prototypes of IoT wearable sensors and devices have grown a lot over the past decade, with applications in many aspects of lifestyle and healthcare, including elderly demographics. A challenge that still remains is their acceptance, apparent as a factor in many studies. Acceptance entails ease-of-use of both hardware and software user interfaces, comfortability, size, weight, and battery life/energy consumption parameters. An optimal balance between such comfort parameters, usually met in lifestyle application of retail products, and performance, accuracy, and higher suitability for biometric applications in healthcare, is needed.

Another limitation is the lack of interoperability and a common platform. Many studies have presented segmented AAL projects in the area. Moreover, most studies integrate sensors and implement their own data acquisition techniques. Data interoperability post-acquisition is also limited across studies.

Finally, security, privacy, and ethics are a remaining concern. While standard secure storage and authentication techniques exist and are implemented in most systems, the sector could benefit from IoT specific frameworks for more efficient or autonomous authentication of devices. Privacy and ethics are also managed in an ad hoc manner per study, and could benefit from common frameworks established across vendors and organizations.

6. Conclusions and Future Work

Efficient, affordable, and accessible healthcare for the ever-growing demographics of elders and ailments pertinent to them is eminently needed. IoT wearable sensors and devices have been

Figure 11. Case studies with evaluation according to their outcome measures.
growing immensely in the last decade, penetrating the market and with both lifestyle and biomedical applications. The review presented in this paper explored literature in the sector exploring, identifying, and analysing common aspects among earlier reviews and individual case studies. Healthcare aspects range from chronic ailments, primarily AD and other forms of dementia, PD, frailty, and CVD, to general eldercare and AAL. IoT technologies are prominently wearables, as well as smart home sensors, cameras, microphones, and indoor and outdoor tracking. The major aims include assessment of cognitive state, frailty, and other conditions, as well as support, assistance, and prevention of falls. Besides assessment and monitoring, some studies constitute interventions themselves to improve the individual’s healthcare states. Open issues include common frameworks for interoperability, privacy, and security management tailored to IoT.

In accordance to that, future works in the form of novel studies or literature reviews could focus on the human aspects of IoT for eldercare. Such aspects entail technological hardware and software features and how they match human needs, particularly to elders and respective ailments. The balance between technological capabilities in terms of accuracy, performance, and modalities and human requirements for comfort, durability, and often esthetics is everchanging and could be investigated. Another aspect is the duration of the studies. With more advanced, durable, and comfortable technology, only made available recently, studies that explore longer-term effects and benefits could emerge. Constitution of Big Data from IoT wearables could soon emerge as predictive medical tools and digital biomarkers for elderly enabling care at home, as well as pharmaceutical treatment by accelerating and optimizing clinical trials.

**Author Contributions:** Conceptualization, T.G.S.; methodology, T.G.S.; software, L.M.; validation, T.S., S.N., and I.K.; formal analysis, T.G.S.; investigation, A.P.; resources, I.K.; data curation, A.P.; writing—original draft preparation, T.G.S., A.P., and L.M.; writing—review and editing, T.G.S., S.N., and I.K.; visualization, L.M.; supervision, S.N. and I.K.; project administration, T.G.S., S.N., and I.K.; funding acquisition, T.G.S., S.N., and I.K. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research was funded by (1) the RADAR-AD project, which has received funding from the Innovative Medicines Initiative 2 Joint Undertaking under grant agreement No 806999. This Joint Undertaking receives support from the European Union’s Horizon 2020 research and innovation programme and EFPIA (www.imi.europa.eu) and (2) Co-financed by the European Union and Greek national funds through the Operational Program Competitiveness, Entrepreneurship, and Innovation, under the call RESEARCH-CREATE-INNOVATE, project code: T1EDK-02668. The APC was funded by the IMI, RADAR-AD Project. This communication reflects the views of the RADAR-AD consortium and neither IMI nor the European Union and EFPIA are liable for any use that may be made of the information contained herein.

**Conflicts of Interest:** The authors declare no conflict of interest.

**References**

1. Department of Economic and Social Affairs PD. *World Population Ageing 2019*; Nations Department of Economic: Bangkok, Thailand, 2019.
2. Australia, D.; Baker, S.; Banerjee, S. Others Alzheimer’s Disease International. In *World Alzheimer Report 2019: Attitudes to Dementia*; Alzheimer’s Dis. Int.: London, UK, 2019.
3. *Alzheimer’s Disease Facts and Figures Includes a Special Report on Alzheimer’s Detection in the Primary Care Setting: Connecting Patients and Physicians*; Alzheimer’s Dis. Int.: London, UK, 2019.
4. Li, R.; Lu, B.; McDonald-Maier, K.D. Cognitive assisted living ambient system: A survey. *Digit. Commun. Netw.* 2015, 1, 229–252. [CrossRef]
5. Afifalo, J.; Karunananthan, S.; Eisenberg, M.J.; Alexander, K.P.; Bergman, H. Role of Frailty in Patients with Cardiovascular Disease. *Am. J. Cardiol.* 2009, 103, 1616–1621. [CrossRef] [PubMed]
6. Haghi, M.; Thurov, K.; Stoll, R. Wearable Devices in Medical Internet of Things: Scientific Research and Commercially Available Devices. *Healthc. Inform. Res.* 2017, 23, 4. [CrossRef] [PubMed]
7. Stavropoulos, T.G.; Meditskos, G.; Kompatsiaris, I. DemaWare2: Integrating sensors, multimedia and semantic analysis for the ambient care of dementia. *Pervasive Mob. Comput.* 2016. [CrossRef]
8. Ienca, M.; Fabrice, J.; Elger, B.; Caon, M.; Scoccia Pappagallo, A.; Kressig, R.W.; Wangmo, T. Intelligent Assistive Technology for Alzheimer’s Disease and Other Dementias: A Systematic Review. *J. Alzheimer’s Dis.* 2017, 56, 1301–1340. [CrossRef] [PubMed]

9. Talboom, J.S.; Huentelman, M.J. Big data collision: The internet of things, wearable devices and genomics in the study of neurological traits and disease. *Hum. Mol. Genet.* 2018, 27, R35–R39. [CrossRef]

10. Al-Shaqi, R.; Moursheed, M.; Rezgui, Y. Progress in ambient assisted systems for independent living by the elderly. *SpringerPlus* 2016, 5, 624. [CrossRef]

11. Patel, S.; Park, H.; Bonato, P.; Chan, L.; Rodgers, M. A review of wearable sensors and systems with application in rehabilitation. *J. Neurol. Rehabil.* 2012, 9, 21. [CrossRef]

12. Banae, H.; Ahmed, M.; Loutfi, A.; Banae, H.; Ahmed, M.U.; Loutfi, A. Data Mining for Wearable Sensors in Health Monitoring Systems: A Review of Recent Trends and Challenges. *Sensors* 2013, 13, 17472–17500. [CrossRef]

13. Salih, A.; Salih, M.; Abraham, A. A Review of Ambient Intelligence Assisted Healthcare Monitoring. *Int. J. Comput. Inf. Syst. Ind. Manag. Appl.* 2013, 5, 741–750.

14. Rashidi, F.; Mihailidis, A. A Survey on Ambient-Assisted Living Tools for Older Adults. *IEEE J. Biomed. Heal. Inf.* 2013, 17, 579–590. [CrossRef] [PubMed]

15. Surendran, D.; Janet, J.; Prabha, D.; Anisha, E. A Study on devices for assisting Alzheimer patients. In Proceedings of the 2018 2nd International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC) IEEE, Palladam, India, 30–31 August 2018; pp. 620–625.

16. Spasova, V.; Iliev, I. A survey on automatic fall detection in the context of ambient assisted living systems. *Int. J. Adv. Comput. Res.* 2014, 4, 94–109.

17. Wang, Z.; Yang, Z.; Dong, T.; Wang, Z.; Yang, Z.; Dong, T. A Review of Wearable Technologies for Elderly Care that Can Accurately Track Indoor Position, Recognize Physical Activities and Monitor Vital Signs in Real Time. *Sensors* 2017, 17, 341. [CrossRef] [PubMed]

18. Piwek, L.; Ellis, D.A.; Andrews, S.; Joinson, A. The Rise of Consumer Health Wearables: Promises and Barriers. *PLoS Med.* 2016, 13, 1–9. [CrossRef] [PubMed]

19. Dimitrov, D.V. Medical Internet of Things and Big Data in Healthcare. *Healthc. Inform. Res.* 2016, 22, 156. [CrossRef]

20. Scarpato, N.; Pieroni, A.; Di Nunzio, L.; Fallucchi, F. E-health-IoT universe: A review. *Management* 2017, 21, 46. [CrossRef]

21. Lee, J.; Kim, D.; Ryoo, H.-Y.; Shin, B.-S.; Lee, J.; Kim, D.; Ryoo, H.-Y.; Shin, B.-S. Sustainable Wearables: Wearable Technology for Enhancing the Quality of Human Life. *Sustainability* 2016, 8, 466. [CrossRef]

22. Cedillo, P.; Sanchez, C.; Campos, K.; Bermeo, A. A Systematic Literature Review on Devices and Systems for Ambient Assisted Living: Solutions and Trends from Different User Perspectives. In Proceedings of the 2018 International Conference on eDemocracy & eGovernment (ICEDEG) IEEE, Ambato, Ecuador, 4–6 April 2018; pp. 59–66.

23. Baig, M.M.; Afifi, S.; GholamHosseini, H.; Mirza, F. A Systematic Review of Wearable Sensors and IoT-Based Monitoring Applications for Older Adults—A Focus on Ageing Population and Independent Living. *J. Med. Syst.* 2019, 43, 233. [CrossRef]

24. Seneviratne, S.; Hu, Y.; Nguyen, T.; Lan, G.; Khalifa, S.; Thilakarathna, K.; Hassan, M.; Seneviratne, A. A Survey of Wearable Devices and Challenges. *IEEE Commun. Surv. Tutor.* 2017, 19, 2573–2620. [CrossRef]

25. Blackman, S.; Matlo, C.; Bobrovitskiy, C.; Waldoch, A.; Fang, M.L.; Jackson, P.; Mihailidis, A.; Nygård, L.; Astell, A.; Sixsmith, A. Ambient Assisted Living Technologies for Aging Well: A Scoping Review. *J. Intell. Syst.* 2016, 25, 55–69. [CrossRef]

26. Peetoom, K.K.B.; Lexis, M.A.S.; Joore, M.; Dirksen, C.D.; De Witte, L.P. Literature review on monitoring technologies and their outcomes in independently living elderly people. *Disabil. Rehabil. Assist. Technol.* 2015, 10, 271–294. [CrossRef] [PubMed]

27. Reisberg, B.; Prichep, L.; Mosconi, L.; John, E.R.; Glodzik-Sobanska, L.; Boksay, I.; Monteiro, I.; Torossian, C.; Vedvyas, A.; Ashraf, N.; et al. The pre-mild cognitive impairment, subjective cognitive impairment stage of Alzheimer’s disease. *Alzheimer Dement.* 2008, 4, S98–S108. [CrossRef] [PubMed]
28. Azzawi, M.A.; Hassan, R.; Azmi, K.; Bakar, A. A Review on Internet of Things (IoT) in Healthcare IEEE 802.11aa Intra-AC Prioritization View project A Rule-Based Technique to Detect. Router Advertisement Flooding Attack Against Web Application View project. *Int. J. Appl. Eng. Res.* **2016**, *11*, 10216–10221.

29. Chen, S.; Lee, H.; Chen, C.; Huang, H.; Luo, C. Wireless Body Sensor Network With Adaptive Low-Power Design for Biometrics and Healthcare Applications. *IEEE Syst. J.* **2009**, *3*, 398–409. [CrossRef]

30. Rodrigues, D.; Luis-Ferreira, F.; Sarraia, J.; Goncalves, R. Behavioural Monitoring of Alzheimer Patients with Smartwatch Based System. In Proceedings of the 2018 International Conference on Intelligent Systems (IS) IEEE, Funchal-Madeira, Portugal, 25–27 September 2018; pp. 771–775.

31. Ehrler, F.; Lovis, C. Supporting elderly homecare with smartwatches: Advantages and drawbacks. *Stud. Health Technol. Inform.* **2014**, *205*, 667–671. [PubMed]

32. Sharma, J.; Kaur, S. Gerontechnology—The study of alzheimer disease using cloud computing. In *Proceedings of the 2017 International Conference on Energy, Communication, Data Analytics and Soft Computing* (ICECDS) IEEE, Chennai, India, 1–2 August 2017; pp. 3726–3733.

33. Aljehani, S.S.; Alhazmi, R.A.; Aloufi, S.S.; Aljehani, B.D.; Abdulrahman, R. iCare: Applying IoT Technology for Monitoring Alzheimer’s Patients. In Proceedings of the 2018 1st International Conference on Computer Applications & Information Security (ICCAIS) IEEE, Riyadh, Saudi Arabia, 4–6 April 2018; pp. 1–6.

34. Creation of an Assisted Living Environment for Elderly People using Ubiquitous Networking Technologies. Available online: [https://www.iimcal.ac.in/sites/all/files/sirg/1-1-ageing-creation-assisted-living.pdf](https://www.iimcal.ac.in/sites/all/files/sirg/1-1-ageing-creation-assisted-living.pdf) (accessed on 15 May 2020).

35. Karakaya, M.; Şengül, G.; Bostan, A. Remotely Monitoring Activities of the Elders Using Smart Watches. *Int. J. Sci. Res. Inf. Syst. Eng.* **2017**, *3*, 56.

36. Barri Khojasteh, S.; Villar, J.R.; de la Cal, E.; González, V.M.; Sedano, J.; Yazgan, H.R. *Evaluation of a Wrist-Based Wearable Fall Detection Method;* Springer: Cham, Switzerland, 2018; pp. 377–386.

37. Algase, D.L.; Beattie, E.R.A.; Leitsch, S.A.; Beel-Bates, C.A. Biomechanical activity devices to index wandering behaviour in dementia. *Am. J. Alzheimer Dis.* **2003**, *18*, 85–92. [CrossRef]

38. Chong, Z.H.K.; Tee, Y.X.; Toh, L.J.; Phang, S.J.; Liew, J.Y.; Queck, B.; Gottipati, S. Predicting Potential Alzheimer Medical Condition in Elderly Using IOT Sensors—Case Study; Singapore Management University: Singapore, 2017.

39. Thorpe, J.R.; Ronn-Andersen, K.V.H.; Bierü, P.; Özkil, A.G.; Forchhammer, B.H.; Maier, A.M. Pervasive assistive technology for people with dementia: A UCD case. *Healthc. Technol. Lett.* **2016**, *3*, 297–302. [CrossRef]

40. Ellis, R.J.; Ng, Y.S.; Zhu, S.; Tan, D.M.; Anderson, B; Schlaug, G.; Wang, Y. A Validated Smartphone-Based Assessment of Gait and Gait Variability in Parkinson’s Disease. *PLoS ONE* **2015**. [CrossRef]

41. Weiss, A.; Herman, T.; Mirelman, A.; Shiratzky, S.S.; Giladi, N.; Barnes, L.L.; Bennett, D.A.; Buchman, A.S.; Hausdorff, J.M. The transition between turning and sitting in patients with Parkinson’s disease: A wearable device detects an unexpected sequence of events. *Gait Posture* **2019**, *67*, 224–229. [CrossRef]

42. Mc Ardle, R.; Morris, R.; Hickey, A.; Del Din, S.; Koychev, I.; Gunn, R.N.; Lawson, J.; Zamboni, G.; Ridha, B.; Sahakian, B.J.; et al. Gait in Mild Alzheimer’s Disease: Feasibility of Multi-Center Measurement in the Clinic and Home with Body-Worn Sensors: A Pilot Study. *J. Alzheimers Dis.* **2018**, *63*, 331–341. [CrossRef][PubMed]

43. Silva, A.R.; Pinho, M.S.; Macedo, L.; Moulin, C.; Caldeira, S.; Firmino, H. It is not only memory: Effects of sensecam on improving well-being in patients with mild alzheimer disease. *Int. Psychogeriatr.* **2017**, *29*. [CrossRef][PubMed]

44. Costa, L.; Gago, M.F.; Yelshyna, D.; Ferreira, J.; Silva, H.D.; Rocha, L.; Sousa, N.; Bicho, E. Application of Machine Learning in Postural Control Kinematics for the Diagnosis of Alzheimer’s Disease. *Comput. Intell. Neurosci.* **2016**. [CrossRef][PubMed]

45. Zhou, H.; Sabbagh, M.; Wyman, R.; Liebsack, C.; Kunik, M.E.; Najafi, B. Instrumented Trail-Making Task (iTMT) to Differentiate Persons with No Cognitive Impairment, Amnestic Mild Cognitive Impairment, Alzheimer’s Disease-Proof of Concept Study. *Gerontology* **2017**. [CrossRef]

46. Hsu, Y.-L.; Chung, P.-C.; Wang, W.-H.; Pai, M.-C.; Wang, C.-Y.; Lin, C.-W.; Wu, H.-L.; Wang, J.-S. Gait and Balance Analysis for Patients With Alzheimer’s Disease Using an Inertial-Sensor-Based Wearable Instrument. *IEEE J. Biomed. Health Inf.* **2014**, *18*, 1822–1830. [CrossRef]

47. Abbate, S.; Avvenuti, M.; Light, J. Usability Study of a Wireless Monitoring System among Alzheimer’s Disease Elderly Population. *Int. J. Telem. Appl.* **2014**. [CrossRef]
48. Woodberry, E.; Browne, G.; Hodges, S.; Watson, P.; Kapur, N.; Woodberry, K. The use of a wearable camera improves autobiographical memory in patients with Alzheimer’s disease. *Memory* 2015, 23, 340–349. [CrossRef]

49. Leuty, V.; Boger Masc, J.; PhD, L.Y.; Hoey, J.; Mihailidis, A.; Boger, J.; Young, L. Engaging Older Adults with Dementia in Creative Occupations Using Artificially Intelligent Assistive Technology. *Assist. Technol.* 2013, 25, 72–79. [CrossRef]

50. Lancioni, G.E.; Singh, N.N.; O’reilly, M.F.; Sigafoos, J.; Renna, C.; Ventrella, M.; Pinto, K.; Minervini, M.G.; Oliva, D.; Groeneweg, J. Supporting daily activities and indoor travel of persons with moderate Alzheimer’s disease through standard technology resources. *Res. Dev. Disabil.* 2013. [CrossRef]

51. Aloulou, H.; Mokhtari, M.; Tiberghien, T.; Biswas, J.; Phua, C.; Kenneth Lin, J.H.; Yap, P. Deployment of assistive living technology in a nursing home environment: Methods and lessons learned. *BMC Med. Inform. Decis. Mak.* 2013, 13, 1–17. [CrossRef] [PubMed]

52. Pot, A.M.; Willemse, B.M.; Horjus, S. A pilot study on the use of tracking technology: Feasibility, acceptability, and benefits for people in early stages of dementia and their informal caregivers. *Aging Ment. Health* 2012, 16, 127–134. [CrossRef] [PubMed]

53. Cagnin, A.; Jelcic, N.; Agostini, M.; Meneghello, F.; Parise, S.; Galano, A.; Tonin, P.; Dam, M.; Busse, C. Feasibility and efficacy of cognitive telerehabilitation in early Alzheimer’s disease: A pilot study. *Clin. Interv. Aging* 2014, 1605. [CrossRef] [PubMed]

© 2020 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (http://creativecommons.org/licenses/by/4.0/).