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# Wearable Sensors for Monitoring and Preventing Noncommunicable Diseases: A Systematic Review

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**Abstract:** Ensuring healthy lives and promoting a healthy well-being for all at all ages are listed as some of the goals in Agenda 2030 for Sustainable Development. Considering that noncommunicable diseases (NCDs) are the leading cause of death worldwide, reducing the mortality of NCDs is an important target. To reach this goal, means for detecting and reacting to warning signals are necessary. Here, remote health monitoring in real time has great potential. This article provides a systematic review of the use of wearable sensors for the monitoring and prevention of NCDs. In addition, this article not only provides in-depth information about the retrieved articles, but also discusses examples of studies assessing warning signals that may result in serious health conditions, such as stroke and cardiac arrest, if left untreated. One finding is that even though many good examples of wearable sensor systems for monitoring and controlling NCDs are presented, many issues also remain to be solved. One major issue is the lack of testing on representative people from a sociodemographic perspective. Even though substantial work remains, the use of wearable sensor systems has a great potential to be used in the battle against NCDs by providing the means to diagnose, monitor and prevent NCDs.

**Keywords:** wearable sensors; sensor systems; remote health monitoring; preventing; noncommunicable diseases; research shortcomings; user demography

## 1. Introduction

Noncommunicable diseases (NCDS) are the leading cause of death worldwide in high-, as well as low- and middle-income countries [1]. Examples of NCDs include cardiovascular disease, stroke, cancer, chronic respiratory diseases and diabetes. According to the World Health Organization (WHO), forty million of the 60 million global deaths in 2015 were due to NCDs. This number corresponds to >71% of the global deaths in 2015 [1]. Considering only low- and middle-income countries, NCDs cause premature deaths. WHO reports that 48% of the deaths in low- and middle-income countries in 2015 occurred before the age of 70 [1].

Preventive actions can be taken against NCDs. The majority (80%) of the risk factors that can result in premature cardiovascular disease, stroke and diabetes are factors that can be modified by the spread of knowledge. These risk factors include tobacco, harmful use of alcohol, unhealthy diet, insufficient physical activity, being overweight/obesity and raised blood pressure, blood sugar or cholesterol levels [1].

Wearable sensors play an important role in monitoring various physiological parameters related to NCDS. They are very useful in health trend monitoring. As such, smart sensor systems can be used to promote health and even save lives. Wearable technology/remote monitoring by sensors is foreseen to be useful in reducing healthcare costs and improving healthcare efficiency [2,3]. As an example,

remote sensor monitoring is predicted to yield an annual cost savings of three billion Euros to the Swedish healthcare system by 2025 [3].

This article is partly based on a previously published systematic review by Kristoffersson and Lindén (2020) [4] on the use of wearable body sensors for health monitoring. The original article provided a qualitative synthesis of sociodemographic and research methodological aspects in a total of 73 articles retrieved during a literature search conducted 24–25 April 2019. In this article, we narrow the scope to articles relating to the monitoring and prevention of NCDs. However, considering that more than one year has passed since the previous literature search was conducted, we repeated the literature search on 6 August 2020. Therefore, Section 2 provides a description of the systematic method used for selecting articles from the two literature searches. A vast number of abbreviations will be used within this article for readability reasons. These are defined in Section 3. The majority of the works reported upon in this article relate to techniques for monitoring NCDs such as asthma/COPD, cardiovascular diseases and diabetes. These are reported upon in Section 4. A few articles relate to nutrition assessment. Therefore, these are presented separately in Section 5 rather than being reported upon in relation to the NCD diabetes. Studies on stress and sleep are presented in Section 6, while Section 7 reports on the studies on articles not clearly relating to an NCD or any of the modifiable risk factors. Finally, Section 8 provides a discussion on how wearable sensors can assist in reducing the number of NCD cases.

## 2. Methodology

Following the requirements of MDPI Information, a systematic review following the PRISMA guidelines [5] was conducted. This literature search covered the period 2019–August 2020. A total of seven databases were searched, including Web of Science Core Collection, MEDLINE, Scopus, ScienceDirect, Academic Search Elite, ACM Digital Library and IEEE Xplore. It is worth noting that Web of Science Core Collection includes six indices: SCI-EXPANDED, SSCI, A&HCI, CPCI-S, CPCI-SSHand ESCI. For completeness, we report on the search phrases used and the number of identified articles in April 2019 and August 2020 in Table 1. During the searches conducted in April 2019, none of the searches were limited to a time span. The searches conducted in August 2020 were limited to publications from January 2019 to August 2020.

**Table 1.** An overview of search phrases and databases used during article retrieval. The numbers indicate the number of identified articles during the two literature searches.

| Database | Search Phrase | April 2019 | August 2020 |
|---|---|---|---|
| Web of Science Core Collection | ALL FIELDS: ((“body sensor” or “wireless body sensor” or “wireless wearable technology” or “biomedical sensor” or “IoT”) and (“Ecare” or “mHealth” or “eHealth’) and (“Social impact” or “Compliance” or “Acceptance” or “Clinical trial” or ‘Pilot test” or ‘Human input” or “Feedback” or “Pilot application” or “Human in the loop”)) | 7 | 4 |
| Web of Science Core Collection | ALL FIELDS:((“body sensor” or “wireless body sensor” or “wireless wearable technology” or “biomedical sensor” or “IoT”) and (“care” or “Health”) and (“Social impact” or “Compliance” or “Acceptance” or “Clinical trial” or “Pilot test” or “Human input” or “Feedback” or “Pilot application” or “Human in the loop”)) | 142 | 69 |

**Table 1.** *Cont.*

| Database | Search Phrase | April 2019 | August 2020 |
|---|---|---|---|
| MEDLINE (Web of Science) | TOPIC: ((((((“body sensor”) OR “wireless body sensor”) OR “wireless wearable technology”) OR “biomedical sensor”) OR “IoT”) AND (“care”) OR “Health”)) AND ((((((((“Social impact”) OR “Compliance”) OR “Acceptance”) OR “Clinical trial”) OR “Pilot test”) OR “Human input”) OR “Feedback”) OR “Pilot application”) OR “Human in the loop”)) Timespan: All years. Indexes: MEDLINE. | 25 | 9 |
| Scopus | ALL(body sensor OR wireless body sensor OR wireless wearable technology OR biomedical sensor) AND (ecare OR mhealth OR ehealth) AND (Social impact OR compliance OR acceptance OR Clinical trial OR Pilot test) Limited to English | 187 | 89 |
| ScienceDirect | Title, abstract, keywords: “wearable sensors” and health and impact. Limited to review articles, research articles, conference abstracts, case reports. | 13 | 7 |
| ScienceDirect | Title, abstract, keywords: “body sensor” and health and impact. Limited to review articles, research articles, conference abstracts, case reports. | 5 | 1 |
| Academic Search Elite | Free text search: “body sensor” and health and impact English. | 8 | 3 |
| Academic Search Elite | Free text search: “body sensor” and health and acceptance | 3 | 1 |
| ACM Digital Library | (+“body sensor” +and +health +and +impact) | 12 | 25 |
| IEEE Xplore | “body sensor” and health and impact | 81 | 19 |
| IEEE Xplore | “body sensor” and health and trial | 12 | 2 |

### *2.1. Article Selection, Inclusion and Exclusion Criteria*

In [4], we described the article selection, inclusion and exclusion criteria regarding the search conducted in April 2019, a search that resulted in 495 articles and 73 articles selected for inclusion. The study selection process for the April 2019 search is depicted in Figure 1. We followed an almost similar procedure regarding the August 2020 search that resulted in 229 articles. However, many articles retrieved in the August 2020 search could be excluded without assessing the full text. Thirty-eight duplicate articles were eliminated. Thereafter, fifty-eight articles were excluded prior to screening due to being reviews or articles not published in conferences/journals. The titles and abstracts for the remaining 133 articles were screened. Articles that did not match the main research question “How are wearable sensors used for health monitoring?” were excluded from further consideration. One of the outlined reasons for exclusion in the previous article [4] was “Technical/privacy”. During the screening of the articles retrieved in August 2020, a total of 17 articles were already excluded for this reason during the screening phase. Then, pdf copies of all the 72 remaining articles were downloaded and screened for eligibility. The eligibility criteria for inclusion in the review were as follows:

- Articles should be published as a journal article or in conference proceedings.
- Articles should consider wearable technology and monitoring.

- Articles should present results from studies where sensor data were collected using humans. Alternatively, the articles present information on a system in which the user trial is planned for but not yet conducted.
- Articles should be in English.

Overviewing the remaining 72 articles, it was found that 31 articles matched the inclusion criteria. A total of 41 articles were excluded. The study selection process for the August 2020 search is depicted in Figure 2.

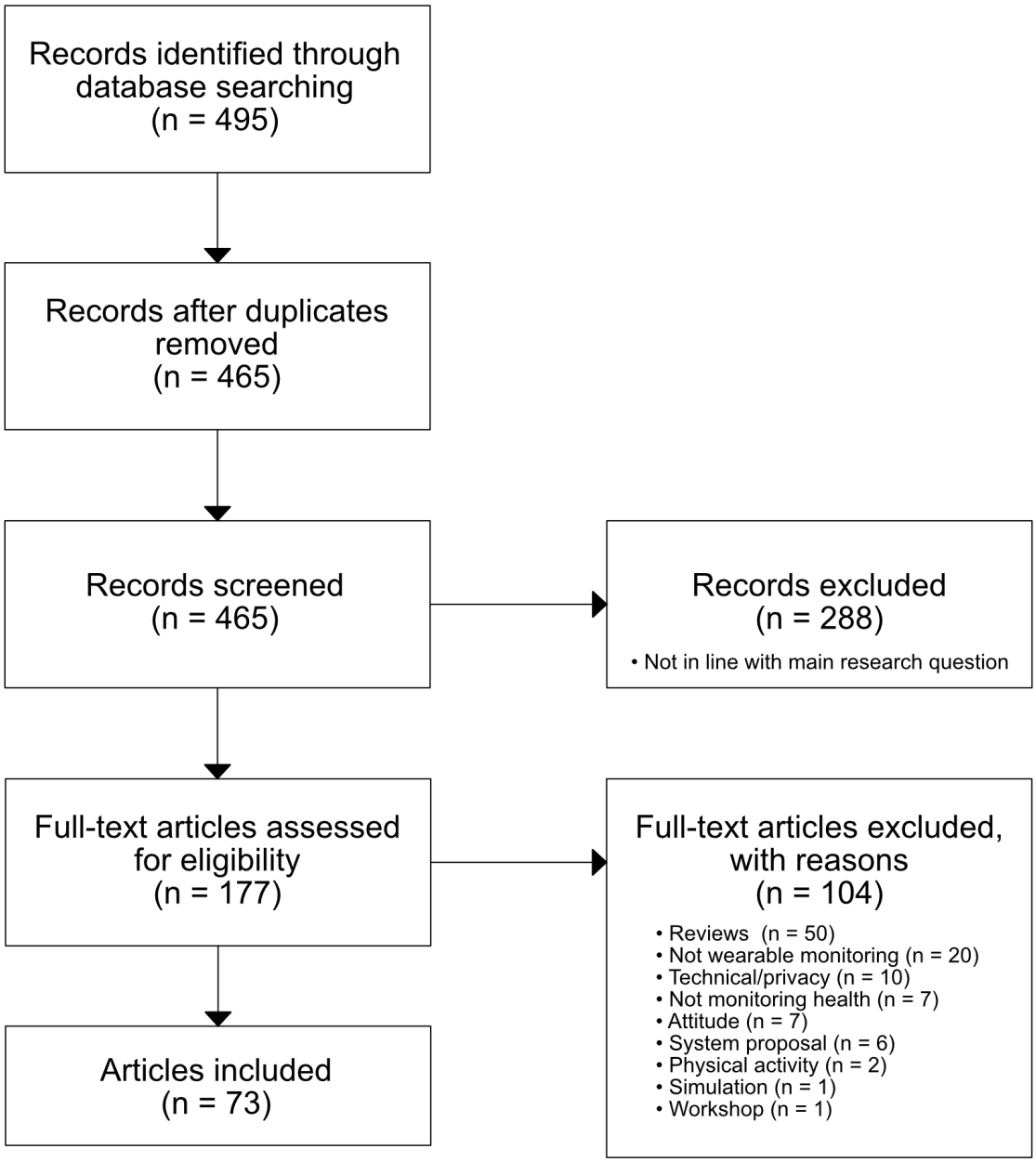


**Figure 1.** The article selection process for the April 2019 search [4].

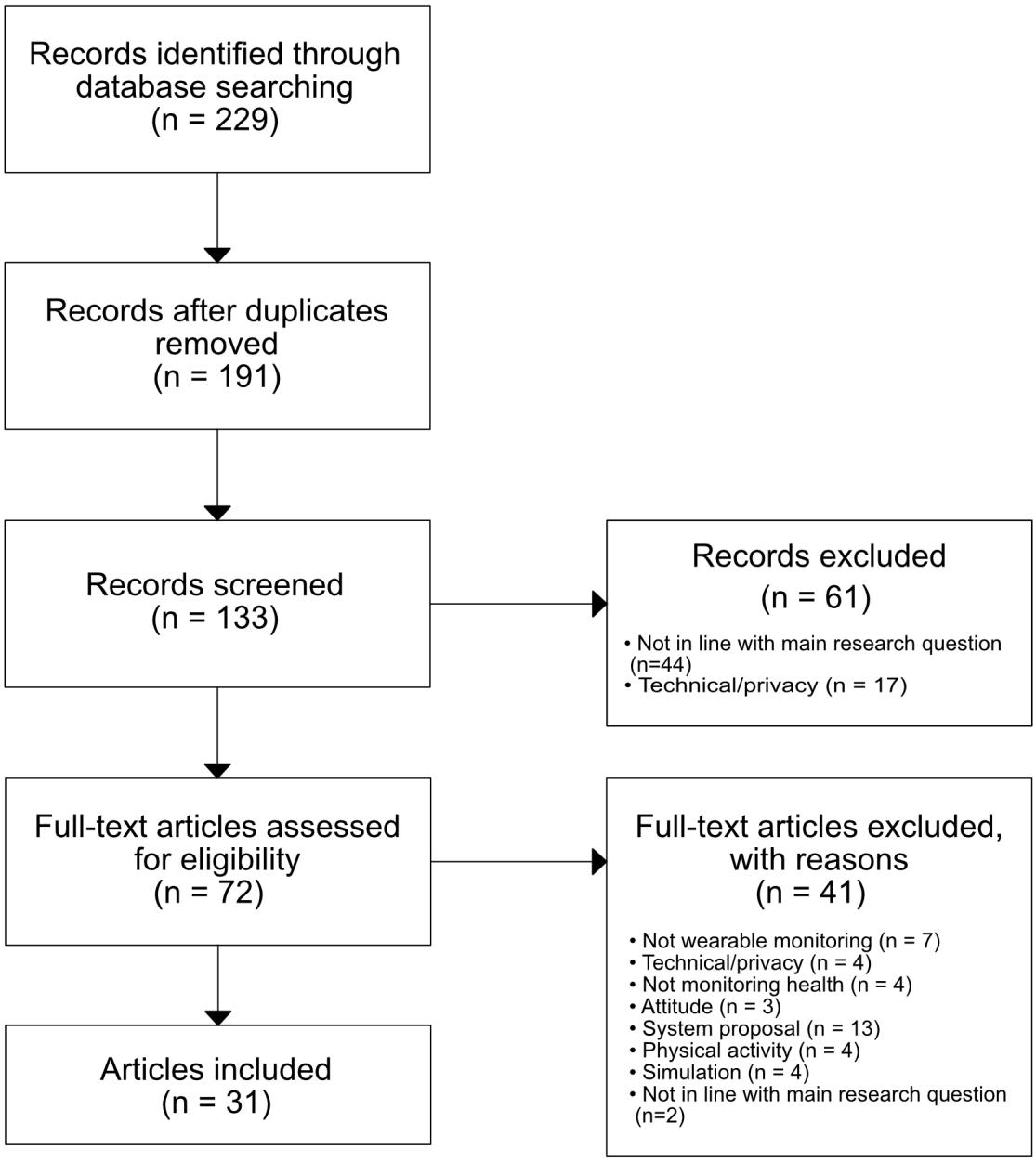


**Figure 2.** The article selection process for the August 2020 search.

### *2.2. Overall Distribution of Articles*

The two literature searches resulted in a total of 104 articles matching the inclusion criteria. We divided the original 73 articles [4] into nine categories, which are shown in Table 2. We also divided the additional 31 articles retrieved in August 2020 into the same categories. Readers may note the category "Additional (all)"; this category includes articles that were not clearly related to any of the remaining eight article categories.

**Table 2.** Overall distribution of selected articles from literature searches conducted in April 2019 and August 2020.

| Article Category | April 2019 Search | August 2020 Search |
|---|---|---|
| Asthma/COPD | 6 | 1 |
| Cardiovascular diseases | 8 | 7 |
| Diabetes and nutrition | 5 | 1 |
| Gait and fall | 15 | 2 |
| Neurological diseases | 8 | 1 |
| Physical activity recognition | 7 | 5 |
| Rehabilitation | 7 | 2 |
| Stress and sleep | 7 | 2 |
| Additional (all) | 10 | 10 |

### *2.3. Selection of Articles for this Review*

In this article, we present more in-depth information on a subset of the 104 above articles. We narrow the scope of the review to articles on the use of wearable technology for monitoring and/or preventing NCDs, i.e., articles falling into the categories: "Gait and fall", "Neurological diseases", "Physical activity recognition" and "Rehabilitation" are out of the scope in this review. Articles within the "Additional (all)" category that related to certain instances, e.g., physical activity rather than NCDs, were also excluded.

### *2.4. Articles Included in This Review*

In this article, we divided the category "Diabetes and nutrition" into two new categories: "Diabetes" and "Nutrition assessment". Hence, the articles presented in this review are divided into six article categories: "Asthma/COPD", "Cardiovascular diseases", "Diabetes, Nutrition assessment", "Stress and Sleep" and "Additional". The article category Additional includes information on conducted studies in areas that did not yet directly fit into any of the aforementioned categories within the scope of this review. In total, this review includes 45 articles. The distribution of these is shown in Table 3.

**Table 3.** Articles and adopted article categories in this review.

| Article Category | Number of Articles |
|---|---|
| Asthma/COPD | 7 |
| Cardiovascular diseases | 15 |
| Diabetes | 2 |
| Nutrition assessment | 4 |
| Stress and sleep | 9 |
| Additional | 8 |

The 45 included articles were published between 2011 and 2020, i.e., spanning approximately 9.5 years. The distribution per year was the following (number of articles in parentheses): 2011 (1), 2012 (1), 2014 (4), 2015 (5), 2016 (4), 2017 (7), 2018 (5), 2019 (13), and 5 articles published and listed in any of the databases used prior to August 10, 2020.

## 3. Abbreviations Used within This Article

The number of wearable sensor types used in the included articles are numerous. Broadly, they can be divided into the sensor categories physical activity, vital signs, electrocardiography (ECG) and other. Physical activity sensors reported include accelerometers, pedometers, 6D (i.e., 3D accelerometer and 3D gyroscope) inertial measurement units (IMUs) and 9D IMUs (i.e., a 3D accelerometer, a 3D gyroscope and a 3D magnetometer). Vital signs include the following parameters: blood pressure (BP), body temperature (BT), heart rate (HR)/pulse, peripheral oxygen saturation ($SpO_2$) and

respiratory rate (RR). Sensors in the category other include: breathing rate (BR), diameter pulse wave (DPW), electrical respiratory muscle activity of the diaphragm (EMGdi), electrodermal activity (EDA), electroencephalogram (EEG), galvanic skin response (GSR), heart rate variability (HRV), photoplethysmography (PPG), pulse wave velocity (PWV), respiratory plethysmography (RIP), skin temperature (ST) and wheezing. In addition, some of the studies also use nonwearable sensors measuring ballistocardiography (BCG), blood glucose (BG) and body weight (BW).

## 4. Use of Wearable Sensors for Monitoring Noncommunicable Diseases

### *4.1. Asthma/COPD*

The works reported upon in this section are mainly related to chronic obstructive pulmonary disease (COPD). Counteracting the effects of having COPD was in focus in [6–8]. Work on smart vests for lowering the number of readmissions to hospitals [9] and for extracting RR, inspiration time and expiration time during pulmonary rehabilitation was reported in [8]. Another work extracting RR and HR noninvasively was presented in [10]. Despite the fact that asthma is the most common NCD in the world among children and that 235 million people live with the disease [11], only two articles reporting on the use of wearable sensors in the assessment of asthma were retrieved [12,13] in this literature search.

Table 4 shows that only four studies [6–8,12] reported on the participants' age. The majority of the participants were men, and three studies [9,10,12] involved only men. The majority of the studies included only patients, exceptions being [10] and a sub-study in [8]. One article [12] did not report this information. Four articles [7,8,10,12] reported on studies with a maximum of 10 participants. Two articles [6,9] reported on studies with more than 45 participants. The majority of the studies were observational, the exception being [9], which reported on a randomized control study. As shown in Table 5, there is no consistency in the types of sensors used, their location and the study aim in the article category Asthma/COPD.

Pulmonary rehabilitation is a means to counteract the effects of having COPD. Aiming at understanding the potential and validity of conducting pulmonary rehabilitation remotely at home, Bonnevie et al. (2019) [6] conducted an observational study on patients with chronic respiratory disease who were referred to pulmonary rehabilitation. First, they underwent an assessment comprising pulmonary function tests, two sets of a six minute walk test (6MWT) and a cardiopulmonary exercise test. Second, they were instructed how to record and transmit data while using a telemonitoring system consisting of a pulse oximeter. Thereafter, they conducted prescribed exercises on a cycle while wearing the pulse oximeter. At a later exercise session, the participants were told to record and transmit data independently. Failing in this process resulted in having the instructions repeated and participation in a later exercise session. The majority of the participants were recording and transmitting data autonomously already after one exercise session. The validity of the data was checked by comparing it with data from a subgroup of five participants who conducted five exercise sessions during a period of ten days. The data from 98% of the exercise sessions were usable and had few artefacts (0.9%); these were mainly due to movement of the pulse oximeter's finger probe during the exercising. The participants were satisfied with the system that they found easy to use, and ninety-eight percent of them agreed to use it throughout their pulmonary rehabilitation program [6].

In addition, aiming at counteracting the effects of COPD, Caulfield et al. (2014) [7] conducted a study where COPD patients were instructed to wear Fitbit One during waking hours for a period of six weeks. Reminders to wear the device were provided via phone calls and text messages. During Weeks 1–2, the wearable device's display was occluded; hence, no feedback was provided. After Week 2, the label occluding the display was removed, and the participants could access online and on-device feedback. Exercise capability was assessed using 6MWT at baseline, after Week 2 and after Week 6. Health-related quality was simultaneously assessed using the St Georges Respiratory Disease Questionnaire. The participants were visited twice: once for installing and testing the wearable

device and once for removing the occluding label and for providing information on how the device was working and what feedback it provided. The participants were encouraged to look at the feedback, but not asked to conduct physical exercises. Comparing the average number of steps taken per hour during Weeks 1–2 and Weeks 3–6, the number of steps taken increased significantly after Week 2. The results on the 6MWT also improved significantly while health-related quality remained unchanged. The participants found the wearable device easy to use, but were concerned about remembering to wear it every day [7].

**Table 4.** Participant demographics for studies on Asthma/COPD. - = no information.

| Ref. | Research Design | No. of Participants | Age Group | Age Statistics | Male/Female | Patient/Healthy |
|---|---|---|---|---|---|---|
| [6] | Observational | 104 | 57–70 | 64 | 67/37 | 104/0 |
| | | 5 | 50–66 | 62 | - | 5/0 |
| [7] | Observational | 10 | - | 61.5 ± 5.7 | 5/5 | 10/0 |
| [8] | Observational | 2 | 36 and 42 | | 2/0 | 0/2 |
| | | 9 | 55–76 | 64 ± 6.6 | 6/3 | 9/0 |
| [9] | Randomized control | 48 | - | - | 48/0 | 48/0 |
| [10] | Observational | 1 | - | - | 1/0 | 0/1 |
| [12] | Observational | 1 | 28 | 28 | 1/0 | - |

**Table 5.** Study characteristics for studies on Asthma/COPD. ST, skin temperature; EMGdi, electrical respiratory muscle activity of the diaphragm.

| Ref. | Sensor and Amount | Sensor Location | Aim |
|---|---|---|---|
| [6] | 1 Pulse oximeter: HR and $SpO_2$ | wrist and finger probe | understanding the potential and validity of pulmonary rehabilitation at home |
| [7] | 1 Fitbit One: accelerometer | wrist | studying effect of wearing an activity monitor and feedback device |
| [8] | 1 smart elastic vest with 2 metal electrodes | electrodes on sternum and back | extraction of RR, inspiration rate, expiration time, and evaluating respiratory rehabilitation efficacy |
| [9] | 1 Healthwear (knitted clothing): 6 lead ECG, pulse rate, respiratory movements, 1 portable patient unit: $SpO_2$, ST, body position | Healthwear on upper body, position for portable patient unit is unclear other than the use of a finger probe | lowering the number of readmissions and emergency room visits due to COPD exacerbations after hospital release |
| [10] | 1 Shimmer3: bipolar EMGdi + reference electrode, 1 Biopac: bipolar EMG 100C + reference electrode, and Pmouth: inspiratory mouth pressure | Both electrode pairs on lower right chest next to each other, Shimmer3 reference electrode in middle of the clavicle, Biopac reference electrode on ankle | noninvasive recording of electrical respiration muscle activity (EMGdi) and the extraction of HR and RR |
| [12] | wheezing sensor | chest | detect wheezing sounds |
| [13] | 1 spirometer, 2 dust sensors, 1 smartwatch: 6D IMU, HR, GPS | wrist | Support monitoring and control of paediatric asthma. |

Aiming at lowering the number of readmissions after being hospitalized due to a COPD exacerbation, Katsaras et al. (2011) [9] developed the knitted wearable clothing "Healthwear" and a portable patient unit (PPU). The authors conducted a randomized control study. One group received conventional care and was discharged using current criteria and practices, while the other group was discharged early (after 3–5 days), but monitored at home using Healthwear, the PPU and regular

video checkups; the lengths of the hospital stays were 6.8 and 3.6 days, respectively. The number of readmissions and emergency room visits were also lower among the participants in the early discharge group. However, they required more visits from nurses in accordance with patient needs. The majority found Healthwear acceptable, although approximately 17% found it inconvenient.

In another work, Naranjo-Hernández et al. (2018) used a smart vest equipped with two electrodes for taking physiological measures on COPD patients while resting between respiratory rehabilitation exercises [8]. The authors conducted studies with two healthy subjects and nine COPD patients to validate the sensors. The mobile and wireless clinical system Oxycon from CareFusion was used as a reference measurement system. Oxycon is normally used for cardiopulmonary stress testing. The healthy participants performed a sequence of actions while being seated after which they stood up and increased inspiration and expiration times in a controlled way. The experiment was conducted twice. The results were mixed; the mean error for inspiration time was positive, which indicates an overestimation, while the mean error for expiration time was negative, which indicates an underestimation. The COPD patients followed a respiratory rehabilitation program and measures were taken for 2 min between exercises. This 2 min measure has been proposed as a method for evaluating respiratory rehabilitation efficacy [14] and improvement of breathing skills [15]. The correlation between the smart vest and reference system measures for the COPD patients was high.

Preliminary work on noninvasive recording of the electrical respiratory muscle activity of the diaphragm (EMGdi) was presented by Estrada et al. (2016) [10]. A bipolar Shimmer3 and lab equipment from Biopac were used to collect EMGdi data from one healthy participant. Simultaneously, inspiratory mouth pressure was measured using Pmouth. The correlation between the EMGdi signals increased with increased respiratory load. The extracted RR and HR from the EMGdi signals showed high accuracy. Estrada et al. (2016) [10] reported that previous works have found that RR is a parameter for detecting COPD exacerbation episodes [16] and that resting HR is used in risk prediction [17]. Future studies are planned that include assessing the potential of using the technology with more participants.

Moving on to the use of wearable sensors to detect the asthma symptom of wheezing, Khan et al. (2020) [12] presented work on a flexible acoustic sensor to be mounted on the chest. The 2 cm square-shaped sensor has a metal foil diaphragm. The sensor functionality was demonstrated by the ability to distinguish between sensor recordings from one young person who was asked to say hello, cough and make humming sounds to imitate wheezing.

A smartwatch-based system aimed to support the monitoring and control of paediatric asthma was reported upon by Buonocore et al. (2017) in [13]. The system incorporates a wireless spirometer, two environmental sensors (for monitoring particulate matter and dust density), a smartwatch and a smartphone. The smartwatch includes a 6D IMU, a sensor measuring HR and GPS. The smartphone is used for collecting data and for administering ecological momentary assessment (EMA) questionnaires. The system is an extension to the BREATHEapplication, which did not feature EMA. Notifications on EMA questionnaires are both scheduled and random. Scheduled questions include asking how the wearer slept in the morning and how school was in the afternoon. EMA questionnaires can also be triggered after the spirometer is used, if the system detects air quality changes or when the energy expenditure is high and after physical activity. No study has been conducted yet, but a clinical trial is planned.

### *4.2. Cardiovascular Diseases*

The works reported upon in this section include 24/7 systems for ECG monitoring [18–20], a preliminary work on person identification aiming toward zero-effort monitoring of cardiovascular diseases [21], three works aiming toward estimating BP continuously without wearing a BP cuff [22–24] and work on a bipolar wireless ECG monitor [25,26]. The device was later certified as a medical device, and Reference [27] reported on a number of studies conducted with the device. Furthermore, this section reports on two works focusing on extracting HRV data [28,29]: one work

assessing the accuracy of the Apple watch for monitoring atrial fibrillation (AF) [30] and two works focusing on the triage of patients with cardiovascular disease [31,32].

Table 6 shows that there are significant shortcomings in the retrieved articles reporting on participant demographics. Five studies [18,19,22,31,32] did not provide any information on the participants' age. Only five of the reported studies [21,25,28–30] and one of the sub-studies in [27] reported on the participants' gender. Two articles [21,25] reported on studies conducted solely with healthy participants. The number of participants varied between studies, and few studies or sub-studies involved more than 60 participants. Shifting focus to research design, five works [18,20,25,31,32] lacked this information. As shown in Table 7, mainly ECG sensors with a varying number of leads were used in the studies. However, a few works reported on the use of other sensors.

An overview of the WE-CARE system that provides 24/7 health monitoring using a wearable mobile seven lead ECG device was presented by Huang et al. (2014) in [19]. The system's performance and validity were evaluated in a case-control study including both healthy users and patients diagnosed with a cardiovascular disease. Using several databases for validating the performance of the system's R wave and T wave detection algorithms, the authors observed detection rates of 99.4% and 97.7%, respectively. The system also yielded a high anomaly detection rate. In another work [18], Huang et al. (2014) evaluated WE-CARE collection of data using a five lead ECG. The study included 225 participants, but the information provided was insufficient for interpreting how the study was conducted.

Another 24/7 prototype of a telehealth system integrating a portable ECG sensor via the interface Alive ECG was presented by Raad et al. (2015) [20]. Preliminary work collecting data from 30 students and two elderly patients with arrhythmia showed that data can be transmitted to a PC where HR and the QRScomplex of the ECG analysis could be retrieved from the filtered signal.

**Table 6.** Participant demographics for studies on cardiovascular diseases. - = no information; * no information provided in the included article; more information may be available in prior publications; ** the number of participants included differs between [23] and [24]; and information on whether they are healthy participants is lacking in [24].

| Ref. | Research Design | No. of Participants | Age Group | Age Statistics | Male/Female | Patient/Healthy |
|---|---|---|---|---|---|---|
| [18] | - | 225 | - | - | | 225/0 |
| [19] | Case-control | 84 | - | - | - | 1 group/1 group |
| [20] | - | 30 | 20–23 | | - | - |
| | | 2 | - | - | - | 2/0 |
| [21] | Observational | 60 | - | 26.9 ± 6.1 | 28/32 | 0/60 |
| [22] | Observational | 16 | - | - | - | - |
| [23] | Observational | 16 | 16–72 | - | - | 0/11 |
| | | 3 | 25–27 | - | - | 0/3 |
| | | 25 ** | 20–73 | - | - | 11/14 |
| | Dataset: [33] | 7 | 20–74 | - | - | 0/7 |
| [24] | Observational | 16 | 16–72 | - | - | 0/11 |
| | | 3 | 25–27 | - | - | 0/3 |
| | | 14 ** | 20–73 | - | - | ** |
| | | 21 | 15–54 | - | - | - |
| | Dataset:[33] | 7 | 20–74 | - | - | 0/7 |
| [25] | - | 13 | - | 50.6 ± 9 | 8/5 | 0/13 |
| [27] | Observational | 100 | * | * | * | 100/0 |
| | Observational | 47 | * | * | * | 100/0 |
| | Observational | 2 | * | * | 0/2 | 0/2 |
| | Observational | 23 | * | * | * | * |
| [28] | Observational | 1 | 25–30 | - | 1/0 | - |
| [29] | Observational | 20 | - | 25.3 ± 6.2 | 60%/40% | patients? |
| | Dataset: [34] | 3658 | - | - | - | 4 classes of ECG waveforms |
| [30] | Observational | 50 | - | 61.4 ± 10.4 | 36/14 | 50/0 |
| [31] | - | - | - | - | - | 500/0 |
| [32] | - | - | - | - | - | 572/0 |

**Table 7.** Study characteristics for studies on cardiovascular diseases. - = no information. BCG, ballistocardiography; DPW, diameter pulse wave; HRV, heart rate variability.

| Ref. | Sensor and Amount | Sensor Location | Aim |
|---|---|---|---|
| [18] | 1 portable 5 lead ECG | electrodes wired to phone-sized machine: chest, left/right arm, left/right leg | enable an mHealth solution with a bench-marked ECG anomaly recognition rate |
| [19] | 1 portable 7 lead ECG | - | enable an mHealth solution with a bench-marked ECG anomaly recognition rate |
| [20] | 1 2 lead ECG | chest | a telehealth system |
| [21] | 1 BCG, 1 Shimmer 2r ECG | BCG in floor tile, ECG on chest | recognize users |
| [22] | 1 DPW, 1 BP monitor, 1 PPG | DPW and PPG in wristband above radial artery, BP on upper arm | a noninvasive and continuous method to estimate BP |
| [23] | 1 BP monitor, 1 Cooking leads 3 lead ECG, 1 180 eMotion FAROS 3 lead ECG, 1 Zephyr Bioharness 1 lead ECG, dataset | BP monitor on arm, either ECG sensor on chest | estimate BP without wearing a BP cuff |
| [24] | 1 BP monitor, 1 Cooking leads 3 lead ECG, 1 180 eMotion FAROS 3 lead ECG, 1 Zephyr Bioharness 1 lead ECG, dataset, Savvy ECG | BP monitor on arm, either ECG sensor on chest | estimating BP without a BP cuff, predictive modelling of BP through multilevel information fusion of data |
| [25] | 1 2 lead PCARD ECG, | chest | excluding or confirming arrhythmia |
| [27] | 1 2 lead Savvy ECG (previously called PCARD) | chest | recording long-term ECG data of high quality that are sufficient for medical analysis |
| [28] | 1 Samsung Gear S3, Bioharness (IMU and ECG) | wrist and chest | determining the impact of signal quality on different prediction models of RR intervals (HRV) in real-world settings |
| [29] | 1 KardioMobile (1 lead ECG), 1 MAC800 (12 lead ECG) | KardioMobile: Simultaneous touching of 2 fingertips from each hand. MAC800: in Mason-Likar placement [35] | detecting AF using low-cost sensors |
| [30] | 1 Apple Watch (HR) and 6 lead ECG | ECG on chest and Apple Watch randomly assigned to be worn on left or right wrist | assessing Apple Watch' accuracy, compared to ECG telemetry, when measuring HR on patients with AF |
| [31,32] | ECG, $SpO_2$ and BP | - | triage patients with cardiovascular disease and select hospital |

Starting from the standpoint that BCG, a measure of body vibrations caused by ejection of blood into aorta, can potentially be used for zero-effort monitoring of cardiovascular diseases, Javaid et al. (2018) [21] conducted work aiming at identifying people using BCG in a home. They built a BCG sensor with four load cells into a glass tile, i.e., a floor tile. Sixty healthy young participants, who also wore a Shimmer 2r ECG sensor, were asked to stand still on the tile in an upright position for 60 s. They were then asked to perform a 15 s long Valsalva manoeuvre, i.e., close the mouth, pinch the nose and blow up a balloon. Thereafter, they were asked to rest in an upright position on the tile for 5 min. The task was repeated three times. Data from eight participants had to be excluded in the analysis: four participant's data for physiological reasons, i.e., abnormal BP drop, preventricular

contractions in the ECG or involuntary movement, and four for technical problems with the tile. The authors found that the BCG signal contains information that can be used for identifying a person.

Another work by Susič and Stanič (2015) focused on excluding or confirming arrhythmia [25]. Data from 13 healthy volunteers were collected for a period of a few hours to a day using a prototype sensor with bipolar leads (PCARD, a system that can collect data for up to three days without recharging the battery). Participants found that the sensor was easy to wear and did not disturb them or their family. Data were also collected from five patients, but the information was insufficient for reporting on the data in this article. Information on four upcoming pilot studies for evaluating PCARD's validity and impact at various stages of care in Slovenia was presented by Depolli et al. (2016) [26].

Since then, PCARD has been certified as a class IIa device according to the Medical Devices Directive MDD 93/42/EEC. The device is available on the market under the name SavvyECG. Detailed information on the hardware and firmware design of Savvy ECG was provided by Rashkovska et al. (2020) in [27], which also compared the device with three other CE-marked and/or FDA-approved devices for measuring ECGs (SEEQ$^{TM}$, ZIO®XT and Philips' wearable biosensor) with respect to design concepts. A main difference is the fact that Savvy ECG is rechargeable, while the others are for single-use scenarios. The battery time has been extended, and the Savvy ECG sensor can now collect data for up to 10 days between recharges. Hence, Savvy ECG allows for data collection over a longer period of time. Compared to a 12 lead ECG, the Savvy ECG can be positioned at different locations and in different orientations. Furthermore, Reference [27] reported brief information from two pilot studies [36,37] that we presume correspond to the first two pilots outlined in [26]. The aim of [36] by Kocjančič and Avbelj (2018) was to obtain insights on the practical use of PCARD on patients in whom there is a suspected heart rhythm disorder. Rashkovska et al. (2020) [27] reported that the physicians involved in [36] decided to follow up on 63.5% of 100 patients at the Health Centre Ljubljana using the sensor. Out of these, eighteen-point-three percent were referred to a cardiologist. In addition, further testing and prescription of new medicine were the actions taken for 6.7% and 6.7%, respectively. It was concluded that the use of a personal ECG sensor such as PCARD can lead to new pathways for patients with cardiovascular diseases. The aim of [37] by Ĉarman et al. (2018) was to assess PCARD's ability to detect post-surgery AF in comparison to the currently established clinical protocols. In the study, forty-seven patients wore the ECG sensor continuously from Day 1 to 5 post-surgery. Out of these, thirteen patients developed a paroxysmal AF. All of these cases were detected by the sensor, but only nine of them were detected through the clinically established protocols.

Furthermore, Rashkovska et al. (2020) [27] reported on two additional studies. It was found in Rashkovska and Avbelj (2017) [38] that foetal ECG measured using Savvy was only sufficient for detecting heart rates. However, the study included only two pregnant women. Širaiy et al. (2019) [39] studied the applicability of ECG measurements for monitoring heart rhythm during the conduction of intensive activity. Aiming at evaluating ECG distortion levels in relation to the sensor position and fixation method, twenty-three participants conducted a total of four exercise stress tests (EST) during four days, i.e., two while cycling on an ergometer and two while running on a treadmill. Resting of 5 min was allowed after four electrodes (of two types, namely, PREMIER T-60 and ELITE FS-VB01) were mounted and after the end of the test. The participants' ECGs were also recorded during the resting period. During the first two days, the participants conducted the EST using the same device, i.e., the cycle ergometer or the treadmill, with sensors mounted on the LIand LSpositions. On the second day, the sensors were secured using self-adhesive tape. The process was repeated for the last two days on the other device. It was reported in [39] that the signal quality obtained using both fixed and non-fixed sensors was good at the LI position. The signal quality of the data from the LS position was less acceptable than the signal quality of the data from the LI position due to the influence of shoulder movement, particularly during the treadmill EST.

Aiming toward a noninvasive and continuous method for estimating BP, Li et al. (2019) [22] studied the phase difference between two pulse waves collected at the wrist. Data were collected

from 16 participants wearing an electronic BP monitor on the upper arm and a wristband measuring PPG and DPV above the radial artery. While insufficient details were provided for interpreting how the experiments were conducted, the authors found that the phase difference is highly correlated with BP and blood flow fluctuation. However, contraction and relaxation of muscles can influence estimation accuracy.

In an additional attempt to estimate BP without wearing a BP cuff, Simjanoska et al. (2018) [23] developed a method for estimating BP from ECG signals. Data were collected from 51 people with ages 16–83 using three different commercial ECG biosensors (Cooking hacks 3 lead, 180 eMotion FAROS 3 lead and Zephyr Bioharness 1 lead) and a dataset containing ECG recordings using medical equipment from seven people. Reference BP values were taken using a BP monitoring device. After filtering and segmenting the data, the authors applied a machine learning algorithm combining stacking-based classification and regression for predicting systolic BP (SBP), diastolic BP (DBP) and mean arterial pressure (MAP). The predictions were presented in three BP classes (normal, prehypertension and hypertension) or in numeric values. Using unobtrusive sensors, the authors achieved results that were comparable to prior work. An updated report on the work was provided in Simjanoska et al. (2020) [24]. In this work, additional data were added from participants wearing the Savvy ECG. In addition, eleven participants from the third experiment reported upon in [23] were excluded. We assume that the excluded data were collected from unhealthy participants and that the data from healthy participants were kept. In addition, Reference [24] presented 17 performance metrics for evaluating the seven classification models used. Then, PROMETHEE2 was used for a pairwise comparison between all classifiers for each performance metric. PROMETHEE methods are used for decision making, and the classifiers were ranked by calculating positive and negative performance preferences in relation to the other classifiers. Additional information on the methodology was provided in [24]. A similar approach was used to rank the regression models. Then, information of all regression models was fused. Predicted values of SDP, DBP and MAP were obtained. These were better than the values observed in [23] when there were data available for training. However, Simjanoska et al. (2020) [24] stated that further effort is needed before the approach is acceptable for clinical purposes.

Gonzalez et al. (2019) [28] compared the impact of the inclusion of signal quality on different predictive models of RR intervals (i.e., HRV) in real-world settings. The analysed data were collected from one young male participant performing daily activities. The data represent a subset of a data collection. Data from IMUs (it is unclear whether these were accelerometers, 6D IMUs or 9D IMUs) were collected using a smartwatch and the wearable Bioharness from which ECG data were also retrieved. The data were collected during 21 sessions lasting for approximately 2 h each. All sessions took place during a period of approximately seven weeks. Information on the participant's specific activity during a session was not provided. Starting from the fact that behaviours and environments impact noise, Reference [28] used the MATLAB PhysioNet Cardiovascular Signal Toolbox [40] to compute RR intervals and normalized signal quality at a sampling rate of 1 Hz to match the sampling rate of extracted and normalized time- and frequency-domain data from the IMUs. Three different prediction models were trained using the IMU features: linear regression (LR), a random forest (RF) and a long-short term memory network (LSTM). A four-fold cross-validation that retained intact individual sessions was performed on each model. This ensured that data from one session were not included in both training and validation datasets. The models were evaluated by calculating the root mean squared error (RMSE). Thereafter, all models were modified by also taking a signal quality index (SQI) as the input. The addition of the new feature had a marginal effect on all prediction models' RMSE. Aiming at predicting the RR interval using the trends of the physiological responses rather than learning to predict incorrect RR intervals due to noise, Reference [28] also removed data based on the SQI using two different approaches: first, by training the models using all of the data and then removing any noise data from the validation set based on an SQI threshold. The authors calculated the RMSE for each of the three models when varying the SQI threshold. The RF was found to outperform

the two other models. The optimal SQI threshold resulting in the lowest RMSE for both the LR and RF was 0.95. This resulted in a removal of 30% of the data. In the second approach, data segments were removed from both training and validation data based on a varied SQI threshold, i.e., the model learned by using only data with a high signal quality. In this attempt, the LSTM's performance was improved with an optimal SQI threshold value of 0.95. In addition, the LR and RF were positively impacted by the second approach. Notably, the RF was found to outperform the LR at lower SQI values while the LR outperformed the RF at higher SQI. Gonzalez et al. (2019) [28] reasoned that simpler models may predict the RR intervals when the SQI is high, i.e., light activities and sedentary activities where the noise is lower. Further comparison against additional measurements of signal quality and inclusion of data from more participants are planned.

Aiming at predicting AF, Pérez-Valero et al. (2020) [29] also used HRV as a basis in their algorithms. First, they provided information on their already published Recurrence Analysis to Detect Atrial Fibrillation (ReAD-AF) algorithm [41], which can be employed on the time series of HRV data to distinguish between normal sinus (NS) and AF patients. The HRV extracted from an ECG signal was taken as the input. In ReAD-AF [41], the signal is converted into symbols. Thereafter, a matrix containing the recurrences of all symbols observed is defined. The plots of these matrices from NS and AF patients are different. The distribution appears structured for an NS patient and unstructured for an AF patient. Thereafter, a logistic model estimating the probability of patient category is applied. The ReAD-AF algorithm was validated through a k-fold cross-validation procedure using a publicly available dataset provided by Physiobank [42]. The calculated sensitivity and specificity were approximately 95% and found to increase with the selected window size. Further information on the algorithm can be found in [41], and the pseudocode for the algorithm is presented in [29]. In [29], Pérez-Valero et al. (2020) presented information on and an initial validation of a fully functional prototype capable of extracting HRV data from PDF and JPEG files that can be of low resolution. The prototype consists of four modules: digitalization, signal processing, calibration and the application of the ReAD-AF algorithm. The ECG signal is digitalized using the MATLAB function *imread* at a 600 dpi resolution and by selecting the ECG part of the file. Since ECG charts typically include a grid, an RGB threshold is applied to remove the background. Thereafter, the RGB colour images are converted into binary images. In the next module (signal processing), the signal is preprocessed by removing noise, smoothing and amplifying the QRS slope. Thereafter, the MATLAB function *findpeaks* is used to obtain signal peaks. In the third module, data are calibrated against a 12 lead gold standard ECG (MAC800) using an LR model. Finally, the ReAD-AF algorithm presented in [41] is applied for distinguishing between NS and AF patients. For validating the calibration procedure, HRV was obtained from 20 patients using a one lead ECG (KardiaMobile) and MAC800. Twenty samples from each patients were collected; however, it is unclear what the patients were doing. All patients had a normal NS, which leads us to believe that patients should be regarded as participants and not patients. To estimate the error after calibration, the mean squared error (MSE) was used. Two MSEs were calculated. First, the MSE between the uncalibrated signals using the one lead ECG and the MAC800 was obtained, yielding an MSE of 0.001971. Second, the MSE between the calibrated one lead ECG signal and the MAC800 was obtained, yielding an even lower MSE of 0.000355. For validating the classification model, a dataset containing 3658 ECG recordings using KardiaMobile was used [34]. The dataset contained four different classes of ECGs (NS, AF, other rhythms and noisy recordings), and only those being classified as NS and AF were used for validation. The classification performance was analysed using both raw and calibrated data. It was found that the sensitivity, specificity and accuracy were rather similar when running ReAD-AF on raw and calibrated data. Regarding the raw data, the sensitivity, specificity and accuracy performance achieved was 0.8765, 0.9186 and 0.9133, respectively, i.e., the algorithm correctly detected AF in 87.65% of the cases and NS in 91.86% of the cases. Overall, the data were correctly classified in 91.33% of the cases. In addition, the results in [29] were compared with results achieved with other methods in the literature. Using only nine features instead of 30 or more features in the comparative algorithms, the ReAD-AD algorithm performed good

and sometimes better. It was reported in [29] that future work includes extending the logistic model such that it can detect several types of arrhythmia and not only AF. Data from medical records should also be used in the logistic model.

Seshadri et al. (2020) [30] reported on the results of a pilot study aiming at assessing the accuracy of the Apple Watch for monitoring patients with AF in comparison to telemetry. A total of 50 postoperative cardiac surgery patients wore a watch for a maximum of 5 min on a randomly decided wrist. An equal portion of them had AF and NS. A minimum of three assessments per day for at least two days were made. A total of five watches and five iPhone 8s were used. According to Lin's concordance correlation coefficients ($r_c$), there was an overall agreement of 0.7 between the AW and telemetry assessments. It was also found that the HR was measured more accurately among the patients with AF ($r_c = 0.86$) than among patients with an NS ($r_c = 0.64$). The overall $r_c$ value of 0.7 was found to be lower than prior results obtained by the authors' team, and further studies are needed.

The two last works in this article category are notably different from the others reported. A.S. Albahri et al. (2019) [31] presented a smart real-time health recommender framework for remote chronic heart services provision. The input was taken from wearable sensors (ECG, $SpO_2$ and BP) and text. Data from 500 patients with different symptoms were used to triage patients into the groups: normal, sick, urgent or at risk. Different healthcare service packages need to be provided to these patients, particularly during challenging scalability situations. Therefore, Reference [31] ranked 12 hospitals in Baghdad based on what they offer to patients with a chronic disease. Three packages were provided in which the hospitals offering the first package had the most services to offer. Experts were used for ranking the hospitals and the importance of the different services. The triage indicated that 66 patients required the first healthcare service package, 151 required the second one and 260 required the third one. Further information on decision-making techniques and validation thereof was provided in [31]. In addition, O.S. Albahri et al. (2019) [32], i.e., the same research group, presented work in this area. Aiming for generalizability, they presented a fault-tolerant framework on mHealth in an IoT context. Triage is done locally, and the medical centre receives a warning if there is a failure related to a sensor. Then, hospital selection taking into account both available healthcare service packages and the factor of time of arrival at the hospital (TaH) is proposed. TaH is particularly important for urgent patients. Two datasets were used in [32], one with 572 patients with chronic heart disease and one with the 12 Baghdad hospitals. The latter includes information on the maximum capacity per hospital. In addition, an assumed dataset with 12 hospitals in Kuala Lumpur was used. The results showed that the hospital ranking depends both on TaH and the availability of services. For further information, please refer to [32].

### *4.3. Diabetes*

There is a rapid and steady increase in the number of cases and the prevalence of diabetes worldwide. It is estimated that the number of adults with diabetes has increased from 108 million in 1980 to 422 million in 2014. During the same period, the global prevalence of adults with diabetes has increased from 4.7% to 8.5% [43]. However, our inclusion criteria resulted in the retrieval of only two preliminary articles [44,45]. As shown in Table 8, only one of them [45] reported on a research design, as well as the age and gender of the participants. However, both studies were conducted with patients. On a positive note, Reference [45] also reported on a randomized control study. Table 9 shows that both studies made use of an Internet of Things (IoT) paradigm, although with a varying number of sensors.

The results of an acceptability study of an IoT system including a BP cuff worn on the wrist, a pulse rate monitor, a BG monitor and a BW scale were presented in [44] by Al-Taee et al. (2015). The IoT system aimed to support self-management of diabetes, and the acceptability level among 22 diabetes patients exceeded 80%. Further studies assessing the clinical impact and quality of life are planned. In another work, Onoue et al. (2017) [45] presented initial information on a randomized control study with diabetes patients who were not on dialysis or treated with insulin. The effects of

using an IoT system consisting of a wristband activity tracker (pedometer), a BP monitor and a BW scale and receiving feedback from physicians were compared to self-management using an ordinary pedometer, BP monitor and BW scale. The article presented baseline data and information on expected outcomes of a six month study in which information on the changes in glycated haemoglobin HbA1c, BW, BP, fasting BG, total cholesterol, low-density lipoprotein cholesterol, high-density lipoprotein cholesterol, triglycerides and medication were studied.

**Table 8.** Participant demographics for studies on diabetes. - = no information.

| Ref. | Research Design | No. of Participants | Age Group | Age Statistics | Male/Female | Patient/Healthy |
|---|---|---|---|---|---|---|
| [44] | - | 22 | - | - | - | 22/0 |
| [45] | Randomized control | 101 | - | 57.1 ± 12.5 | 56/45 | 101/0 |

**Table 9.** Study characteristics for studies on diabetes. BW, body weight; BG, blood glucose.

| Ref. | Sensor and Amount | Sensor Location | Aim |
|---|---|---|---|
| [44] | 1 IoT system including BP monitor, 1 pulse rate monitor, 1 BW scale, 1 BG monitor | BP monitor and pulse rate monitor on wrist | determining acceptability of an IoT-system |
| [45] | IoT-system including: 1 BP monitor, 1 pedometer, 1 BW scale. Alternatively, 1 ordinary BP monitor, pedometer and BW scale | upper arm and wrist | comparing guidance for diabetes patients using an IoT system with conventional guidance. |

## 5. Use of Wearable Sensors for Nutrition Assessment

In this section, we report on four works focusing on food or drink intake. Although less important for assessing the validity of the studies, Table 10 shows that none of the studies was conducted with patients. The three works [46–48] reporting gender information involved both male and female participants. Two works [46,49] did not report on the participants' age. The studies were of an observational nature, and different techniques for sensing were used (see Table 11).

**Table 10.** Participant demographics for studies on nutrition assessment. - = no information.

| Ref. | Research Design | No. of Participants | Age Group | Age Statistics | Male/Female | Patient/Healthy |
|---|---|---|---|---|---|---|
| [46] | Observational | 14 | - | - | 9/5 | 0/14 |
| [47,48] | Observational | 10 | 20–40 | - | 8/2 | - |
| | | 20 | 20–40 | - | 12/8 | - |
| [49] | Observational | 12 | - | - | - | - |

**Table 11.** Study characteristics for studies on nutrition assessment. RIP, respiratory plethysmography.

| Ref. | Sensor and Amount | Sensor Location | Aim |
|---|---|---|---|
| [46] | 2 RIPs, 1 accelerometer, 1 video camera | RIPs in belts on chest and abdomen, accelerometer on wrist of dexterous hand | monitoring food intake |
| [47,48] | 1 piezoelectric (vibration) sensor | necklace | classifying swallows |
| [49] | 1 Android Smartwatch (6D IMU, GPS) | wrist | diet monitoring in natural environments |

Aiming at classifying swallows, Alshurafa et al. (2014) [47] and Alshurafa et al. (2015) [48] reported on the development of and experimentation with a necklace prototype including piezoelectric

sensors. The results of a first observational experiment were reported in [47]. The efficacy of the algorithm for detecting and classifying swallows was evaluated by analysing data from 20 participants consuming three types of solids and two types of liquids (hot tea and water). For feature selection, three different classifiers were tested: RF, Bayesian networks and k-nearest neighbours (kNN) with k = 3. RF provided the best results, and the findings showed that the classifier can be used for distinguishing between liquids and solids, as well as for between the two liquids. The work [47] also showed that there is a potential to distinguish between different solids (approximately 80%). RF outperformed the other algorithms in this attempt. The experiment was also one of two experiments reported upon in [48].

Starting from the standpoint that poor eating habits, such as not having breakfast and eating at night or too often may cause obesity, Dong and Biswas (2017) [46] presented work on a system that can detect hand movements and swallow apneas. The system includes two RIP belts worn on the chest and abdomen and an accelerometer. Swallow apneas are detected using the RIP belts and are improved by the detection of hand movements. To evaluate the system, fourteen participants took part in at least three experimental sessions of two types, each lasting for approximately 45 min. Apart from wearing the sensors, a video camera was used for recording the mouth and laryngopharynx (part of the throat where both food and air passes). The recordings were used as the ground truth, i.e., indicating talk and for validating swallows. The authors trained a hierarchical support vector machine classifier and a hidden Markov model for the estimation of mealtime and the duration thereof by combining swallowing features from the breathing signal with detected hand movements. In conclusion, Reference [46] found the proposed mechanism feasible for monitoring food intake. More experiments with humans to validate the mechanism and evaluate its effectiveness if used day-to-day are planned.

Solis et al. (2019) [49] took another approach toward diet monitoring in natural environments and presented a model for detecting eating that takes environmental information into account. Users of the system receive annotation requests when the system is uncertain on whether the users are eating or not. The system uses new observations to retrain the model. The system is based on an Android smartwatch featuring an accelerometer, a gyroscope, an HR monitor and GPS. A case study aiming to show the system's ability to improve eating recognition was conducted. Twelve participants wore the smartwatch every day for two weeks and labelled the eating moments through audio recordings. The smartwatch had to be recharged every day due to a battery time of 15 h. Only data from six participants could be used. The other six participants labelled eating data at incorrect times or forgot to label eating at all. The results indicated that access to environmental data improved the accuracy of the eating detection model by 2.4%. The model's accuracy also improved when more data from a participant were collected. The labelled data were used for estimating the effect of probing the users for annotation requests to resolve uncertainty. The results showed that the model's accuracy improved with access to labels. Future work includes studies focusing on prediction of food intake. In addition, temporal shifts in labelling are to be considered.

## 6. Use of Wearable Sensors for Assessing Stress and Sleep

The works presented in this section focus on variations in sleep cycles between different groups [50,51], sleep phase monitoring [52,53], stress management [54] and relationships between physiological parameters and stress [55]. In addition, we report on [56], in which the aim was to monitor sleep without wearing sensors, on [57], which investigated the relationship between BT and mental/physical condition, and [58], which focused on integrating and fusing data from inaccessible and accessible sources. Looking at the articles' reporting on participant demographics, which are presented in Table 12, one article provided no such information [53]. Two of the works [55,58] provided no information on age. Five works [50,52,54,57,58] presented information on gender distribution. Four works [51,52,55,57] reported that the participants were healthy, whereas the remaining works lacked information on the participants being healthy or patients. The research design varies:

two works [50,51] reported on case-control studies, whereas one work [54] reported on a randomized control study. However, only one study [51] involved more than 25 participants. As shown in Table 13, there was no consistency regarding sensor types and sensor locations.

Regarding sleep cycles, Lin et al. (2012) [50] used two accelerometers worn on the ankle and wrist to estimate circadian rhythm among different chronotypes and social zeitgebers. Both the chronotype and social zeitgebers were found to impact circadian rhythm. Sleep parameters among young non-shift working participants with the same chronotype living in a small town or in the largest metropole of South America were collected and presented by Umemura et al. (2017) in [51]. To register sleep habits, participants wore a device recording accelerometry, light and BT for a period of two weeks. In addition, participants filled out questionnaires regarding sleep quality, sleepiness and chronotype. Comparing the data, the participants in the metropolitan group slept less, and their sleep efficiency was lower. The authors discussed that the differences may be explained by different social and working habits, which can enforce longer awake times, but also by the group's lower exposure to natural light [51].

**Table 12.** Participant demographics for studies on stress and sleep. - = no information.

| Ref. | Research Design | No. of Participants | Age Group | Age Statistics | Male/Female | Patient/Healthy |
|---|---|---|---|---|---|---|
| [50] | Case-control | 18 (6/12) | 19–22 overall | - | 5/1<br>11/1 | -<br>- |
| [51] | Case-control | 54 (26/28) | -<br>- | 22<br>21 | -<br>- | 0/54<br>- |
| [52] | Observational | 4 | 25–36 | - | 4/0 | 0/4 |
| [53] | Observational | - | - | - | - | - |
| [54] | Randomized control | 25 | 19–33 | - | 15/10 | - |
| [55] | Observational | 10 | - | - | - | 0/10 |
| [56] | Observational<br>Observational | 3<br>1 | 25–28<br>- | -<br>- | -<br>- | -<br>- |
| [57] | Observational | 8 | 20–24 | - | 4/4 | 0/8 |
| [58] | Observational | 4 | - | - | 4/0 | - |

**Table 13.** Study characteristics for studies on the stress and sleep. - = no information. BT, body temperature; BR, breathing rate; EDA, electrodermal activity.

| Ref. | Sensor and Amount | Sensor Location | Assessment |
|---|---|---|---|
| [50] | 2 accelerometers | ankle and wrist | circadian rhythm |
| [51] | 1 accelerometer, BT, light, environmental temperature | unclear | sleep parameters |
| [52] | ear-EEG, scalp-EEG | ear and scalp | sleep stage classification |
| [53] | ECG, 1 6D IMU | watch-like | - |
| [54] | BR, EDA, HRV | unclear | self-regulation of stress based on biofeedback |
| [55] | GSR, ECG | GSR on wrist, ECG on chest | relationship between GSR and HR during stressed and calm periods |
| [56] | 1 accelerometer, 1 electromagnetic probe, 1 airflow sensor | 1 m above bed, in nose, on chest | sleep monitoring |
| [57] | 1 in-cloth sensor including 1 BT and 1 environmental temperature sensor | clipped on pants | relationship between BT and mental/physical condition |
| [58] | 1 Fitbit Blaze: HR, sleep time, sleep efficiency, sleep levels (wake, light, deep, REM, Equivital EQ01: HR and RR-interval, RR, ST, accelerometer | wrist and chest belt | integrating and fusing data from accessible and indirectly accessible sources |

Continuing onto sleep phase monitoring, Velicu et al. (2016) [53] reported that HR and accelerometry data were collected and used for classifying sleep according to two principles: the fewer the body movements and the more stable the HR are, the deeper the sleep cycle is. Information on participant demographics and the circumstances in which data were collected is insufficient for further reporting herein.

Starting from the standpoint that clinical sleep analysis is inconvenient, namely (1) long-term sleep monitoring is not supported and (2) a person's sleep may be affected by an unfamiliar environment, Nakamura et al. (2017) [52] conducted a preliminary study with four participants on ear-EEG. Data were analysed in two scenarios: (1) classifying the sleep stage from ear-EEG against a manually scored hypnogram based on ear-EEG and (2) classifying the sleep stage from ear-EEG against a manually scored hypnogram based on scalp-EEG. Both the two class (wake vs. sleep and W-N1 vs. N2-N3, where W = awake, N1 = non-rapid eye movement NREM sleep stage 1, etc.) and four class classification (W, N1, N2, N3) were considered. For the first scenario, the accuracies for the two class classifications indicated an almost perfect and substantial agreement of Cohen's Kappa coefficients. The accuracy for the four class classification indicated a substantial agreement. Regarding the second scenario, the accuracies for all three classifications achieved a Cohen's Kappa coefficient indicating a substantial agreement. In addition, a comparison of automatic labels against manual labels showed a significant match. It was concluded that the ear-EEG method conveyed sufficient information for robustly evaluating human sleep. Further studies with more participants and overnight scenarios are planned [52].

The relationship between an individual's BT during sleep and mental/physical condition was explored by Katsumata et al. (2019) [57]. BT and environmental temperature were collected using a wearable sensor "Ran's Night". Eight participants wore the sensor during 29 nights. In addition, they filled out three questionnaires every day: one questionnaire about how they felt before sleep and upon awakening and one questionnaire about sleep quality in the morning. Sensor data were analysed if a recording indicated at least 6 h of sleep. Analysing the data closely, only data from five participants could be used. Unfortunately, the information on the data extracted was poorly presented, but the results indicated a relation between average BT after 90 min of sleep and focus level upon awakening. Those with a BT above 35.65 °C were more likely to be focused upon awakening.

Neubert et al. (2019) [58] presented a mobile data collection system that fuses data from direct and indirect accessible data sources such as Fitbits. The system is stated to support various use cases of health monitoring, but the validation experiment presented was a sleep monitoring scenario. Four male participants wore a Fitbit Blaze on the wrist and the sensor system Equivital EQ01 in a chest belt overnight. A timeline visualizing ST, RR, body orientation, Fitbit HR and level of sleep, as well as a timeline visualizing the HR measured using the two sensors were provided for two of the participants. The presented comparison was scant, but Reference [58] found that the HR measured on the wrist had a lower dependency on usual movements and breathing during sleep. Further investigations considering physical, physiological and environmental data collection under medical supervision are planned.

Moving on to the works focusing on stress [54,55], a biofeedback game that monitors the player's physiology and adapts the game depending on whether the player is relaxed or shows high arousal (stress) was presented by Parnandi and Gutierrez-Osuna (2017) [54]. The game's front end consists of a mobile video game and sensors measuring EDA, HRV and BR. The backend provides game adaption and an arousal estimation algorithm. The player is rewarded if relaxed and penalized if stressed. The system's effectiveness in teaching self-regulation of stress was studied in a randomized control experiment with 25 participants [54]. Young participants were assigned to one out of five groups: three biofeedback groups (EDA, HRV or BR), a control group or a group that received standard treatment. Physiological measures were continuously taken regardless of group. The data were used for monitoring and for game adaptation (if the player was in a biofeedback group). The experimental protocol had four phases. In Phase 1 (baseline), the players breathed six times per min according to an

audio signal. In Phase 2 (pretest), the players conducted a modified version of the Stroop Color Word Test (CWT) [59] for 4 min. The CWT has two modes: in congruent mode, the player is shown the name of a colour that is displayed in the respective ink; in incongruent mode, the name of the colour and the displayed ink are in conflict. In Phase 2, the mode switches every 30 s; each stimulus flashes for 1 s; and the players had to respond regarding what the ink colour was within 3 s. The order of the answer buttons and their locations on the screen varied. The treatment was provided in Phase 3, which lasted 8 min. The players in the biofeedback groups were instructed to do their best and try to achieve a maximum score while staying calm and breathing slowly. The game was adapted depending on the biofeedback measure corresponding to the group. The players in the control group received the same instructions, but the game never adapted. The participants in the standard treatment group never played the game; instead, they were instructed to stay calm and breathe slowly according to the same audio signal as in Phase 1. The CWT was repeated for 4 min in Phase 4. The results of the experiment indicated that a game adapting to BR was the most effective in inducing relaxation during gameplay. The participants in the BR group also had a better retention of the relaxation level during Phase 4.

The relationship between physiological parameters (e.g., HR and GSR) and stress was explored by Uday et al. (2018) in [55]. The authors developed an IoT system prototype consisting of two sensor modules (GSR and three lead ECG), a microcontroller and a communication module that enables transmission of data to the Open IoT platform ThingsSpeak, which eases data analysis. To collect data, ten healthy participants watched a number of 5 min long calm videos. A video inducing stress was shown for 10 min in between each calm video. There was a significant difference between the GSR and HR data obtained during stress inducing and calm periods. The two parameters are shown to be negatively correlated at $-0.81$, i.e., GSR decreases when stress is induced and increases during calm periods. HR has the opposite trend. The authors wrote that further system development can provide constant monitoring and regular feedback on the stress level [55].

SleepSense, which is a contactless system using an electromagnetic probe located 1 m above a person for detecting on-bed movements, bed exits and breathing events, was reported upon by Zhuang et al. (2015) [56]. To collect ground truth data, two experiments using an airflow sensor and an accelerometer were conducted. In the first experiment, three participants were instructed to lay down on their back on a mattress and to make four sets of on-bed movements and ten bed exits. An on-bed movement was defined as laying on the back for 25 s, turning around and remaining still for 25 s, then turning around again to lie on the back. The accuracy of the authors' [56] sleep event detection algorithm was found to be 95.1%, while 93/108 on-bed movements and 21/30 bed exits were correctly labelled. The authors mentioned that some of these errors may be caused by the fixed frame length, i.e., one movement can be divided into different frames. The algorithm labelled 405/408 breathing events correctly. In addition, more long-term data were collected by asking a participant to take a 75 min nap. Classifying the data collected by using the electromagnetic probe resulted in 8 frames labelled as on-bed movements, 1 frame labelled as a bed exit and 868 frames labelled as breathing events. Again, the authors mentioned that the on-bed movements had a longer duration than the fixed frame length, leading to consecutive frames labelled as on-bed movement. Overall, the algorithm's accuracy was 99.54%. Comparing the calculated BR with ground truth data, the curves matched, but the following phenomena were observed: (1) the BR varied during sleep, that is it was more irregular while falling asleep and more stable when sleeping; and (2) BR was reduced when the sleep position changed. The errors in BR labelling increased when the person moved. Because of difficulties encountered while extracting BR using the electromagnetic probe during movement, data from the preceding frame were used. In addition, chest displacement on the y-axis, i.e., the measure used for calculating BR, was less significant when a person was sleeping on the side. Future work includes addressing window size segmentation and side sleep issues [56].

## 7. Additional Use of Wearable Sensors in Contexts Related to NCDs

In this section, we present information from eight works that did not clearly fit into any of the aforementioned article categories. Table 14 provides information on the participant demographics reported. Due to the varying nature of the articles, the study characteristics also varied; see Table 15.

Aiming to assist in overcoming the obesity problem, Rawasdeh et al. (2017) [60] developed a demo of a cloud-based system to be composed of wearable sensors (ECG, BP, BG and muscular activity), a knowledge management system and a constant alert and notification system that notifies both the user and user's therapist. Using this information, the user can modify lifestyle and food intake, while the therapist can provide advice or ensure that healthcare is provided if needed. A demo including an ECG sensor and the possibility of receiving information on heart activity in real time was evaluated. A total of 55 young participants of varying weight were included after a medical examination and physician approval. They wore the ECG sensor for two weeks during which they exercised (conducted physical activities (PAs)) for 20 min a day. The results showed that HR increased during the conduction of PAs and that the HR during exercise sessions was doubled when compared to the average HR during a day. There was also a difference between the obese participants' and others' HR. Their HR was slightly higher at all times and 17% higher during PAs. Comparing the HR of obese men and women, the men's HR was similar during resting activities, but higher during PAs. The authors found that this information should be taken into consideration when recommending PAs to obese people such that the PA level is optimized and does not put a user in danger [60].

Aiming toward designing a mobile health monitoring system from first principles, Wannenburg and Malekian (2015) [61] implemented a PPG sensor for estimating HR, $SpO_2$ and pulse transit time for estimating BP. The system was also comprised of a digital temperature sensor for measuring ST, a microcontroller for data transmission and an Android phone for providing information and sending notifications to physicians. One PPG sensor and the temperature sensor were attached to the palm. An additional PPG sensor was attached to the pinky fingertip. A number of tests were conducted for verifying the system. Four participants wore the system and a commercial oximeter. The system can estimate HRs between 48 and 214 BPM. The algorithm for estimating HR worked with an accuracy of $\pm 7$ beats per minute (BPM) at a 90% confidence interval. The capability of obtaining the $SpO_2$ was derived by calibrating the PPG sensor's curve to the oximeter readings for 1 min. $SpO_2$ can be estimated at an accuracy of 1.1%. The attempt to estimate BP failed since some user-specific parameters were assumed rather than calibrated. The sensor signals had different amplitudes and lag times due to their locations. The digital temperature sensor's accuracy was only assessed by placing the two temperature sensors into a container with warm water, resulting in the digital temperature sensor readings being 0.25 °C higher.

**Table 14.** Participant demographics for the additional conducted user studies. - = no information. M = male, F = female.

| Ref. | Research Design | No. of Participants | Age Group | Age Statistics | Male/Female | Patient/Healthy |
|---|---|---|---|---|---|---|
| [60] | Observational | 55 | 18–22 | - | 50%/50% | - |
| [61] | Observational | 4–8 (4/4) | - | - | - | - |
| | | | - | - | - | - |
| [62] | Observational | 20 | - | - | - | 0/20 |
| [63] | Observational | 5 | 22–30 | 25.40 ± 2.88 | 3/2 | 0/5 |
| [64] | Observational | 1 | 29 | 29 | 1/0 | - |
| | | 11 | 27–48 | 45 ± 17.91 | - | - |
| [65] | Observational | 10 | 18–25 | - | 5/5 | - |
| [66] | Observational | 18 | 65–74 | M:69 ± 3.2, F:69.7 ± 5.8 | 7/11 | 18/0 |
| [67] | Observational | - | - | - | - | - |

**Table 15.** Study characteristics for the additional conducted user studies. PA = physical activity. PA, physical activity.

| Ref. | Sensor and Amount | Sensor Location | Aim |
|---|---|---|---|
| [60] | ECG | chest | overcoming the obesity problem by taking HR into consideration while providing recommendations on PA |
| [61] | 2 PPGs, 1 commercial oximeter, 1 digital thermometer sensor for measuring ST, 1 additional temperature sensor connected to a multimeter | PPG sensors on palm and pinky finger, oximeter on fingertip, temperature sensors in warm water | design a mobile health monitoring system from first principles, estimating HR, $SpO_2$, pulse transit time, and BP |
| [62] | 4 textile electrodes | garment | developing flexible textile electrodes for ECG monitoring |
| [63] | EEG: conductive and stretchable electrodes made of Ag NWs/PDMS covered in 3D-printed support cases, and Ag/Cl electrode for validation and Gold Cup electrode for grounding. ECG: leads in carbon-foam with an electret gel layer, and Shimmer3 for validation. RR: graphene-based fibre on elastic belt and Grael PSG for validation. | Smart hat made of elastic fabric belts with the disposable Ag NWs/PDMS electrodes, Smart vest with sewn on RR belt around chest, and ECG sensors on fourth intercostal space on right sternum (V1) and fourth intercostal space at left sternum (V2). Shimmer3 sensors on V1 and V2. Grael PSG device in thorax belt. | long-term monitoring of vital signs |
| [64] | 1 Polar M600 Smartwatch, 1 bottle equipped with PPG sensor | wrist and fingertip position on bottle | design a health monitoring system that combines data from wearables and smart objects, assessing PWV and HR |
| [65] | 1 Hexoskin (1-channel ECG, HRV; BR, breathing volume, PA, sleep parameters), 1 wired DigiAID (pulse oximeter, airflow, position) | on chest | Determining the viability of a wired off-the-shelf sensor system for measuring health parameters. Assessing HR and RR. |
| [66] | 2 Fitbit Charge 2 (3D accelerometer, HR, altimeter), 2 Garmin VivoSmart HR+ (3D accelerometer, HR, altimeter, GPS), 2 Philips Health Watch (3D accelerometer, HR), 2 Withings PulseOx (3D accelerometer, HR, altimeter, $SpO_2$), 2 Actigraph GT9X-BT (9D IMU), 1 Omron HJ-720ITC (2D accelerometer), 1 Polar H7 (ECG) | Wrists (Fitbit Charge 2, Garmin VivoSmart HR+, Philips Health Watch, Withings PulseOx), Waist and ankle dominant side (Actigraph GT9X-BT), Chest with skin contact (Polar H7) | Exploring the performance of different activity trackers in estimating steps, distance and HR with a cohort of healthy older people. |
| [67] | 1 Polar H7 (ECG and BT) | chest | detecting over exertion, preventing hazards |

PWV is a clinical measure for assessing the stiffness of arteries, which also provides an indirect measure of BP [68]. Jovanov et al. (2019) [64] implemented a PPG sensor for estimating HR and PWV.

Starting from the idea that taking input from sensors embedded in objects frequently used can facilitate monitoring and annotation of various vital signs, the authors provided information on a preliminary evaluation of a smart bottle in which a PPG sensor was embedded. In a first experiment, one person wearing a smartwatch was asked to pick up the bottle by holding the ring fingertip on the bottle's PPG sensor. PWV was calculated using the calculated time delay and the distance between the two sensors. The estimated PWV values for three heart beats were 4.4, 4.3 and 4.8 m/s, which was in line with expected PWV for a person of that age. The authors reported that further analysis and validation of the results are planned both using smartwatches and ECG patches. In a second experiment, the authors asked 11 participants to use the bottle for a period of time. Analysing the data collected, it was found that there were on average 34.2 heartbeats detected, i.e., heartbeats during 45.1% of the interaction time, per bottle use and that the bottle was touched 15 times per day on average. It was found that using a smart bottle could allow for automatic and frequent data collection [64].

An effort in the area of flexible textile electrodes for ECG monitoring was made by Wu et al. (2018) [62]. Four textile electrodes composed of different conducting materials and with varying internal construction structures were designed. To be comfortable to wear, elastic fabric with 10 × 10 cm electrodes was used and evaluated by 20 participants wearing different garments. Comfort level, the signal-to-noise ratio (SNR), skin-electrode impedance and the electrical characteristics of the retrieved ECG signals were considered. It was found that the textile electrodes composed of 30% cotton and 70% nylon fibre coated in silver provided the least air resistance and the best tactile comfort while having a reasonable SNR and better thermal conductivity than the other three electrodes.

Chen et al. (2019) [63] presented work on sensors for long-term monitoring of vital signs outside a clinical environment. Information on developed sensors built into a smart hat for monitoring EEG and a smart vest for monitoring ECG and respiration rate were presented. The EEG sensors were composed of silver nanowires/polydimethylsiloxane (Ag Nws/PDMS) covered in a 3D-printed plastic cover. The ECG sensors were composed of a metal lead, an electret gel layer and carbon foam. The RR sensor was made of a graphene-based fibre on an elastic belt. For more detailed information about the sensors developed, please refer to [63] and [69–71]. Chen et al. [63] (2019) evaluated the material of the EEG sensor against clinically used Ag/Cl electrodes and the Gold Cup electrode for grounding and the ECG sensor against the Shimmer3 sensor. Furthermore, they conducted a biosignal acquisition system evaluation of all three sensors. However, only one experiment was reported to a sufficient degree for presentation within this review. Five healthy and young participants wore the smart hat while conducting a steady-state visual evoked potentials (SSVEP) task. The smart hat was equipped with the developed Ag NW/PDMS electrodes placed near the Oz position according to the international 10/20 system and reference and ground electrodes placed on the earlobes (positions A1 and A2). Data from the participants were collected during two sessions, each consisting of three trials. During each trial, visual stimulus was provided for 30 s, which was followed by a 5 s rest. The visual stimulus provided during the first session was a flickering LED that altered at 20 Hz. A higher frequency 30 Hz was used in the second session. The results showed that the dominant frequencies in the EEG spectrum were corresponding to the visual stimulus, 19.96 Hz and 29.97 Hz, respectively. The authors found the sensors reliable and stable for EEG signal acquisition.

Talpur et al. (2019) [65] presented a wearable, but wired off-the-shelf sensor network, DigiAID, that included a pulse oximeter for measuring HR, an airflow sensor for measuring RR and a position sensor. The viability of using the wired DigiAID for measuring HR and RR was determined by comparing the sensor data collected with data collected using the Hexoskin garment. Ten young participants of an equal gender distribution were asked to sit, walk and sleep while wearing the two systems. Each activity was conducted for 30 min. The two systems' performance during the different activities against a reference table of normal HR and RR ranges retrieved from [72] was compared. Starting with the activity of walking, the two systems performed equally well in collecting RR values. HR values collected using Hexoskin were stable, while the values collected using the wired DigiAID

deviated significantly during certain time intervals. Studying the data collected while sitting, RR values captured from the female participants were within range for both systems. The collected RR values for men were higher than the reference values for both systems. It was also seen that the values captured by the Hexoskin fluctuated more. The authors reasoned that the main reason was the Hexoskin's use of a stretch-based sensor, while the wired DigiAID uses an air flow sensor. The HR values collected during sitting were within the reference range for both systems, although the HR values collected using Hexoskin were more stable. This is not strange considering that Hexoskin collects data using a one-channel ECG sensor. Talpur et al. (2019) [65] noted that the HR values collected using the wired DigiAID were acceptable, but not satisfactory. Studying the sleep activity data, the RR data were fluctuating for both systems, but within the reference RR range for all participants with the wired DigiAID. There were a few cases when the Hexoskin values were outside the RR range. HR values were stable for both systems. While the wired DigiAID was found to perform well in comparison with Hexoskin, participants found that being connected to a wired sensor system prohibited smooth performing of the activities. Therefore, the authors [65] also presented a wireless version of DigiAID that takes input from nine sensors (IRIS motes). An equal number of participants, although it was unclear whether they were the same ten participants as in the first experiment or not, conducted the activities while data were collected. However, the data presented from this experiment were purely technical and focused on power results. Since this was outside the scope of this review, we refer the interested reader to find more details in [65]. The aim is to conduct further experiments to validate the wireless DigiAID.

Tedesco et al. [66] conducted a study aiming at determining the accuracy of seven different wrist-worn activity trackers while worn by 18 older healthy people. The study was conducted between October 2017 and March 2018. Each participant conducted a number of walking activities, household activities and sedentary activities during a 3 h long session. The focus of this review paper is the use of wearable sensors for monitoring and preventing NCDs; therefore, we present only the results relating to the ability to measure HR in this article. A limitation with the study is that some of the devices required the participants to be static and immobile for a few seconds before acquiring HR. Hence, the HR measures presented in [66] were one-time static measures and were not based on continuous HR monitoring. HR was measured during the walking activities and household activities. Each participant was asked to walk on a treadmill at 1, 1.5 and 2 km/h for 3 min. Household activities included the following: walking while carrying a box, walking with a rollator and walking up two flights of stairs (20 steps in total) and down again. Each household activity was conducted for 3 min. Each activity was conducted twice because four different wrist-worn activity trackers were tested during the experiment. This allowed for wearing only two of them at once. The participant could rest as long as desired between each activity. The analysis of the static HR measures from the walking activities indicated an intraclass correlation (ICC) that had moderate-to-excellent (0.5 or higher) reliability at 2 km/h and moderate-to-good (between 0.5 and 0.9) reliability at the other two walking velocities. The obtained RMSE values for the different sensors were comparable for all walking speeds. The best mean absolute percentage error (MAPE) achieved was 4.54%, and the worst was 13.89%. Regarding the household activities, ICC indicated a good-to-excellent (0.75 or higher) reliability at all speeds and activities. Studying the RMSE values, the worst result (12.45 BPM) was achieved with the Fitbit Charge 2 worn on the non-dominant wrist. The best RMSE (3.76 BPM) was achieved for a Fitbit Charge 2 worn on the dominant wrist. MAPE varied between 3.57% and 9.42%. No information was provided on which sensor scored best and worst. Tedesco et al. (2019) [66] mentioned that the results were obtained with healthy older participants and that the results were not generalizable. Further evaluations with more participants and non-healthy participants are required. Studies collecting more than one time stamp of HR data per activity also need to be conducted. It is possible that interference between sensing devices occurred. Further investigation is needed.

Costin et al. [67] reported on a case study in which workers' HR and BT were monitored using Polar H7 at a hazardous critical mining site. Thresholds were used to alert the safety managers to

potentially unsafe conditions. Software provided visual alerts when the workers' exertion level reached 90% or higher for more than 5 min. The safety managers developed a scheme with working and resting guidelines for different work categories (light -> very heavy) and BT. For each work category and BT, the scheme provides an interpretation: no restriction, a recommended min of work/min of rest or the need for physiological monitoring. During the test period (May–August 2019), there were no recordable incidents on the site. This represents an improvement with respect to previous years. The technology used in the case study is one application in an active leading indicators (ALIs) IoT-based framework aimed at improving construction safety and productivity. Further information on the ALI framework was provided in [67].

## 8. Toward Reducing the Number of NCD Cases Using Wearable Sensors

We have now provided in-depth information on 45 works related to the monitoring and/or prevention of noncommunicable diseases (NCDs). As already stated, NCDs are the leading cause of death, although preventive actions can be taken. For example, the World Health Organization (WHO) [1] writes that 80% of premature cardiovascular diseases, strokes and diabetes can be prevented. First, this can be accomplished by reducing the risk factors related to the way we live our lives, i.e., reduce the consumption of tobacco, alcohol and unhealthy food and by increasing our physical activity (PA) level. Second, we can react to and take action when warning signals, such as raised blood pressure (BP), blood glucose (BG) and cholesterol, arise. Wearable sensors and E-health systems play an important role in health trend monitoring. By using smart Internet of Things (IoT) systems, we may detect and react to health issues and take appropriate action. In addition, we can ascertain that an intervention has the intended effect. The authors expect that IoT systems will be given even more attention in the upcoming years due to the COVID-19 pandemic. For example, in Sweden, older people (>70 years of age) have been asked to isolate themselves since mid-March 2020. No end date for this isolation has been provided at the time of writing this article in September. Self-isolation means cancelled dentist appointments, cancelled regular health-checkups and isolation that emanates from a social perspective.

Hypertension, or high BP, increases the risk for cardiovascular, brain and kidney diseases. The WHO [73] estimates that 1.13 billion people have hypertension. The majority of these live in low- and middle-income countries. In 2015, twenty-five percent of the men and 20% of the women had hypertension. Few of them, namely 20%, have their BP under control. Reducing the prevalence of hypertension by 25% between 2010 and 2025 is one of WHO's global targets for NCDs [74]. There are both modifiable risk factors (diet, PA, tobacco, alcohol, overweight/obesity) and non-modifiable risk factors (inheritance, age > 65, other diseases including diabetes and kidney disease) for hypertension [73]. BP is commonly measured using a BP cuff; however, attempts to continuously estimate BP using photoplethysmography (PPG) and diameter pulse wave (DPV) on the wrist [22], PPG on the wrist and fingertip [61] or from an ECG signal [23,24] have been presented. Furthermore, an indirect measure of BP through pulse wave velocity (PWV) was presented in [64].

Arrhythmia, i.e., a heart beating too fast (tachycardia), too slow (bradycardia) or irregularly, is an important indicator of an increased risk for a number of life-threatening complications. These complications include stroke, heart failure and cardiac arrest [75]. An important step in preventing these complications is the detection of arrhythmia, but the aforementioned risk factors for hypertension are reoccurring also for arrhythmia in [75]. For this, screening of arrhythmia using a portable ECG monitor has been suggested in [25]. Additional evaluations of the portable ECG monitor were presented in [27]. The device has been used to detect patients with suspected heart rhythm disorder and post-surgery atrial fibrillation (AF). Another measure for distinguishing between normal sinus (NS) patients and AF patients is heart rate variability (HRV). Both [28] and [29] were focused on this measure.

Two of the modifiable risk factors pointed out above are diet and overweight/obesity. In this article, we provided information on four works focusing on the monitoring of food intake. Two of

them [47,48] distinguished between different kinds of solids and drinks using a piezoelectric sensor in a necklace. Another work [46] detected hand movements and swallow apneas using an accelerometer and two respiratory plethysmographies (RIPs). The fourth [49] took environmental data into account when detecting eating events. An effort that aims to assist in overcoming the obesity problem by notifying users and therapists was presented in [60]. The system includes sensors for measuring ECG, BP, BG and muscular activity, but only information on real-time heart activity during PA has been analysed so far.

Moving on to asthma/COPD and diabetes, the studies on asthma/COPD mainly focus on counteracting the effects. Prediction of COPD was mentioned in [10], and Reference [12] focused on detecting wheezing using a wearable acoustic sensor. Neither of the two studies included more than one healthy person. The studies on diabetes used IoT systems for controlling diabetes. A shortcoming of such approaches is that they make use of the finger prick method for measuring BG. Validated means for performing this noninvasively would be a clear improvement over such systems. Initiatives using light, a clip on the earlobe, smart contact lenses and sweat patches exist [76]. However, these initiatives have not yet reached sufficient acceptance in clinical practice.

Looking at the reviewed articles' sociodemographic information from a gender or ageing perspective, an increased number of studies with older participants, men and women and patients would add valuable information. For example, women are under-diagnosed and under-treated with regard to cardiovascular diseases [77]. Further differences between sex and gender were outlined in [78], e.g., women having anaemia more often and suffering later from coronary artery disease.

It is not uncommon that older people have sleep disturbances [79]. While the quality of sleep may be altered during ageing, other factors, such as illnesses, medications and our daily habits, may also impact sleep [80]. Objective sleep monitoring is commonly done by performing polysomnography at hospitals [79]. Here, data recorded using different physiological parameters were analysed by experts. The authors discussed how the assessment method may affect the sleep, the cost and the impracticality in using these methods in larger studies. In Section 6, we outline seven articles [50–53,56–58] presenting results from sleep assessment studies based on data collected using wearable or contactless sensors. However, these were conducted with young people who are not representative of older people. Shifting our focus to stress, Reference [81] studied gender differences on health and well-being in later life and found that women more often take the role as a primary caregiver. Being a primary caregiver of older people is associated with a higher risk of stress. Nevertheless, none of the studies on stress [54,55] were conducted with older people or people who can be assumed to be primary caregivers.

Agenda 2030 for Sustainable Development [82] includes 17 goals adopted by all United Nation (UN) Member States in 2015. Goal 3 presents actions to ensure healthy lives and promote well-being for all at all ages, and one of the Goal 3 targets is the statement: "By 2030, reduce by one third premature mortality from non-communicable diseases through prevention and treatment and promote mental health and well-being." p. 16 [83]. Four years later, the UN provided an analysis [84] on whether the right foundations for reaching the goals have been laid. It was stated that concentrated efforts are required for addressing the growing burden of NCDs. The need to monitor and prevent NCDs is unquestionable and urgently needed. The earlier health issues related to NCDs can be recognized and identified, the higher is the chance to take action. In addition, systems that advise the user to adopt a healthier lifestyle are important.

This article provided a number of examples of how wearable sensors are used in the scope of monitoring and controlling NCDs and for providing advice regarding lifestyle. However, many issues remain. For example, our analysis of the sociodemographic data provided in the reviewed articles shows that the majority of sensor systems presented are not tested on a representative group of people, namely often healthy volunteers are used and both genders are not equally represented. In fact, men are often over-represented; the age of test persons is often much lower than the intended user group; and the number of test persons is often much too low. On top of this, several studies did not even present these kinds of qualitative data. This has been, and still is, a common issue in health-related

research. Nevertheless, even if considerable work remains, the use of wearable sensor systems is foreseen to play an important role in the battle against NCDs. The increased number of articles in 2019 support this claim. By following health trends on a regular basis, early deterioration can be detected, and preventive actions can be taken. The wearable sensor systems can be tailored for a specific patient, providing support to handle his or her specific NCDs. It is very often the case that a patient has not only one, but several NCDs interacting with each other. The sensor systems can also be important tools for both the individual being monitored and the professional caregiver, that is not only to measure and follow trends, but also to give support in the form of advice on how to manage the disease. The COVID-19 pandemic and enforced self-isolation have stressed the importance of access to such tools.

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## References

1. World Health Organization. Noncommunicable Diseases (NCD). Available online: https://www.who.int/gho/ncd/en/ (accessed on 8 June 2020).
2. Li, H.; Wu, J.; Shi, Y. Examining individuals' adoption of healthcare wearable devices: An empirical study from privacy calculus perspective. *Int. J. Med Inform.* **2016**, *88*, 8–17. [CrossRef] [PubMed]
3. McKinsey&Company. Värdet av Digitalteknik i den Svenska Vården. 2016. Available online: https://www.mckinsey.com/industries/healthcare-systems-and-services/our-insights/digitizing-healthcare-in-sweden (accessed on 8 June 2020).
4. Kristoffersson, A.; Lindén, M. A systematic review on the use of wearable body sensors for health monitoring: A qualitative synthesis. *Sensors* **2020**, *20*, 1502. [CrossRef] [PubMed]
5. Moher, D.; Liberati, A.; Tetzlaff, J.; Altman, D.G.; The PRISMA Group. Preferred Reporting Items for Systematic Reviews and Meta-Analyses: The PRISMA Statement. *Ann. Intern. Med.* **2009**, *151*, 264–269. [PubMed]
6. Bonnevie, T.; Gravier, F.E.; Elkins, M.; Dupuis, J.; Prieur, G.; Combret, Y.; Viacroze, C.; Debeaumont, D.; Robleda-Quesada, A.; Quieffin, J.; et al. People undertaking pulmonary rehabilitation are willing and able to provide accurate data via a remote pulse oximetry system: A multicentre observational study. *J. Physiother.* **2019**, *65*, 28–36. [CrossRef]
7. Caulfield, B.; Kaljo, I.; Donnelly, S. Use of a consumer market activity monitoring and feedback device improves exercise capacity and activity levels in COPD. In Proceedings of the 2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Chicago, IL, USA, 26–30 August 2014; pp. 1765–1768. [CrossRef]
8. Naranjo-Hernández, D.; Talaminos-Barroso, A.; Reina-Tosina, J.; Roa, L.M.; Barbarov-Rostan, G.; Cejudo-Ramos, P.; Márquez-Martín, E.; Ortega-Ruiz, F. Smart vest for respiratory rate monitoring of copd patients based on non-contact capacitive sensing. *Sensors* **2018**, *18*, 2144. [CrossRef]
9. Katsaras, T.; Milsis, A.; Rizikari, M.; Saoulis, N.; Varoutaki, E.; Vontetsianos, A. The use of the "Healthwear" wearable system in chronic patients' early hospital discharge: Control randomized clinical trial. In Proceedings of the 2011 5th International Symposium on Medical Information and Communication Technology, Montreux, Switzerland, 27–30 March 2011; pp. 143–146. [CrossRef]
10. Estrada, L.; Torres, A.; Sarlabous, L.; Jané, R. Evaluating respiratory muscle activity using a wireless sensor platform. In Proceedings of the 2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Orlando, FL, USA, 16–20 August 2016; pp. 5769–5772. [CrossRef]

11. World Health Organization. Asthma. Available online: https://www.who.int/news-room/q-a-detail/asthma (accessed on 10 December 2019).
12. Khan, S.M.; Qaiser, N.; Shaikh, S.F.; Hussain, M.M. Design Analysis and Human Tests of Foil-Based Wheezing Monitoring System for Asthma Detection. *IEEE Trans. Electron Devices* **2020**, *67*, 249–257. [CrossRef]
13. Buonocore, C.M.; Rocchio, R.A.; Roman, A.; King, C.E.; Sarrafzadeh, M. Wireless Sensor-Dependent Ecological Momentary Assessment for Pediatric Asthma mHealth Applications. In Proceedings of the 2nd IEEE International Conference on Connected Health: Applications, Systems and Engineering Technologies (CHASE 2017), Philadelphia, PA, USA, 17–19 July 2017; pp. 137–146. [CrossRef]
14. Bastianini, F.; Silvestri, S.; Magrone, G.; Gallotta, E.; Sterzi, S. A preliminary efficacy evaluation performed by opto-electronic plethysmography of asymmetric respiratory rehabilitation. In Proceedings of the 31st Annual International Conference of the IEEE Engineering in Medicine and Biology Society: Engineering the Future of Biomedicine, Minneapolis, MN, USA, 3–6 September 2009; pp. 849–852.
15. Coutinho Myrrha, M.; Vieira, D.; Moraes, K.; Lage, S.; Parreira, V.; Britto, R. Chest wall volumes during inspiratory loaded breathing in COPD patients. *Respir. Physiol. Neurobiol.* **2013**, *188*, 15–20. [CrossRef]
16. Yañez, A.M.; Guerrero, D.; de Alejo, R.P.; Garcia-Rio, F.; Alvarez-Sala, J.L.; Calle-Rubio, M.; de Molina, R.M.; Falcones, M.V.; Ussetti, P.; Sauleda, J.; et al. Monitoring Breathing Rate at Home Allows Early Identification of COPD Exacerbations. *Chest* **2012**, *142*, 1524–1529. [CrossRef] [PubMed]
17. Jensen, M.T.; Marott, J.L.; Lange, P.; Vestbo, J.; Schnohr, P.; Nielsen, O.W.; Jensen, J.S.; Jensen, G.B. Resting heart rate is a predictor of mortality in COPD. *Eur. Respir. J.* **2013**, *42*, 341–349. [CrossRef]
18. Huang, A.; Xu, W.; Li, Z.; Xie, L.; Sarrafzadeh, M.; Li, X.; Cong, J. System Light-Loading Technology for mHealth: Manifold-Learning-Based Medical Data Cleansing and Clinical Trials in WE-CARE Project. *IEEE J. Biomed. Health Inform.* **2014**, *18*, 1581–1589. [CrossRef]
19. Huang, A.; Chen, C.; Bian, K.; Duan, X.; Chen, M.; Gao, H.; Meng, C.; Zheng, Q.; Zhang, Y.; Jiao, B.; et al. WE-CARE: An intelligent mobile telecardiology system to enable mHealth applications. *IEEE J. Biomed. Health Inform.* **2014**, *18*, 693–702. [CrossRef]
20. Raad, M.W.; Sheltami, T.; Deriche, M. A Ubiquitous Telehealth System for the Elderly. In *Internet of Things: User-Centric Iot, Pt I*; Lecture Notes of the Institute for Computer Sciences Social Informatics and Telecommunications Engineering; Giaffreda, R., Vieriu, R.L., Pasher, E., Bendersky, G., Jara, A.J., Rodrigues, J., Dekel, E., Mandler, B., Eds.; Springer: Berlin/Heidelberg, Germany, 2015; Volume 150, pp. 159–166. [CrossRef]
21. Javaid, A.Q.; Chang, I.S.; Mihailidis, A. Ballistocardiogram Based Identity Recognition: Towards Zero-Effort Health Monitoring in an Internet-of-Things (IoT) Environment. In Proceedings of the 2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Honolulu, HI, USA, 18–21 July 2018; Volume 2018, pp. 3326–3329. [CrossRef]
22. Li, Y.; Li, S.; Song, H.; Shao, B.; Yang, X.; Deng, N. Noninvasive blood pressure estimation with peak delay of different pulse waves. *Int. J. Distrib. Sens. Netw.* **2019**, *15*, 1550147719837877. [CrossRef]
23. Simjanoska, M.; Gjoreski, M.; Gams, M.; Bogdanova, A.M. Non-invasive blood pressure estimation from ECG using machine learning techniques. *Sensors* **2018**, *18*, 1160, [CrossRef] [PubMed]
24. Simjanoska, M.; Kochev, S.; Tanevski, J.; Bogdanova, A.M.; Papa, G.; Eftimov, T. Multi-level information fusion for learning a blood pressure predictive model using sensor data. *Inf. Fusion* **2020**, *58*, 24–39. [CrossRef]
25. Susič, T.P.; Stanič, U. Penetration of the ICT technology to the health care primary sector—Ljubljana PILOT. In Proceedings of the 2016 39th International Convention on Information and Communication Technology, Electronics and Microelectronics (MIPRO), Opatija, Croatia, 30 May–3 June 2016; pp. 436–441. [CrossRef]
26. Depolli, M.; Avbelj, V.; Trobec, R.; Kališnik, J.M.; Tadej, K.; Susič, A.P.; Stanič, U.; Semeja, A. PCARD platform for mhealth monitoring. *Informatica* **2016**, *40*, 117–123.
27. Rashkovska, A.; Depolli, M.; Tomašić, I.; Avbelj, V.; Trobec, R. Medical-Grade ECG Sensor for Long-Term Monitoring. *Sensors* **2020**, *20*, 1695. [CrossRef] [PubMed]
28. Gonzalez, L.; Paniagua, T.; Starliper, N.; Lobaton, E. Signal Quality for RR Interval Prediction on Wearable Sensors. In Proceedings of the 2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Berlin, Germany, 23–27 July 2019; pp. 2525–2528. [CrossRef]

29. Pérez-Valero, J.; Garcia-Sanchez, A.J.; Marín, M.R.; Garcia-Haro, J. A prototype framework design for assisting the detection of atrial fibrillation using a generic low-cost biomedical sensor. *Sensors* **2020**, *20*, 896. [CrossRef]
30. Seshadri, D.R.; Bittel, B.; Browsky, D.; Houghtaling, P.; Drummond, C.K.; Desai, M.; Gillinov, A.M. Accuracy of the Apple Watch 4 to Measure Heart Rate in Patients With Atrial Fibrillation. *IEEE J. Transl. Eng. Health Med.* **2020**, *8*, 1–4. [CrossRef]
31. Albahri, A.S.; Albahri, O.S.; Zaidan, A.A.; Zaidan, B.B.; Hashim, M.; Alsalem, M.A.; Mohsin, A.H.; Mohammed, K.I.; Alamoodi, A.H.; Enaizan, O.; et al. Based Multiple Heterogeneous Wearable Sensors: A Smart Real-Time Health Monitoring Structured for Hospitals Distributor. *IEEE Access* **2019**, *7*, 37269–37323. [CrossRef]
32. Albahri, O.S.; Albahri, A.S.; Zaidan, A.A.; Zaidan, B.B.; Alsalem, M.A.; Mohsin, A.H.; Mohammed, K.I.; Alamoodi, A.H.; Nidhal, S.; Enaizan, O.; et al. Fault-Tolerant mHealth Framework in the Context of IoT-Based Real-Time Wearable Health Data Sensors. *IEEE Access* **2019**, *7*, 50052–50080. [CrossRef]
33. Goldberger, A.; Amaral, L.; Glass, L.; Hausdorff, J.; Ivanov, P.; Mark, R.; Mietus, J.; Moody, G.; Peng, C.K.; Stanley, H. Physiobank, physiotoolkit, and physionet. *Circulation* **2000**, *101*, 215–220. [CrossRef] [PubMed]
34. Clifford, G.D.; Liu, C.; Moody, B.; Lehman, L.H.; Silva, I.; Li, Q.; Johnson, A.E.; Mark, R.G. AF classification from a short single lead ECG recording: The PhysioNet/computing in cardiology challenge 2017. In Proceedings of the 2017 Computing in Cardiology (CinC), Rennes, France, 24–27 September 2017; pp. 1–4.
35. Papouchado, M.; Wakjer, P.R.; James, M.A.; Clarke, L.M. Fundamental differences between the standard 12–lead electrocardiograph and the modified (Mason—Likar) exercise lead system. *Eur. Heart J.* **1987**, *8*, 725–733. [CrossRef]
36. Kocjančič, S.; Avbelj, V. Electrocardiographic sensor: How to use it among general physicians. In Proceedings of the 21st International Multiconference Information Society-IS, Ljubljana, Slovenia, 8–12 October 2018; pp. 35–36.
37. Ĉarman, D.; Cvetkovič, T.; Avbelj, V.; Kališnik, J. A study of postoperative atrial fibrillation. In Proceedings of the 21st International Multiconference Information Society-IS, Ljubljana, Slovenia, 8–12 October 2018; pp. 7–10.
38. Rashkovska, A.; Avbelj, V. Abdominal foetal ECG measured with differential ECG sensor. In Proceedings of the 2017 40th International Convention on Information and Communication Technology, Electronics and Microelectronics (MIPRO), Opatija, Croatia, 22–26 May 2017; pp. 289–291.
39. Širaiy, B.; Trobec, R.; Ilić, V. Quality of One-channel Telemetric ECG Sensor Signal in Maximum Exercise Stress Tests. *Meas. Sci. Rev.* **2019**, *19*, 79–85. [CrossRef]
40. Vest, A.; Da Poian, G.; Li, Q.; Liu, C.; Nemati, S.; Shah, A.; Clifford, G. An open source benchmarked toolbox for cardiovascular waveform and interval analysis. *Physiol. Meas.* **2018**, *39*, 105004. [CrossRef]
41. Pérez-Valero, J.; Caballero Pintado, M.; Melgarejo, F.; García-Sánchez, A.J.; Garcia-Haro, J.; García Córdoba, F.; García Córdoba, J.; Pinar, E.; García Alberola, A.; Matilla-García, M.; et al. Symbolic Recurrence Analysis of RR Interval to Detect Atrial Fibrillation. *J. Clin. Med.* **2019**, *8*, 1840. [CrossRef]
42. Moody, G.B.; Mark, R.G. The impact of the MIT-BIH Arrhythmia Database. *IEEE Eng. Med. Biol.* **2001**, *20*, 45–50. [CrossRef] [PubMed]
43. World Health Organization. *Global Report on Diabetes*; World Health Organization: Geneva, Switzerland, 2016.
44. Al-Taee, M.A.; Al-Nuaimy, W.; Al-Ataby, A.; Muhsin, Z.J.; Abood, S.N. Mobile Health Platform for Diabetes Management Based on the Internet-of-Things. In Proceedings of the 2015 IEEE Jordan Conference on Applied Electrical Engineering and Computing Technologies, Amman, Jordan, 3–5 November 2015.
45. Onoue, T.; Goto, M.; Kobayashi, T.; Tominaga, T.; Ando, M.; Honda, H.; Yoshida, Y.; Tosaki, T.; Yokoi, H.; Kato, S.; et al. Randomized controlled trial for assessment of Internet of Things system to guide intensive glucose control in diabetes outpatients: Nagoya Health Navigator Study protocol. *Nagoya J. Med. Sci.* **2017**, *79*, 323–329. [CrossRef]
46. Dong, B.; Biswas, S. Meal-time and duration monitoring using wearable sensors. *Biomed. Signal Process. Control* **2017**, *32*, 97–109. [CrossRef]
47. Alshurafa, N.; Kalantarian, H.; Pourhomayoun, M.; Sarin, S.; Liu, J.J.; Sarrafzadeh, M. Non-invasive monitoring of eating behavior using spectrogram analysis in a wearable necklace. In Proceedings of the 2014 IEEE Healthcare Innovation Conference (HIC), Seattle, WA, USA , 8–10 October 2014; pp. 71–74. [CrossRef]

48. Alshurafa, N.; Kalantarian, H.; Pourhomayoun, M.; Liu, J.J.; Sarin, S.; Shahbazi, B.; Sarrafzadeh, M. Recognition of Nutrition Intake Using Time-Frequency Decomposition in a Wearable Necklace Using a Piezoelectric Sensor. *IEEE Sens. J.* **2015**, *15*, 3909–3916. [CrossRef]
49. Solis, R.; Pakbin, A.; Akbari, A.; Mortazavi, B.J.; Jafari, R. A Human-centered Wearable Sensing Platform with Intelligent Automated Data Annotation Capabilities. In Proceedings of the 2019 International Conference on Internet of Things Design and Implementation, Montreal, QC, Canada, 15 April 2019; pp. 255–260. [CrossRef]
50. Lin, C.; Gamble, J.; Yang, Y.; Wang, J. Estimating the influence of chronotype and social zeitgebers on circadian rhythms using an accelerometer-based sensor network. In Proceedings of the 2012 IEEE-EMBS International Conference on Biomedical and Health Informatics, Hong Kong, China, 2012; pp. 285–288, [CrossRef]
51. Umemura, G.S.; Pinho, J.P.; Furtado, F.; Gonçalves, B.S.B.; Fomer-Cordero, A. Comparison of sleep parameters assessed by actigraphy of healthy young adults from a small town and a megalopolis in an emerging country. In Proceedings of the 2017 IEEE Healthcare Innovations and Point of Care Technologies (HI-POCT), Bethesda, MD, USA, 6–8 November 2017; pp. 200–203. [CrossRef]
52. Nakamura, T.; Goverdovsky, V.; Morrell, M.J.; Mandic, D.P. Automatic Sleep Monitoring Using Ear-EEG. *IEEE J. Transl. Eng. Health Med.* **2017**, *5*, 1–8. [CrossRef]
53. Velicu, O.R.; Madrid, N.M.; Seepold, R. Experimental sleep phases monitoring. In Proceedings of the 2016 3rd IEEE Embs International Conference on Biomedical and Health Informatics, Las Vegas, NV, USA, 24–27 February 2016; pp. 625–628.
54. Parnandi, A.; Gutierrez-Osuna, R. Physiological Modalities for Relaxation Skill Transfer in Biofeedback Games. *IEEE J. Biomed. Health Inform.* **2017**, *21*, 361–371. [CrossRef]
55. Uday, S.; Jyotsna, C.; Amudha, J. Detection of Stress using Wearable Sensors in IoT Platform. In Proceedings of the 2018 Second International Conference on Inventive Communication and Computational Technologies, Coimbatore, India, 20–21 April 2018; pp. 492–498.
56. Zhuang, Y.; Song, C.; Wang, A.; Lin, F.; Li, Y.; Gu, C.; Li, C.; Xu, W. SleepSense: Non-invasive sleep event recognition using an electromagnetic probe. In Proceedings of the 2015 IEEE 12th International Conference on Wearable and Implantable Body Sensor Networks (BSN), Cambridge, MA, USA, 9–12 June 2015; pp. 1–6. [CrossRef]
57. Katsumata, K.; Noda, Y.; Isokawa, N.; Katayama, S.; Okoshi, T.; Nakazawa, J. SleepThermo: The Affect of in-Cloth Monitored Body Temperature Change during Sleep on Human Well-Being. In Proceedings of the 2019 ACM International Joint Conference on Pervasive and Ubiquitous Computing, London, UK, 9–13 September 2019. [CrossRef]
58. Neubert, S.; Geißler, A.; Roddelkopf, T.; Stoll, R.; Sandmann, K.H.; Neumann, J.; Thurow, K. Multi-Sensor-Fusion Approach for a Data-Science-Oriented Preventive Health Management System: Concept and Development of a Decentralized Data Collection Approach for Heterogeneous Data Sources. *Int. J. Telemed. Appl.* **2019**, *2019*. [CrossRef]
59. Stroop, J.R. Studies of interference in serial verbal reactions. *J. Exp. Psychol.* **1935**, *18*, 643–662. [CrossRef]
60. Rawashdeh, M.; Al-Qurishi, M.; Al-Rakhami, M.; Al-Quraishi, M.S. A multimedia cloud-based framework for constant monitoring on obese patients. In Proceedings of the 2017 IEEE International Conference on Multimedia & Expo Workshops (ICMEW), Hong Kong, China, 10–14 July 2017; pp. 139–144. [CrossRef]
61. Wannenburg, J.; Malekian, R. Body Sensor Network for Mobile Health Monitoring, a Diagnosis and Anticipating System. *IEEE Sens. J.* **2015**, *15*, 6839–6852. [CrossRef]
62. Wu, W.; Pirbhulal, S.; Sangaiah, A.K.; Mukhopadhyay, S.C.; Li, G. Optimization of signal quality over comfortability of textile electrodes for ECG monitoring in fog computing based medical applications. *Future Gener. Comput. Syst.* **2018**, *86*, 515–526. [CrossRef]
63. Chen, C.; Wang, Z.Y.; Li, W.; Chen, H.Y.; Mei, Z.N.; Yuan, W.; Tao, L.K.; Zhao, Y.T.; Huang, G.S.; Mei, Y.F.; et al. Novel Flexible Material-Based Unobtrusive and Wearable Body Sensor Networks for Vital Sign Monitoring. *IEEE Sens. J.* **2019**, *19*, 8502–8513. [CrossRef]
64. Jovanov, E. Wearables Meet IoT: Synergistic Personal Area Networks (SPANs). *Sensors* **2019**, *19*, 13. [CrossRef]
65. Talpur, A.; Shaikh, F.K.; Baloch, N.; Felemban, E.; Khelil, A.; Alam, M.M. Validation of Wired and Wireless Interconnected Body Sensor Networks. *Sensors* **2019**, *19*, 3697–3697. [CrossRef]

66. Tedesco, S.; Sica, M.; Ancillao, A.; Timmons, S.; Barton, J.; O'Flynn, B. Accuracy of consumer-level and research-grade activity trackers in ambulatory settings in older adults. *PLoS ONE* **2019**, *14*, e0216891. [CrossRef]
67. Costin, A.; Wehle, A.; Adibfar, A. Leading Indicators-A Conceptual IoT-Based Framework to Produce Active Leading Indicators for Construction Safety. *Safety* **2019**, *5*, 26. [CrossRef]
68. Pereira, T.; Correia, C.; Cardoso, J. Novel Methods for Pulse Wave Velocity Measurement. *J. Med. Biol. Eng.* **2015**, *35*, 555–565. [CrossRef]
69. Yuan, W.; Wu, X.; Gu, W.; Lin, J.; Cui, Z. Printed stretchable circuit on soft elastic substrate for wearable application. *J. Semicond.* **2018**, *39*, 015002. [CrossRef]
70. Zhao, Y.; Huang, G.; Li, Y.; Edy, R.; Gao, P.; Tang, H.; Bao, Z.; Mei, Y. Three-dimensional carbon/ZnO nanomembrane foam as an anode for lithium-ion battery with long-life and high areal capacity. *J. Mater. Chem. A* **2018**, *6*, 7227–7235. [CrossRef]
71. Cheng, Y.; Wang, R.; Sun, J.; Gao, L. A Stretchable and Highly Sensitive Graphene-Based Fiber for Sensing Tensile Strain, Bending, and Torsion. *Adv. Mater.* **2015**, *27*, 7365–7371. [CrossRef]
72. Milenković, A.; Otto, C.; Jovanov, E. Wireless sensor networks for personal health monitoring: Issues and an implementation. *Comput. Commun.* **2006**, *29*, 2521–2533. [CrossRef]
73. World Health Organization. Hypertension. Available online: https://www.who.int/news-room/fact-sheets/detail/hypertension (accessed on 23 June 2020).
74. World Health Organization. *Global Action Plan for the Prevention and Control of Noncommunicable Diseases 2013–2020*; World Health Organization: Geneva, Switzerland, 2013.
75. National Heart, Lung, and Blood Institute. Arrhythmia. 2020. Available online: https://www.nhlbi.nih.gov/health-topics/arrhythmia (accessed on 23 June 2020).
76. Young, E. Non-invasive glucose monitoring for diabetes: five strategies under development. *Pharm. J.* **2017**, *299*. [CrossRef]
77. Mehta, L.S.; Beckie, T.M.; DeVon, H.A.; Grines, C.L.; Krumholz, H.M.; Johnson, M.N.; Lindley, K.J.; Vaccarino, V.; Wang, T.Y.; Watson, K.E. Acute Myocardial Infarction in Women A Scientific Statement From the American Heart Association. *Circulation* **2016**, *133*, 916–947. [CrossRef]
78. Regitz-Zagrosek, V. Sex and gender differences in health. Science & Society Series on Sex and Science. *EMBO Rep.* **2012**, *13*, 596–603. [CrossRef]
79. Tedesco, S.; Barton, J.; O'Flynn, B. A review of activity trackers for senior citizens: Research perspectives, commercial landscape and the role of the insurance industry. *Sensors* **2017**, *17*, 1277. [CrossRef]
80. Moraes, W.; Piovezan, R.; Poyares, D.; Bittencourt, L.; Santos-Silva, R.; Tufik, S. Effects of ageing on sleep structure throughout adulthood: a population-based study. *Sleep Med.* **2014**, *15*, 401–409. [CrossRef]
81. Carmel, S. Health and Well-Being in Late Life: Gender Differences Worldwide. *Front. Med.* **2019**, *6*, 218, [CrossRef]
82. United Nations. The Sustainable Development Agenda. 2015. Available online: https://www.un.org/sustainabledevelopment/development-agenda/ (accessed on 25 June 2020).
83. General Assembly Resolution 70/1. Transforming Our World: The 2030 Agenda for Sustainable Development, A/RES/70/1. 2015. Available online: https://www.un.org/ga/search/view_doc.asp?symbol=A/RES/70/1 (accessed on 25 June 2020).
84. United Nations. *The Sustainable Development Goals Report 2019*; United Nations Publications: New York, NY, USA, 2019.