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Review

New Perspectives in Nonintrusive Sleep Monitoring for Neurodegenerative Diseases—A Narrative Review

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Abstract: Good sleep quality is of primary importance in ensuring people's health and well-being. In fact, sleep disorders have well-known adverse effects on quality of life, as they influence attention, memory, mood, and various physiological regulatory body functions. Sleep alterations are often strictly related to age and comorbidities. For example, in neurodegenerative diseases, symptoms may be aggravated by alterations in sleep cycles or, vice versa, may be the cause of sleep disruption. Polysomnography is the primary instrumental method to investigate sleep diseases; however, its use is limited to clinical practice. This review aims to provide a comprehensive overview of the available innovative technologies and methodologies proposed for less invasive sleep-disorder analysis, with a focus on neurodegenerative disorders. The paper intends to summarize the main studies, selected between 2010 and 2022, from different perspectives covering three relevant contexts, the use of wearable and non-wearable technologies, and application to specific neurodegenerative diseases. In addition, the review provides a qualitative summary for each selected article concerning the objectives, instrumentation, metrics, and impact of the results obtained, in order to facilitate the comparison among methodological approaches and overall findings.

Keywords: neurodegenerative diseases; sleep monitoring; sleep disorders; Parkinson disease; dementia; Alzheimer Disease; wearable sensors; inertial sensors; video analysis; Internet of Things

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1. Introduction

Sleep plays a fundamental role in the lives of many animals, from some invertebrates to humans. It has both physiological and behavioral connotations and, although its functions and evolutionary significance are not yet fully known, its fundamental role in the maintenance of homeostasis and the adverse effects due to its sub-optimality are well-known in humans. Indeed, it influences attention, memory, mood, blood pressure, immune and inflammatory response, and stress response [1–3]. Under physiological conditions, a sleep phase and a wakefulness phase alternate in a regular manner, constituting the sleep–wake circadian rhythm. The sleep phase is a dynamic process aimed at obtaining the required neurophysiological states at certain times, according to circadian and homeostatic needs and despite external or internal interfering stimuli. Moreover, the so-called macrostructure of sleep, as recorded by electroencephalography (EEG) during polysomnography (PSG), is characterized by a chain of regular and predictable events (cyclic alternation of rapid eye movements (REM) and non-REM (NREM) sleep stages). The process shows an intrinsic variability and has to finely modulate itself in order to maintain the maximum adaptability while preserving sleep macrostructure. In this context, peculiar transient EEG patterns (sleep microstructure) are supposed to play the main role in the building up of

EEG synchronization and in the flexible adaptation against perturbations. Alterations in sleep macro- or microstructure provoke sleep disruption, sleep instability and loss of sleep quantity and quality [4,5]. Sleep and wakefulness influence each other; therefore, sleep quality degradation, when persisting over time, may translate into severe and irreversible symptoms, taking the form of a pathological framework. Therefore, it is very important to create the best possible sleeping conditions and to intervene promptly when sleep disturbances occur, both in their diagnosis and eventual treatments. Even though sleep time and quality lessen with age, sleep disorders are related to comorbidities rather than age [6]. In particular, sleep disorders have a high incidence in neurodegenerative diseases (ND) and are known to influence well-being and quality of life [7]. Indeed, the symptoms of the NDs may be worsened by the sleep disorders, but, at the same time, the latter may be caused or augmented by the neurodegenerative disease, creating a more complex clinical picture. Optimized, sometimes individualized, treatments are being developed in clinical practice [8]. The relationship between sleep abnormalities/disorders and NDs is so close that sleep disorders can be used as criteria for the diagnosis of specific NDs [9]. As an example, stridor co-occurs with multiple system atrophy (MSA), while a REM-sleep behavior disorder may discriminate between Alzheimer's disease (AD) and dementia with Lewy body (DLB). The most interesting discovery in the field is that, in some cases, especially in Parkinson's disease (PD), the onset of sleep disturbance could reflect early alterations in the neural pathways involved, thus constituting a prodromal symptom [10]. This allows earlier intervention in treatment and follow-up; moreover, it will be crucial when neuroprotective drugs become available [11]. The assessment of sleep macro- and microstructure, movements, respiratory pattern or other neurophysiological changes that occur during sleep is essential to verify the quality of sleep and detect sleep disorders. For clinical purposes, PSG is the gold standard for the assessment of sleep disorders, and guidelines are available for recommended uses. In PSG, selected electrophysiological signals are recorded along with other biological signals of interest, such as airflow, oxygen saturation, chest movements or snoring. The type and number of signals that are recorded depends on the reported symptoms and the aim of the PSG. EEG, plectrooculography (EOG), electrocardiography (ECG), and electromyography (EMG) are required for sleep staging, whereas in the detection of sleep apnea, for instance, the primary focus is on oxygen saturation, airflow, and thorax and abdominal movements [12]. Complete polysomnographic examinations are very complex and invasive; they need cumbersome instrumentation, a proper location, night-time assistance by experienced personnel, time, money and they bring discomfort for the patient as well. The medical inspection of the signals (many hours of recording) needs to be performed by qualified experts and it is, however, subjected to inter- operator variability [13,14]. For these reasons, PSG can only be performed in proper settings and usually for in-patients, mainly when precise diagnosis is essential for targeting therapy. Therefore, many alternatives have been proposed in the research to cope with this limitation, in particular for screening or monitoring purposes. They exploit, in general, new technologies and automatic algorithms to reduce the invasiveness of the instrumentation required and the intervention of specialized personnel. This would allow a much more frequent, if not continuous, assessment of the patients' condition with reduced cost and discomfort, providing the conditions for optimized diagnosis and treatments. Research in this area has several objectives:

- To update and simplify the work of medical staff by automating or semi-automating certain procedures—such as sleep staging or sleep disorders diagnosis—through new instrumentation.
- To verify medical treatment efficacy and, eventually, to optimize it, through sleep monitoring.
- To ensure frequent or continuous follow-up by providing instrumentation and protocols to be used in non-hospital settings.

This review wants to explore the available new technologies for minimally invasive sleep monitoring, specifically applied to the field of the NDs, focusing on wearable and

non-wearable solutions. The paper is organized as follows. The next Sections 1.1 and 1.2 provides a general background on clinical aspects of sleep monitoring and an overview on the use of technological approaches in NDs. Section 2 provides the description of the methodology employed for the paper selection in this review, Section 3 illustrates results and, lastly, Sections 4 contains discussion and conclusions.

1.1. Background of Sleep Monitoring in Neurodegenerative Diseases

In NDs, the progressive loss of neurons in particular structures of the central nervous system (CNS) causes dysfunctions of neural pathways, leading to the symptoms typical of each disease. In some cases, treatments are available for symptoms relief, but the neurodegeneration process is unstoppable and irreversible. AD and PD are among the most common neurodegenerative disorders worldwide, with a high incidence in the elderly population [15]. In fact, aging is one of the main risk factors in developing NDs, even though their etiology can vary, and are not completely understood. Moreover, genes and environment are believed to be together responsible of these diseases' onset. Other less common NDs are Huntington disease, DLB, amyotrophic lateral sclerosis (ALS), Friedreich ataxia, and MSA. A brief description of the principal symptoms and characteristics is provided in Table 1, with a focus on the diseases' effects on sleep. In fact, these pathologies have a complex relationship with the sphere of sleep. Sleep disruption and disorders can be commonly found in patients with ND and may constitute an early biomarker. Iranzo in [11] highlights the frequent occurrence of the subsequent sleep disorders in ND:

- Insomnia.
- Excessive daytime sleepiness (EDS).
- Rapid eye movement (REM) sleep behavior disorder (RBD).
- Periodic leg movements in sleep (PLMS).
- Restless legs syndrome (RLS).
- Central or obstructive sleep apnea (CSA, OSA).
- Sleep disordered Breathing (SDS).
- Nocturnal stridor.
- Circadian rhythm disorders.

Further, sleep-quality impairment, sleep-time reduction, and presence of abnormal movements (both excessive and impaired) are other typical features. Sleep symptoms derive from multifactorial causes, including the deterioration of sleep–wake regulatory circuitries caused by the neurodegeneration itself and altered neural pathways, movement or respiratory symptoms specific to each pathology or several indirect mechanisms [16]. Sleep has, in turn, an influence on the neurodegeneration process, realizing a complex bi-directional relationship that could lead to new targeted interventions [17]. For instance, sub-optimal sleep—e.g., lack of sleep, disturbed sleep, sleep disorders—was found correlated to cognitive-impairment severity in AD patients and in the elderly, thus constituting a possible risk factor for the onset of cognitive impairment [18,19]. Lately, the discoveries regarding this relationship have been translated in the clinical practice, renovating disease diagnostic criteria and treatments [20]. However, sleep-related symptoms are still under-reported by patients and under-diagnosed by healthcare professionals. This is a flaw in optimized diagnosis and intervention, because of the reduced descriptive power of a complete clinical framework that considers these aspects. The result is a reduced quality of life for patients, sub-optimal treatments, and, sometimes, late diagnosis or misdiagnosis. In clinical practice, these sleep disruptions and disorders, including abnormal movements, are assessed through different tools, such as individual interviews (anamnesis), sleep diaries, sleep questionnaires, clinical scales, reduced or complete PSG, sleep diaries, and clinical scales; moreover, clinical protocols establish assessing procedures [21,22]. Typical sleep symptoms and main clinical assessing protocols are described in Table 2. PSG is the most complete clinical examination, able to evaluate every aspect of sleep and derive quantitative measures, constituting the gold standard in assessment and diagnosis of sleep-related problems. Sleep staging, REM sleep without atonia, apneas, oxygen saturation, sleep

microstructure including the cyclic alternating pattern (CAP), and sleep parameters computation can be investigated by PSG. Some of the typical sleep parameters employed, besides sleep-stages descriptors, are total sleep time (TST), sleep latency, sleep efficiency, wake after sleep onset (WASO), and REM latency [23]. Standardized semiquantitative evaluation of symptom severity and quality-of-life reduction is provided by clinical rating scales, such as those shown in Table 2. The latter are employed for various sleep disturbances and disorders, including restless legs syndrome (RLS), insomnia, nocturia, breathing disorders, and daytime sleepiness [24]. It must be considered that each subject's clinical history deeply influences the sleep evaluation tools; in fact, perception of symptoms is subjective and can be influenced by the clinical framework. As an example, in dementia, cognitive impairment can make it difficult to obtain a subject's collaboration in clinical interviews and physical exams [25]. In synucleinopathies—such as PD, DBL, and MSA—RBD assessment is particularly relevant because its idiopathic occurrence is known to be a prodromal symptom that can anticipate any other symptom by decades [26]. In contrast, RBD developing after the onset of other symptoms may indicate a particular disease phenotype. For this reason, RBD screening and diagnosis have attracted much clinical attention in the last years.

Table 1. Neurodegenerative diseases (ND) and sleep-related symptoms, and sleep disorders incidence (sleep disorders incidence (SD)) [11].

ND	Symptoms	Sleep Symptoms	SD
Parkinson's disease [27,28]	Motor: tremors, postural issues, bradykinesia, ON/OFF states, dystonia, rigidity, dyskinesias. Non-motor: orthostatic hypotension, depression, gastrointestinal symptoms, speech and writing change	RBD (also prodromal), sleep-disordered breathing, EDS, Insomnia, RLS, PLMS	60–90%
Multiple system atrophy [29]	Parkinsonism, breathing problems	RBD, fragmented sleep, insomnia, stridor, EDS	80–100%
Dementia with Lewy body [30]	Dementia, parkinsonism, fluctuations, and visual hallucinations	Insomnia, circadian rhythm disorder, RBD [1] (also prodromal), confusional awakenings, EDS	80%
Alzheimer's Disease [31]	Cognitive impairment, dementia. Altered behavior, confusion, aggressiveness	Frequent daytime napping, difficulty in falling asleep and early wakeups, sleep fragmentation, reduced deep and REM sleep amounts, OSA, circadian rhythm alterations, slowdown of sleep EEG rhythms.	45%
Huntington Disease [32] (genetic)	Dementia, psychiatric disturbances	Sleep quality loss, insomnia, sleep fragmentation, EDS, circadian rhythm sleep disorders, reduced NREM and REM sleep.	87%
Amyotrophic lateral sclerosis [33]	Weakness, muscle atrophy, spasticity, respiratory dysfunction	Sleep-disordered breathing, nocturnal hypoventilation, nocturia, cramps, insomnia, EDS	17–76%
Friedreich ataxia [34] (genetic)	Impaired gait, balance, coordination, and speech	RBD, RLS, OSA	50%

[1] OSA: obstructive sleep apnea; EEG: electroencephalography; RBD: REM behavior disorder; EDS: excessive daytime sleepiness; RLS: restless leg syndrome. PLMS: periodic limb movements during sleep.

Table 2. Clinical assessing methods in sleep investigation.

Sleep Investigation	Clinical Assessing Methods
Sleep quality [35]	Anamnesis, diaries such as Consensus Sleep Diary (CSD), clinical scales such as Pittsburgh Sleep Quality Index (PSQI) for sleep disturbances, sleep duration, sleep latency, sleep efficiency, use of sleep medication, daytime dysfunction, and sleep-quality subjective evaluation in the past months.
SD: restless leg syndrome (RLS) [36]	Anamnesis, PSG for detecting associated PLMS, International Restless Legs Scale (IRLS).
SD: REM behavior disorder (RBD) [37]	Anamnesis; PSG [1] with sleep staging and REM sleep without atonia scorings; Video-PSG; screening questionnaires; rating scales: RBD Screening Questionnaire (RBDSQ), RBD Single-Question Screen (RBD1Q).
Sleep-related problems severity in PD	Rating scales: Parkinson's disease sleep scale (PDSS), ESS, SCOPA-SLEEP; PSG.
Nocturnal movements in PD [24]	Anamnesis; PSG; Video-PSG, Actigraphy; rating scales: • PDSS for leg or arm restlessness when resting, urgency to move when resting, getting out of bad for urination, nocturnal hypokinesia, painful posturing of the arms or legs, fidgeting. • MDS-UPDRS for turning in bad, getting out of bad. • NMSS for urgency to move when resting. • NMSQ for getting out of bed for urination, acting out dreams, urgency to move when resting. • PSQI, RLS and RBD scales.
Sleep disturbances in AD [25]	Anamnesis (manifestations of the sleep disorders can be atypical, cognitive impairment can make it difficult); RLS and breathing-disorders assessment; PSG; Actigraphy.
EDS [38]	Anamnesis, PSG, Multiple sleep latency test (MSLT), Maintenance of wakefulness test (MWT), Epworth sleepiness scale (ESS)

[1] PSG: polysomnography; SD: sleep disorder; SCOPA-Sleep: Scales for Outcomes in Parkinson's Disease-Sleep Disturbances; MDS-UPDRS: Movement Disorder Society-sponsored revision of the Unified Parkinson's Disease Rating Scale; NMSQ: Non-Motor Symptoms Questionnaire; NMSS: Non-Motor Symptoms Scale

1.2. Overview of Technologies for Neurodegenerative Diseases

Thanks to the progression of technology, many new-generation devices are available to the medical field. Reduction in costs and dimension for greater computational performances is the main followed trend in the hardware technology. This trend is influencing every aspect of medicine, from in-vitro studies to surgery, passing through virtual reality and robotics [39–42]. In particular, the development of good-quality low-cost sensors determined the development of new possible applications. In addition, the growing world population and the increase in life expectancy created new challenges that technologies, sensors, devices, and algorithms may help to resolve. Technologies in this field are being used to guarantee objectivity, continuity of care and massive screening for lower prices, employing wearable sensors, sensors networks, wireless communication, and automatic algorithms [43].

Companies are also riding the wave, in fact, many consumer products, including smartphones and smartwatches, integrate health monitoring tools and are available at affordable prices for the general population, providing new means for screening and the optimization of self-care. The information provided by this kind of technology does not usually have the aim of substituting standard clinical practice and is targeted to healthy population use; therefore, it is rare for these devices to comply with medical regulations. Nevertheless, some applications, such as heart-rate monitoring and movement analysis, have been proposed as medical tools and obtained American Food and Drug Administration (FDA) approval [44,45]. The gaming industry followed, as well, with the introduction of exergames for physical- and cognitive-health assistance and rehabilitation in neurodegenerative pathologies [46–48]. Sleep monitoring tools are also usually included in smartphones, smartwatches, and consoles, due to the well-known effects of sleep in cognitive and physical performances, as well as quality of life. However, the reliability of these devices in this field is not well-known yet [49,50]. Nevertheless, sleep monitoring is a wide field, where many aspects must be considered depending on the required observation (e.g., movements, sleep staging) and the final aim (e.g., diagnosis, screening) and it is influenced by many factors. Hence, it is very difficult to generalize results from general-

purpose instrumentation, especially in the presence of diseases altering sleep characteristics. The latter is the case for NDs, for which sleep disturbances and disorders are important to consider, as presented in the previous section, but which manifest themselves through physical and cognitive symptoms which could influence monitoring tools in unknown and often unpredictable ways. From this perspective, a smaller portion of the research explores this declination, both for single-symptom assessment and generic care of the eldery or frail people. activity of daily living (ADL) recognition and assessment is one of the most interesting topics, because they allow continuous monitoring beyond clinic facilities and provide a multi-potential tool in the wide field of smart homes and assisted living. This is the main objective of Internet of Things (IoT) applications for the elderly. Indeed, due to the incidence of comorbidities in the elderly and their constantly growing number, management of their multiple needs will be possible only through new technologies. In the case of dementia and other NDs, this is one of the followed paths [51–56]. Besides ADLs monitoring, sleep patterns, disease diagnosis and progression assessment, vital signs, agitation, social interactions, compliance with medication intake, movement and fall detection/prevention are interests of these applications. Smart-home applications use a wide range of technological aids—such as radio frequency identification (RFID), wireless communication protocols, global positioning system (GPS), sensors, and cameras—frequently organized in a mixed architecture including wearable and non-wearable sensors. Studies on smart-home monitoring for NDs are reviewed in the dedicated results section (see Section 3.2).

Another trending topic in new technologies for sleep monitoring is the simplification of PSG. PSG is the gold-standard sleep-monitoring exam in clinical facilities. In its conventional set up, it involves multiple high-quality signals recordings. However, the instrumentation is cumbersome and uncomfortable for the subject to wear. In addition, the examination is long to carry out and to analyze, since clinicians have to deal with hours of recordings. This creates an imperative need for an intervention to simplify the whole procedure through new technologies. Moreover, the polysomnogram evaluation involves anomaly identification (REM sleep without atonia, arousals, apneas) and sleep staging which are subjected to intra- and inter-rater variability [13]. Simpler devices and methods are widely proposed in the literature: sleep staging through single-channel physiological recordings, actigraphy, respiratory dynamics and video were attempted [57–60]. Automatic sleep-staging solutions for NDs are reviewed in the dedicated results section (see Section 3.1).

Moreover, a wide range of unobtrusive sensors is employed in the literature for other aspects related to sleep monitoring, including wearables [61–65] or camera-based [66–69] systems. In PD and AD, sensors are widely used in symptoms management and assessment, also with a view to early diagnosis [70–80]. In these disorders, sleep is frequently investigated, especially in studies that focus on motor symptoms, such as the bradykinesia (BK) or dystonia in PD, which can lead to pain or create problems in changing positions or turning in bed. Actigraphy, which provides acceleration recordings from a wrist-worn unit, is already approved by the FDA in the medical field since it enables continuous monitoring (beyond single PSG evaluation). This approach is suitable for the evaluation of excessive daytime sleepiness (EDS), insomnia, and circadian-rhythm sleep disorders, where analysis of time spent in bed and asleep is more relevant. However, its boundary of use in sleep studies is still to be drawn and still a hot topic in the literature, such as in the assessment of NDs' sleep symptoms. In this framework, studies dedicated to NDs compliant with the inclusion criteria of this review are reported in the results section.

2. Materials and Methods

To provide a general overview of the main recent technological approaches used for the analysis of sleep disorders in NDs, an extensive search of the literature was performed through the online databases Web of Science and PubMed over the last 12 years. The search focused on published studies concerning the NDs listed in Table 1 and on the more

exploited unobtrusive approaches for sleep monitoring. To this end, the following search criteria were set through:

- Customized queries using keywords and Boolean operators in the form "(Neurodegenerative Disorder OR Parkinson OR Alzheimer OR Huntington OR Lewy Body OR amyotrophic lateral sclerosis OR Ataxia OR Dementia OR Tremor) AND (sleep monitoring) AND (sensor OR IoT OR smart sensor OR environmental sensor OR inertial sensor OR wearable sensor OR optical sensor OR camera OR bed sensor)".
- Year range restriction to 2010–2022.
- Exclusion of pharmacology, veterinary and construction engineering categories.
- Writing language limitation to English.

No criterion was applied on the characteristics of studies participants, as long as the application proposed was explicitly aimed at use on ND-affected subjects.

3. Results

The total records found on Web of Science and PubMed were 142, of which 43 duplicates were excluded. Screening of the titles and abstracts reduced the records to 58. In the end, the full-text analysis of the remaining records led to a total of 26 articles. The selection procedure is shown in Figure 1.

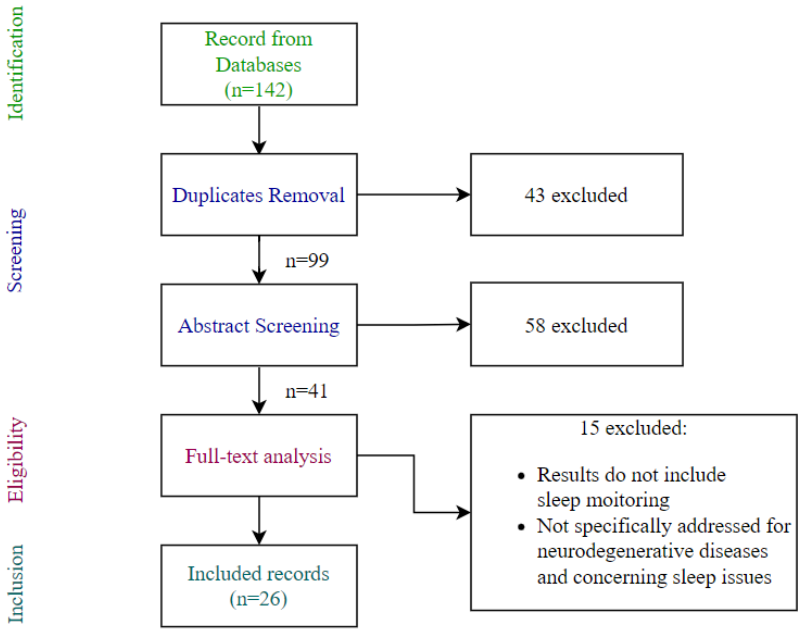

Figure 1. Article selection process.

The selected articles were then categorized considering the three main application domains: automatic sleep staging, at-home sleep monitoring and sleep-quality and movement analysis tools. The papers' distribution according to this categorization is shown in Figure 2a. Moreover, a qualitative synthesis is provided for each article, containing the main aim of the article, the instrumentation, the metrics and obtained results. The instrumentation employed in selected papers largely depended on the application and aims. Figure 2b shows the distribution of articles according to the use of wearable and non-wearable approaches, as well as the tested-sample-size type (e.g., PD-affected patients, healthy subjects). In addition, the collection of the sensors used in the reviewed paper was assessed; it includes: bed sensors, 3D cameras, infrared cameras, inertial sensors, smartwatches, headbands and novel tattooed electrodes. A pie chart summarizing sensors' employment is shown in Figure 3.

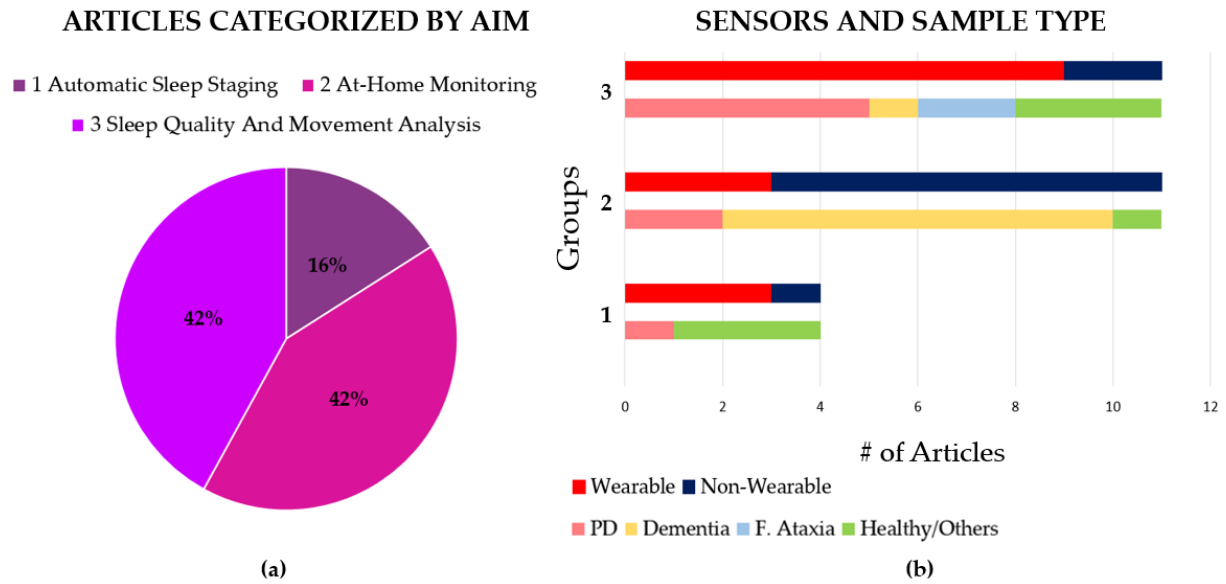

Figure 2. Distribution of selected papers according to chosen categorization. (**a**) Pie chart reporting the percentage of articles for the three mainly investigated categories in the literature; (**b**) bar plots of the distribution of the articles in the three categories of aim, considered sensor type (wearable or non-wearable) and type of targeted population.

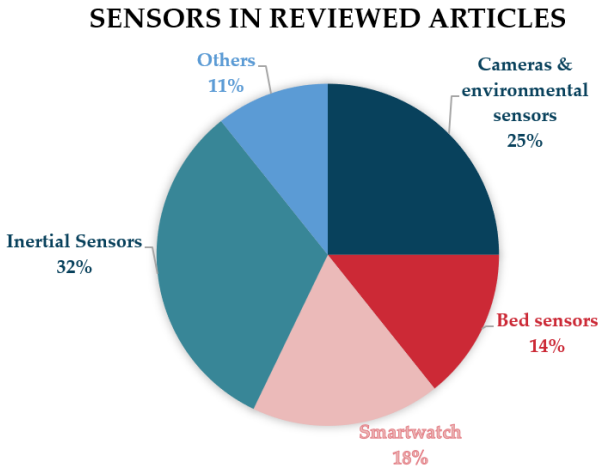

Figure 3. Pie chart reporting the distribution of sensors employed in the reviewed articles.

3.1. Automatic Sleep-Staging Techniques

Various systems for simplifying the sleep-staging procedure are proposed in the literature, whether based on PSG or innovative instrumentation; however, few of these studies consider the peculiar condition of NDs, which, as already mentioned, can have a strong influence on the feasibility of the proposals and the generalizability of the results. Moreover, these diseases, together with their associated sleep disruptions, often require the observation of peculiar phenomena, to which the proposed new systems need to provide sensitivity. The gold-standard PSG or video-PSG procedure is the most descriptive and complete exam used in these cases. The research challenge is to reduce the cumbersome instrumentation needed, without losing the fundamental information for sleep-stage recognition and abnormality identification (e.g., k-complexes, sleep spindles, delta burst, apneas, muscle tone, eyes movements). To do so and understand the best configuration, automatic sleep-staging algorithms are also needed. From this perspective, the literature search provided four articles. Their qualitative analysis is displayed in Table 3.

Table 3. Qualitative summary of the selected articles proposing automatic sleep staging.

Article	Subjects	Instrumentation	Methods	Results
Casciola et al. [81]	12 healthy subjects (12 nights)	(W [1]) two-channel EEG headband (HB)	DL approach to overcome low-quality signals from EEG HB in sleep staging. Manual and automatic corrupted-epoch recognition and discard. Data augmentation. DL training in CNN plus LSTM configuration.	Accuracy: 74 ± 10 % with EEG HB signals, 77 ± 10 % with PSG signals.
Shustak et al. [82]	9 healthy subjects (5 nights)	(W) temporary tattooed dry electrode array: two submental EMG, two EOG and four forehead EEG electrodes. The signals were acquired through a customized wireless recording system and Bluetooth connection. See Figure 4a.	Assessment of sensing performance in three ways: by observing signal behavior in typical facial expression; in comparison with standard video-PSG, through qualitative and correlation measures; and in-home settings for feasibility and electrode-stability evaluation. In addition, the opinions of sleep technicians were collected.	Signals recorded with the temporary tattoo and the 10–20 system were visually similar (e.g., eye blinking, k-complexes, sleep spindles), making them easily interpretable for sleep technicians. Amplitude signal parameters and noise were evaluated in the presence of artifacts such rolling in bed or blinking.
Yi et al. [83]	5 healthy subjects (1 night)	(NW) hydraulic bed sensor.	74 features extraction from cardiac and respiratory signals. Classification into awake, REM, and non-REM stages by SVM and k-NN. Accuracy referred to manual PSG scoring.	Accuracy 85% with 0.74 kappa, in the detection of awake, REM, and non-REM stages.
Ko et al. [84]	30 healthy subjects, 27 PD patients divided into two subgroups: 15 PD patients taking clonezepam (PDcC), 12 PD patients without clonezepam (PDnC)	(W) Smartwatch (PPG). See Figure 4b.	Quantification analysis of light sleep, deep sleep, REM, and abnormal REM sleep. Classification into sleep/awake, light/deep sleep and REM sleep using Cole–Kripke algorithm and k-means clustering. Definition of abnormal REM epochs. Comparison between control group and PD group was conducted in the quantitative analysis of sleep stages.	Statistically significant differences between PD and controls were measured in the percentage of deep sleep and abnormal REM. Abnormal REM sleep was also able to distinguish between PDcC and PDnC.

[1] W: wearable; NW: non-wearable; ML: machine learning; EEG: electroencephalography; EOG: electrooculogram; CNN: convolutional neural network, LSTM: long short-term memory; SVM: support vector machine; PSG: polysomnography; PD: Parkinson diseases; REM: rapid eye movements; PSG: polysomnography; PPG: photoplethysmogram.

Some potential solutions were explored by Casciola et al. in [81], Shustak et al. in [82] and Yi et al. [83], on healthy subjects, whereas Ko et al., in [84], tested the capability of the proposed system for abnormal REM detection on PD patients. Casciola, in [81], considered the condition of dementia in AD, where cumbersome instrumentation is a critical issue, due to the typical patient behavior (fear, confusion, aggressive behavior [85,86]). From this perspective, portable EEG headbands (HB) could provide a solution. The authors wanted to overcome the typical reduced signal quality in HB through a deep learning (DL) approach. Their approach was tested on EEG HB and simultaneous PSG recordings. Accuracies of their automatic scoring algorithm were calculated according to manual scoring of PSG in the two cases (HB and PSG signals). The signal processing of HB included band pass filtering and corrupted-epoch manual identification and removal. This cleaning procedure was further deepened through an automatic identification of corrupted epochs using correlation

metrics between channels and amplitude values. Data were augmented exploiting windows overlapping, and a DL model, based on convolutional neural network (CNN) and long short-term memory (LSTM), was developed and applied. Authors also implemented traditional sleep-staging techniques for performance comparison. In the end, the proposed DL sleep-staging model achieved 74% accuracy on low-quality HB EEG data and 77% with gold-standard PSG with respect to manual scores. Moreover, the balanced accuracy of the proposed DL method increased by almost 20% compared to any other machine-learning sleep-staging method attempted by them. To better understand the power of their method in the NDs' framework, their approach should be tested on a bigger and differentiated population, comprehending pathological subjects. Yi et al., in [83], proposed an automatic sleep-staging algorithm that exploits bed-sensor recordings consisting of four hydraulic bed transducers under the mattress. Their method aimed to classify sleep in awake, REM and NREM stages by computing 74 features and classifying them usingk-nearest neighbour (k-NN) and support vector machine (SVM) classifiers. Features related to temporal and frequency domains of heartbeat and respiration were considered (ballistocardiography signal analysis). The SVM classifier provided the best performances (accuracy 85.3%) and was also used in a hierarchical fashion (binary asleep–wake classification plus binary REM or NREM classification). In contrast, the other classifiers considered in this study showed inferior and similar performance when compared to the PSG manual score.

Regarding instrumentation developments, Shustak et al., in [82], proposed a wearable setup for sleep staging composed of temporary tattooed dry electrodes: two submental EMG, and two EOG and four forehead EEG electrodes. Data amplification and transfer to a laptop exploited a compact wireless recording system (a customized printed circuit board, a Bluetooth low-energy chip, and a battery). The electrode array employed is shown in Figure 4a. Signals were classically band-pass filtered, and a notch filter was also applied. The authors tested their system in three ways: firstly, they validated effectiveness of EOG, EMG, and EEG recordings using typical facial movements (e.g., smiling, blinking swallowing); secondly, they compared their EEG recordings to the gold-standard systems and, lastly, they assessed the feasibility in home environments. The tattooed electrodes provided signals visually similar to the ones from an EEG system with 10–20 international standard. It was possible to observe sleep spindles and k-complexes, and the recordings were easily interpretable for sleep technicians. Stable recordings were achieved both in a hospital environment and in home settings, where subjects reported good reviews and no impairments in sleep.

Lastly, Ko et al. in [84], provided a method for sleep staging and abnormal REM recognition using cardiac and acceleration signals provided by a smartwatch, see Figure 4c. The authors applied a hierarchical classification through machine-learning techniques, classifying firstly sleep/awake conditions with the Cole–Kripke algorithm, then deep and light sleep based on the G-value and, lastly, identifying REM through k-means clustering. They also defined identification criteria of abnormal REM stages, to be sensitive to REM parasomnias such as EDS typical in PD and MSA. They verified sleep-staging results in a clinical trial, comparing sleep stages and abnormal REM percentages in healthy-control versus PD patients treated with therapy for REM sleep behavior disorder (RBD) versus untreated PD patients. Although the classification accuracies were not very high, the results showed statistically significant differences between healthy-control and PD patients in the percentage of deep sleep. In addition, abnormal REM was found to be significantly different between PD patients with and without RBD therapy (in particular, using clonazepam).

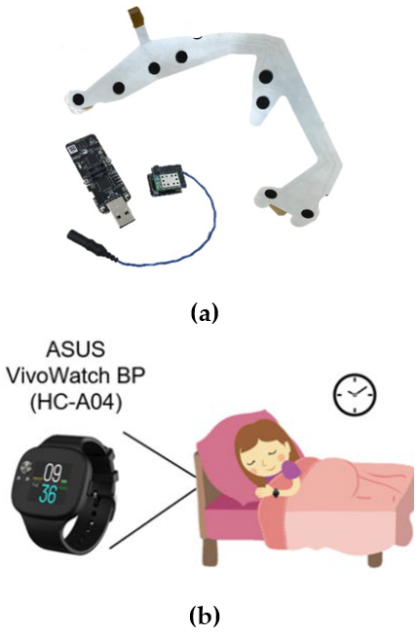

Figure 4. Examples of sensors employed for automatic sleep staging. (**a**) Electrodes array system, adapted from electromyography, electrooculography and electroencephalography, adapted from [82]. (**b**) Smartwatch for cardiac and inertial evaluation, adapted from [84].

3.2. At-Home Sleep Monitoring

The elderly population presents multiple needs simultaneously, since they are usually affected by several diseases with different symptoms. To cope with their conditions, more and more emphasis is being placed on wide-ranging monitoring over time within the home setting. In this way, various parameters can be monitored in a customized manner responding to multiple objectives: to verify health status; to assess the risks for the subject; to make preventive interventions; to diagnose diseases and observe their possible progression; ti check compliance with treatment and, finally, verify the effects of treatments. Such multi-approach monitoring is even more suitable in the presence of a diagnosed ND; in fact, significant efforts are focused on this line of research. Many of these studies include sleep monitoring in their set-up, given its importance for quality-of-life and symptom monitoring. Usually, these systems rely on a network of sensors, wearable and/or non-wearable, which transmit data to cloud services or platforms. In this way, subjects, caregiver, and clinicians can access the data and observe long-term results. Sometimes, these platforms provide custom-made analysis algorithms or they provide a summary of the outputs of the commercial/custom sensors employed. The literature search produced 11 articles in this framework; their summary description is presented in Table 4, where emphasis is placed on the advancement of the sleep-related study and instrumentation adopted.

Regarding cognitive impairment, a smart-home environment for continuous monitoring of elders with dementia is presented by Lazarou et al. in [87]. The article presents the architecture developed in the framework of the Dem@Care FP71 project [88,89]. In the Dem@Care project, the monitoring of sleep, physical activity and ADL were the main goals. In their setup, also used in [90], a commercial under-mattress sensor was employed that was able to determine sleep duration and stages. The proposed solution also involved the integration of the automatic evaluation of daily activity and anomalies by a wide range of sensors, with the assessment and final opinion of clinical experts to target the treatment. In Ref. [87], the authors wanted to verify that their system and the adapted clinical interventions could have positive effects on the physical and cognitive functions of participants. Results concerning sleep included reports of four use cases where, in general, a reduced number of sleep interruptions and increased deep sleep and REM phases were

found. Detailed data of sleep patterns were presented for the four subjects (use cases). In Ref. [90], the long-terms effects of the use of the system were evaluated on a bigger subject sample (twelve mildly cognitive-impaired subjects and six subjects with AD): the results confirmed the previous observations: reporting better sleep quality. The effects of this system installation, along with a personalized non-pharmaceutical intervention suggested by the system, were compared with a control group that underwent traditional interventions and with a second control group that did not receive neither personalized nor traditional interventions. Thomas et al., in [91], proposed an at-home smart monitoring system able to assess treatment efficacy for AD. Part of the platform is shown in Figure 5. They considered sleep monitoring using a smartwatch, evaluating TST and compliance to wearing the watch. Specifically, they found that the watch was worn more during the day than at night (compliance 60%), and that subjects often forgot to put the watch back on their wrist when they put it away for some reason. This last result may suggest that wearable solutions, such wrist bands, may not be optimal for continuous sleep monitoring in elders, especially with any kind of memory impairment such as in mild cognitive impairment (MCI) or dementia. Kikhia et al., in [92], focused on nursing homes and proposed the DemaWare@NH monitoring framework system. The aim was to assess behavioral and psychological symptoms of dementia. Concerning sleep, they employed a smart clock connected with a smartphone able to detect respiration signals and movements. The system provided sleep staging in terms of awake, light-sleep and deep-sleep periods, and a 1–100 sleep score. The clinical staff accepted the system, but the smart-clock recordings were made difficult by patients who frequently interacted with the clock-phone system, moving it during the day or pulling cables. This forced the clinical stuff to set up the sensor only during the night. However, the clinical stuff considered the data provided informative on the status of the subjects. Rose et al., in [93], dealt with symptom assessment in AD. Specifically, they analyzed the correlation between nighttime agitation, sleep disturbances and urinary incontinence outside of the clinical setting. Even in this case, the authors designed a multiple-sensor network. To perform sleep monitoring, they used an under-mattress sensor, a microphone, and TEMPO nodes on wrists, i.e., a wireless inertial sensor net. They were able to detect the aforementioned symptoms and to find a correlation between them.

Table 4. Selected articles that present a system dedicated to neurodegenerative diseases in a smart-home monitoring framework, which includes sleep monitoring.

Article	Stage	Instrumentation	Subjects	Results
Dem@Care FP71 project [87,90]	Platform tested on patients	(NW [1]) Commercial under-mattress sensor providing sleep duration and stages	4 in [87]; 22 MCI + 4AD in [90];	Adaptation of treatment based on clinicians' observation of the platform output resulted in the improvement of the sleep quality, also comparing the results with subjects who received a standard intervention.
Thomas et al. [91]	System feasibility	(W) Smartwatch and automatic measures. See Figure 5.	30 AD + 30 spouses	Evaluation of feasibility, compliance in wearing watch, and total sleep-time extraction.
Kikhia et al. [92]	System feasibility and preliminary results	(NW) Smart clock with a smartphone (movement and respiration detection) able to provide sleep staging (awake, light sleep and deep sleep) and a sleep score.	4 subjects with Dementia	Good acceptability of the system by clinical staff, who were able to assess patients based on the output of the system.

Table 4. *Cont.*

Article	Stage	Instrumentation	Subjects	Results
Rose et al. in [93]	Platform tested on patients	(NW) Matress sensor, TEMPO nodes on wrists and a microphone, from which data are transmitted to an online platform where automatic event detection is performed and available for users' consultation.	12 AD subjects	Monitoring and correlation of symptoms, such as nighttime agitation and incontinence in AD, were performed. The correlation inference process showed a pattern for the time occurrence of symptoms.
Hayes et al. [94]	Platform tested on patients	(NW) Passive infrared sensors with custom automatic algorithm extracting sleep features (ORCATECH platform)	45 seniors, including 16 MCI (amnestic, aMCI, and non-amnestic MCI, naMCI) over 6 months	The comparisons of self-reported and platform measures in the three groups (healthy seniors, aMCI, naMCI) showed that movement in bed during the night, wake after sleep onset, and times up during the night were significantly different.
Au-Yeung et al. [95]	Case study with existing platforms	(NW) Aging & Technology (ORCATECH) platform + Emerald device	2AD, 1 frontotemporal dementia, and a major neurocognitive disorder affected subjects.	Sleep-score comparison in the presence/absence of drug administration. Night-time agitation and PLM assessment.
Rawtaer et al. [96]	Feasibility study	(NW) Bed-occupancy sensor based on fiberoptic technology, providing sleep duration and quality metrics (sleep duration, number of sleep interruptions)	28 MCI and 21 healthy controls (>65 years) subjects (HC)	Comparison of sleep duration and interruptions between MCI and HC subjects.
Abbate et al. [97]	Feasibility study	(W+NW) Bed sensor + EEG HB .	-	General discussion on the feasibility of sleep studies based on Enobio EEG HB and inference of risk of fall.
Branco et al. [98]	Feasibility study	(W) Inertial sensor included in the Datapark platform	22 PD subjects in rehabilitation center, for 2 months	Report of changes in sleep position and wakeups were provided to clinicians and patients along with other measures of general activity. Good acceptability of the system.
Silva de Lima [99]	Study presentation and beginning of recruiting	(W) Smartwatch + app	To be: 1000 PD subjects	The system aims to provide sleep-movement analyses.

[1] W: wearable; NW: non-wearable; MCI: mild cognitive impairment, AD: Alzheimer disease; EEG: Electroencephalography; HB: Headband; HC: healthy controls; PD: Parkinson disease; HB: headband.

Regarding continuous monitoring of AD, Oregon Center for Aging and Technology (ORCATECH) at the Oregon Health and Science University have been developing a home monitoring system since 2004. Their platform was meant to assess disease progression and intervention efficacy, relying on passive IR motion sensors and wireless magnetic-contact sensors. The project design and application are described in detail in [19]. Between the various activity recognition and evaluation, the findings regarding sleep by Heyes, in [94], are within the scope of this review. In this last study, the authors used a previously validated algorithm to automatically assess sleep, extracting sleep duration and permanence in bed features (e.g., WASO; TST; settling time: time from getting into bed until the start of the first 20 min period of no movement; times up at night: when the participant actually got out of bed; and total movement in bed at night). Authors also collected subjective sleep assessments and compared elderly volunteers with amnestic MCI and with non-amnestic MCI subjects. Passive sensing for dementia monitoring were also employed by

Au-Yeung in [95]. Their study evaluated only four subjects, two with the ORCATECH platform and two with the Emerald platform (Emerald Innovations Inc., Cambridge, MA, USA), which provides movement, location, and activity info from radio-wave sensors. They compared sleep scores, as provided by the two systems, in different pharmacological interventions. They were able to detect periodic leg movements, associated with drug side effects, providing a tool for modifying interventions and treatments.

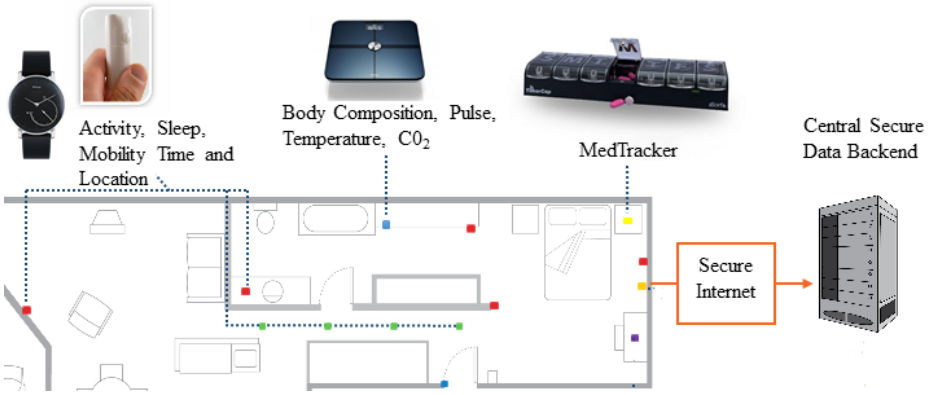

Figure 5. Example of an at-home smart platform for broad-spectrum assessment, including sleep. The Figure is adapted from [91], where a platform for the assessment of treatment efficacy in Alzheimer's disease is presented.

The works of Rawtaer et al. in Ref. [96] and of Abbate et al. in [97] were focused on the field of prevention and early detection. In Ref. [96], the authors evaluated the duration and quality of sleep with a sensor able to detect bed occupancy in terms of sleep duration and interruptions, both on healthy controls and subjects with MCI. The monitoring system reported a worse sleep quality in MCI subjects, in agreement with clinical questionnaires and almost all participants reported good acceptability (41 out of 49). In Ref. [97], the authors proposed a platform exploiting passive and physiological sensing. The study does not report any results on a specific group of subjects, but it claims the feasibility of sleep studies based on Enobio EEG HB (Starlab®, Neuroelectrics, Barcelona, Spain). From sleep data, they also intended to infer the risk of fall. Part of the presented platform architecture is shown in Figure 5a. Regarding Parkinson disease, Branco et al., in [98], presented a data platform (DataPark) able to collect continuous data from an accelerometer. The platform includes quantification algorithms of sleep and physical activity. They obtained preliminary results in a group of PD patients living in a rehabilitation clinic, observing sleep-position changes and wake-ups. In addition, authors reported that patient and personnel feedback were positive, especially regarding physical activity and sleep monitoring. Finally, Silva de Lima, in [99], presented their project and platform, feasibility study and recruiting procedure. Their system relied on a smartwatch connected to a smartphone to detect and analyze sleep movements.

3.3. Sleep Quality and Movement Analysis

In the literature, studies focused on sleep-quality evaluation and movements in sleep were found mainly addressed to PD, Friedreich ataxia and AD. The selected articles in this scope are shown in Table 5. Regarding PD, research focused on analyzing abnormal nocturnal movements during sleep. Those disturbances commonly affect PD patients because of disease-related symptoms or sleep disorders and are clinically assessed by PSG or video-PSG. Actigraphy is also commonly used for this purpose and is FDA-approved, while accelerometers and inertial sensors in various configurations have been gaining ground in this field in recent years [24,100].

Table 5. Selected articles that present a system dedicated to neurodegenerative diseases for sleep-quality and nocturnal-movements assessment.

Article	Subjects	Instrumentation	Methods	Results
Boroojerdi et al. in [101]	21 PD subjects	(W [1]) NIMBLE patch contains an accelerometer and an EMG	Tremor, postural instability, and sleep-quality-measures computation with different patch locations. Comparison with standard clinical scales. Feasibility evaluation.	No correlation between sleep measures and sleep diaries. General good usability and acceptability of the system.
Klingelhoefer in [102]	30 PD subjects with EDS and 33 PD subjects without EDS	(W) PKG (Parkinson's Kineti-Graph)	Bradykinesia and dyskinesia scores to determine disturbed nights. Comparison of the two groups by PKG and sleep-diary data (immobility, sleep duration, sleep interruptions).	In the PD-EDS group, correlation between subjective sleep reports and PKG parameters for quantity and quality of sleep. No correlation in the other group.
Xue in [103]	29 PD subjects, 17 with IBM	(W) multisite inertial sensors	Sleep-quality measure with traditional measures (total sleep time and sleep efficiency) and inertial sensors (acceleration, angular velocity, wakeups, turning in bad, limbs movements). Comparison between the two groups.	Negative correlation between turning-over events and disease duration. Positive correlation between TST and sleep-efficiency parameters and the number of turns in bed. Significant correlation between the number of turns and TST.
Bhidayasiri et al. in [104]	6 PD subjects and 6 spouses	(W) Inertial sensors	Night-time movement analysis, hypokinesia, rolling over description (degrees, duration, velocity, and acceleration) and wakeups	Impairment in turning in PD subjects (less frequent, slower, smaller).
Mirelman et al. in [105]	305 PD + 205 HC subjects	(W) Accelerometer	Nocturnal symptom assessment through lying, turning, and upright time.	Advanced PD subjects showed more upright periods, and a reduction in the number and velocity of their turns. Correlation between the reduction in nocturnal movements and increased PD motor severity, worse dysautonomia and cognition, and dopaminergic medication.
Gavriel et al. in [106,107]	9 F.Ataxia subjects	(W) 1 or 4 of wireless BSN nodes (inertial).	Extraction of biomarkers of Ataxia and Ataxia progression from segmentation of acceleration. They are based on movements and stillness intervals and were correlated to SARA (traditional Ataxia assessment method).	Correlation between the proposed biomarker and SARA assessment.
Wei et al. in [108]	10 healthy young subjects, 10 healthy elders, 8 subjects affected by Dementia	(W) Smartwatch (accelerometer) + actigraph and temperature sensors. See Figure 6.	Confront sleep diaries and accelerometer data. Sleep onset, sleep offset, and sleep duration and nighttime wakeups were calculated. Interday stability and intraday variability were calculated from temperature.	More movement during sleep, measured by actigraphy, in older adults than in the young, with an increasing trend in those with dementia. In addition, less temperature variation between night and day was measured in the elderly.

[1] W: wearable, NW: non-wearable; EMG: electromyogram; EDS: excessive daytime sleepiness; IBM: Impaired Bed Mobility; TST: Total Sleep Time; HC: Healthy Controls; BSN: Body Sensors Network; SARA: Scale for the Assessment and Rating of Ataxia; SAS: sleep apnea syndrome; iRBD: idiophatic behavior disorder.

Boroojerdi et al., in [101], and Klingelhoefer, in [102], focus on sleep-quality evaluation in PD, assessing movements during the night. In particular, Boroojerdi et al., in [101], studied PD motor symptoms with an EMG patch and an accelerometer, evaluating sleep quality in terms of time asleep and postural changes. The authors could not find a correlation between sleep-quality measures and the sleep-diary reports of the subjects. In contrast, Klingelhoefer et al., in [102], studied the effects of disturbed nights, such as daytime sleepiness, through scores for BK and dyskinesia (DK) during sleep computed from Parkinson's KinetiGraphTM (Global Kinectic Pty Ltd, Melbourne Victoria, Australia). The authors were able to correlate their algorithms for the definition of the quantity and quality of sleep, derived from immobility-period identification, to self-assessment reports, in the EDS affected group only. Nocturnal hypokinesia in PD was compared in [103] and [104]. Xue et al., in [103], compared standard clinical scores, such as Unified Parkinson's Disease Rating Scale (UPDRS), Hoehn andYahr (HY), Pittsburg Sleep Quality Index (PSQI), Epworth

Sleepiness Scale (ESS), Parkinson's Disease Sleep Scale (PSS), with sleep-quality parameters extracted from inertial sensor analysis. They mainly considered TST, sleep efficiency and sleep turnings. In this way, they could find that sleep quality is influenced by turnings in bed and correlated to UPDRS or scores. Bhidayasiri et al., in [104], detected nocturnal movements with an inertial sensor as well. Specifically, the authors measured turning frequency and kinematic turnings parameters (e.g., degrees, velocities, accelerations). In addition, they compared turns in bed in PD patients and their spouses, finding significant impairment in PD subjects turnings (fewer, smaller, and slower turnings). The impact of PD on turning in bed was the main focus of [105] by Mirelman et al. as well. Specifically, the authors analyzed the influence of PD on sleep, obtaining information on sleep interruptions, turnings and laying from a single accelerometer, comparing data on 305 PD subjects and 205 healthy controls. In advanced PD, fewer turns, slower turns, and greater upright time were found, as expected. Moreover, newly diagnosed subjects were similar to controls in the number of turns, but differed in the speed and amplitude of turning, suggesting that this type of measurement can be used as a descriptive of disease progression and as a potential diagnostic tool.

Sleep quality and motion description were also considered relevant topics in Friedreich Ataxia by Gavriel et al. in ref. [106] and ref. [107], where a kinematic sensor network was used to assess disease progression and drug effect in an objective manner. Specific kinematic biomarkers were extracted from movement segmentation and compared with Scale for the Assessment and Rating of Ataxia (SARA) scores (standard assessing method). Finally, sleep quality was also explored in the field of dementia, where Wei et al., in [108], compared sleep-quality measures and outcomes in the presence of a dementia diagnosis and in subjects of different ages. They employed a commercial wristband together with a custom one equipped with actigraphy and temperature sensors, as shown in Figure 6a. The authors found significantly lower sleep and wake temperature difference in older adults with dementia. Furthermore, movements during sleep increased with age, and even more in the presence of dementia. Lastly, a group of innovative technologies related to RBD detection and evaluation were selected. In fact, RBD traditional assessment mainly relies on the identification of movements during the REM stage. Therefore, it requires the simultaneous identification of the REM stage and the analysis of EMG recordings, which constitutes one of the most complex procedures. Given its discovered importance in synucleinopathies, interest grew around prodromal RBD, also considering the difficulty in distinguishing it from mimics, i.e., other motor manifestations or parasomnias during sleep. An attempt at simplification was provided by Cesari and Waser in [109,110], respectively, which exploited 3D video analysis to evaluate limbs movements. They used custom algorithms to identify limb movements. The video analysis was based on the motion signal, corresponding to pixel-wise variation in the 3D video frames over time. Specifically, the authors grouped the automatically identified movements into three regions of interest (upper body, lower body, and full body) based on their duration, estimated movement features for each group and, finally, evaluated their accuracy. In addition, they correlated the estimated features, which could better discriminate isolated RBD- [111] from sleep-disordered breathing (SDB)-affected patients for each group regarding REM sleep without atonia episodes. Finally, Filardi et al., in [112], exploited the analysis of rest–wake-cycle analysis obtained from actigraphy to identify subjects with RBD and to compare their features with those of subjects presenting with symptoms that mimic RBD. A qualitative summary of these works is shown in Table 6.

Figure 6. Custom-built wristband for actigraphy and temperature measures, employed for sleep quality assessment. The figure is adapted from [108].

Table 6. Selected articles that present a system dedicated to neurodegenerative diseases for nocturnal movements related to RBD.

Article	Subjects	Instrumentation	Methods	Results
Waser et al. in [110]	122 (40 iRBD, 18 prodromal RBD, 64 participants with mimic symptoms).	(NW[1]) 3D cameras	Custom algorithm for lower limb movement identification in REM. Feature extraction (movements rate, duration, extent, and intensity) and comparison with video-polysomnographic findings.	Significant increase in features analyzed among subjects with iRBD and prodromal RBD and mimic groups. In addition, leg movements with a duration <2 s discriminated iRBD with the highest accuracy (90.4%) from other motor activity during sleep.
Cesari et al. in [109]	20 RBD, 24 SDB subjects	(NW) 3D cameras	Custom algorithm for lower and upper limb movement identification in REM with a max. duration of 5s. Exclusion of breathing movements. Feature extraction (3D rate: the number of movements in REM sleep per hour of REM sleep, and 3D ratio: the total movement-duration time in seconds in REM sleep divided by the total REM-sleep time in seconds) and patient classification were performed (receiver operating characteristic curve to distinguish iRBD , positive class from SDB, negative class).	RBD vs. SDB classification provided an accuracy of 0.91 and F1-score of 0.90
Filardi et al. [112]	19 with iRBD, 19 RLS and 20 with untreated SAS and 16 healthy controls	(W) Micro Motionlogger® Actigraphy Watch (Ambulatory Monitoring, Inc.; NY) + light sensor.	Comparison of video-PSG and RBD-screening-questionnaires findings with the analysis of rest–activity cycles as derived from actigraphy. Features of rest–activity rhythm such as bedtime, wake-up time, midpoint of sleep, estimated wake after sleep onset (eWASO), estimated sleep efficiency (eSE) and activity bouts were extracted.	Lower sleep efficiency, augmented eWASO and increased frequency of prolonged activity bouts for subjects with iRBD compared with those with RLS and controls; no difference compared with SAS patients. In addition, features computed on 24h recording allowed to distinguish iRBD subjects better than screening questionnaires.

[1] NW: non-wearable; W: wearable; EMG: electromyogram; REM: Rapid Eye movement; SDB: sleep disordered breathing; iRBD: idiophatic behavior disorder.

4. Discussion and Conclusions

As discussed in the introduction section, sleep has an important role in guaranteeing a good quality of life, influencing cognitive and physical performances in healthy people and more extensively in the elderly, frail people or subjects with neurodegenerative disorders. Unobtrusive technologies for sleep monitoring are becoming the focus of many companies that develops health and well-being monitoring applications. The use of unobtrusive devices for sleep monitoring would also be of great value in the medical field, especially if applied to subjects affected by NDs, enabling more convenient and even continuous assessment of sleep-related disorders. However, analysis of the articles selected by this review showed that, in the latter area, the multiple proposed solutions still need further validation before application in clinical practice and in patients' daily lives. In fact, many different sensors were used in the reviewed works, showing the feasibility of different sleep monitoring tools, but, it was infrequently considered how these systems could fit into the complex consolidated clinical practice related to NDs.

First, the smart-home monitoring approach, even if interesting, requires the integration of sensors, data and interactions from many stakeholders: the house owner (who is also probably the end user), the company providing the system and the clinical facility that relies on the system and provides the medical service through it. At the moment, there are few healthcare facilities that actually provide these types of telemedicine services. Moreover, the literature search highlighted many smart-home monitoring solutions aimed at ND that included sleep monitoring, but most of them involved feasibility studies or only preliminary results about sleep. Ref. [90] and ref. [94] constitute exceptions, providing results on a moderate number of subjects with cognitive impairment and AD. However, the setup employed by these solutions, consisting of a network of several sensors, presents some drawbacks. For example, the large amount of data collected from all the sensors in continuous monitoring are very difficult (and expensive) to manage and analyze to obtain clinically meaningful results. In addition, custom algorithms should consider many use cases to be robust and subject-oriented, but structured guidelines for continuous home-monitoring applications are lacking in the literature. Moreover, the overall cost could be excessively expensive even in the validation phase of the solution, making these applications apparently suffer from the bottleneck effect typical of many telemedicine solutions [113,114].

Secondly, when there are multiple needs, as in multi-disease patients, it would not be feasible to employ a single device to assess each symptom. Therefore, patients and healthcare institutions need to rely on few trusted tools. From this perspective, actigraphy and inertial sensors are the main solutions for the movement analysis of daytime and nighttime symptoms, in addition or complementary to PSG. The wide applications of these types of sensors (e.g., gait analysis, limb movements, bradykinesia, tremor) make them suitable for integration in patients' daily life and hospitals. Indeed, they proved to be the most widespread and validated solutions. Actigraphy or "equivalent FDA approved devices that uses an accelerometer to measure limb activity associated with movement during sleep for physiologic applications" have already landed in the clinical sleep-monitoring field [115]. However, their use is always contingent on individual circumstances, such as the presence of ND. This is confirmed by the fact that the use of inertial sensors for sleep monitoring in ND is dominant between the reviewed articles, as shown in Figure 2, especially for sleep-quality assessment and movement analysis in a wearable configuration. The inertial sensors are mainly used to determine the permanence in bed, the number of sleep interruptions and the kinematic properties of the movements, such as the turning speed. This makes them good substitutes for sleep diaries, due to their ability to collect quantitative and objective information about sleep. In [102–105], inertial wearable sensors showed the ability of characterizing PD patients with respect to healthy subjects and disease progression; while in refs. [87,90], they were successfully used for AD treatment optimization and in refs. [106,107] for Ataxia characterization through the extraction of biomarkers correlated to standard scores. The feasibility and the importance of sleep evaluations in patients with

ND is, therefore, undoubtable, but a structured protocol of assessment that exploits these sensors has still to be established. For instance, hte optimized number and positioning of inertial sensors in the different disciplines is still to be defined. Fewer sensors would provide a cheaper and more convenient solution, but may not provide sufficient sensitivity to events of interest (e.g., the accelerometer on the arm may ignore foot/limb movements), not to mention that the events of interest depend on the analysis to be performed, which is not always completely defined a priori. Bed sensors are known to be able to provide information on bed occupancy and nighttime movements [116], but no articles presenting their use in ND other than AD were found in the literature search.

A separate discussion should be conducted on movement detection during REM phase to assess REM sleep without atonia for the diagnosis of RBD. In this literature search, two main approaches were found in this direction: 3D-video analysis [109,110] and actigraphy [112]. Both of them showed good performance and are cost-effective solutions. However, they need prior sleep-stage scoring (such as REM-stage recognition for 3D video analysis) or manual event tagging (such as day–night stage recognition for actigraphy). The potential of this type of screening is huge due to the possibility of observing other types of movements of clinical interest, such as thorax/abdomen movements during breathing, or turnings in bed. Therefore, these technologies are a promising line of research that should be further explored, while also considering mixed approaches. Lastly, the selected articles about automatic sleep staging showed interesting results using several types of sensors. However, the samples tested are not sufficient to evaluate a trend in this category. For example, in refs. [81–83], only healthy subjects were enrolled, with sample sizes ranging from 5 to 12 subjects. In contrast, ref. [84] included PD subjects but did not provide an accuracy comparison with PSG results.

To conclude, the literature research conducted in this review seems to demonstrate the feasibility of many different types of unobtrusive methods and technologies for sleep monitoring in ND, but further exploration needs to be performed to better establish the possibilities and limitations of these solutions in this specific scenario. Furthermore, a structured revision of the possible intersection with the actual clinical practice should be considered in order to select and adapt the possible solutions capable to cover, for each neurodegenerative disorder, the widest possible number of their clinical needs.

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Abbreviations

The following abbreviations are used in this manuscript:

AD	Alzheimer's disease
ADL	activity of daily living
ALS	amyotrophic lateral sclerosis
BK	bradykinesia
CAP	cyclic alternating pattern
DK	dyskinesia
CNN	convolutional neural network
CNS	central nervous system
DL	deep learning
DLB	dementia with Lewy body
ECG	electrocardiography
EDS	excessive daytime sleepiness
EEG	electroencephalography
EMG	electromyography
EOG	electrooculography
ESS	Epworth Sleepiness Scale
FDA	American Food and Drug Administration
GPS	global positioning system
HY	Hoehn andYahr
IoT	Internet of Things
k-NN	k-nearest neighbour
LSTM	long short-term memory
MCI	mild cognitive impairment
MSA	multiple system atrophy
ND	neurodegenerative diseases
NREM	non-REM
ORCATECH	Oregon Center for Aging and Technology
OSA	obstructive sleep apnea
PD	Parkinson's disease
PLMS	periodic leg movements in sleep
PSG	polysomnography
PSQI	Pittsburg Sleep Quality Index
PSS	Parkinson's Disease Sleep Scale
RBD	REM sleep behavior disorder
REM	rapid eye movements
RFID	radio frequency identification
RLS	restless legs syndrome
SARA	Scale for the Assessment and Rating of Ataxia
SD	sleep disorders incidence
SDB	sleep-disordered breathing
SVM	support vector machine
TST	total sleep time
UPDRS	Unified Parkinson's Disease Rating Scale
WASO	wake after sleep onset

References

1. Killgore, W.D.S. Effects of sleep deprivation on cognition. *Prog. Brain Res.* **2010**, *185*, 105–129.
2. Spiegel, K. Effect of sleep deprivation on response to immunizaton. *JAMA* **2002**, *288*, 1471–1472. [CrossRef]
3. Knutson, K.L.; Spiegel, K.; Penev, P.; Van Cauter, E. The metabolic consequences of sleep deprivation. *Sleep Med. Rev.* **2007**, *11*, 163–178. [CrossRef] [PubMed]
4. Halász, P. Hierarchy of micro-arousals and the microstructure of sleep. *Neurophysiol. Clin. Neurophysiol.* **1998**, *28*, 461–475. [CrossRef]
5. Parrino, L.; Ferrillo, F.; Smerieri, A.; Spaggiari, M.C.; Palomba, V.; Rossi, M.; Terzano, M.G. Is insomnia a neurophysiological disorder? The role of sleep EEG microstructure. *Brain Res. Bull.* **2004**, *63*, 377–383. [CrossRef] [PubMed]

6. Foley, D.; Ancoli-Israel, S.; Britz, P.; Walsh, J. Sleep disturbances and chronic disease in older adults: Results of the 2003 National Sleep Foundation Sleep in America Survey. *J. Psychosom. Res.* **2004**, *56*, 497–502. [CrossRef] [PubMed]
7. Iranzo, A.; Santamaria, J. Sleep in Neurodegenerative Diseases. In *Sleep Medicine*; Springer: New York, NY, USA, 2015; pp. 271–283.
8. Iranzo, A. Sleep in dementia and other neurodegenerative diseases. In *Sleep Disorders in Neurology*; John Wiley & Sons, Ltd: Chichester, UK, 2018; pp. 229–240.
9. Abbott, S.M.; Videnovic, A. Chronic sleep disturbance and neural injury: Links to neurodegenerative disease. *Nat. Sci. Sleep* **2016**, *8*, 55–61.
10. Priano, L.; Bigoni, M.; Albani, G.; Sellitti, L.; Giacomotti, E.; Picconi, R.; Cremascoli, R.; Zibetti, M.; Lopiano, L.; Mauro, A. Sleep microstructure in Parkinson's disease: Cycling alternating pattern (CAP) as a sensitive marker of early NREM sleep instability. *Sleep Med.* **2019**, *61*, 57–62. [CrossRef]
11. Iranzo, A. Sleep in neurodegenerative diseases. *Sleep Med. Clin.* **2016**, *11*, 1–18. [CrossRef]
12. Mendonca, F.; Mostafa, S.S.; Ravelo-Garcia, A.G.; Morgado-Dias, F.; Penzel, T. A review of obstructive sleep apnea detection approaches. *IEEE J. Biomed. Health Inform.* **2019**, *23*, 825–837. [CrossRef]
13. Younes, M.; Raneri, J.; Hanly, P. Staging sleep in polysomnograms: Analysis of inter-scorer variability. *J. Clin. Sleep Med.* **2016**, *12*, 885–894. [CrossRef] [PubMed]
14. Miladinović, Đ.; Muheim, C.; Bauer, S.; Spinnler, A.; Noain, D.; Bandarabadi, M.; Gallusser, B.; Krummenacher, G.; Baumann, C.; Adamantidis, A.; et al. SPINDLE: End-to-end learning from EEG/EMG to extrapolate animal sleep scoring across experimental settings, labs and species. *PLoS Comput. Biol.* **2019**, *15*, e1006968. [CrossRef] [PubMed]
15. Dorsey, E.R.; Sherer, T.; Okun, M.S.; Bloem, B.R. The emerging evidence of the Parkinson pandemic. *J. Parkinsons. Dis.* **2018**, *8*, S3–S8. [CrossRef] [PubMed]
16. Raggi, A.; Ferri, R. Sleep disorders in neurodegenerative diseases: Sleep in neurodegenerative diseases. *Eur. J. Neurol.* **2010**, *17*, 1326–1338. [CrossRef]
17. Fifel, K.; Videnovic, A. Circadian and sleep dysfunctions in neurodegenerative disorders-an update. *Front. Neurosci.* **2020**, *14*, 627330. [CrossRef]
18. Zhang, Y.; Ren, R.; Yang, L.; Zhang, H.; Shi, Y.; Okhravi, H.R.; Vitiello, M.V.; Sanford, L.D.; Tang, X. Sleep in Alzheimer's disease: A systematic review and meta-analysis of polysomnographic findings. *Transl. Psychiatry* **2022**, *12*, 136. [CrossRef] [PubMed]
19. Lyons, B.E.; Austin, D.; Seelye, A.; Petersen, J.; Yeargers, J.; Riley, T.; Sharma, N.; Mattek, N.; Dodge, H.; Wild, K.; et al. Corrigendum: Pervasive computing technologies to continuously assess Alzheimer's disease progression and intervention efficacy. *Front. Aging Neurosci.* **2015**, *7*, 232. [CrossRef] [PubMed]
20. Voysey, Z.J.; Barker, R.A.; Lazar, A.S. The treatment of sleep dysfunction in neurodegenerative disorders. *Neurotherapeutics* **2021**, *18*, 202–216. [CrossRef]
21. American Academy of Sleep Medicine. *International Classification of Sleep Disorders—Third Edition (ICSD-3)*; American Academy of Sleep Medicine (AASM): Darien, IL, USA, 2014.
22. Wood, E.A.; McCall, W.V. Assessment methodologies in sleep medicine clinical trials. *Clin. Investig.* **2013**, *3*, 791–800. [CrossRef]
23. Shrivastava, D.; Jung, S.; Saadat, M.; Sirohi, R.; Crewson, K. How to interpret the results of a sleep study. *J. Community Hosp. Intern. Med. Perspect.* **2014**, *4*, 24983. [CrossRef]
24. Zampogna, A.; Manoni, A.; Asci, F.; Liguori, C.; Irrera, F.; Suppa, A. Shedding light on nocturnal movements in Parkinson's disease: Evidence from wearable technologies. *Sensors* **2020**, *20*, 5171. [CrossRef]
25. Urrestarazu, E.; Iriarte, J. Clinical management of sleep disturbances in Alzheimer's disease: Current and emerging strategies. *Nat. Sci. Sleep* **2016**, *8*, 21–33. [CrossRef] [PubMed]
26. Claassen, D.; Josephs, K.; Ahlskog, J.; Silber, M.; Tippmann-Peikert, M.; Boeve, B. Rem sleep behavior disorder preceding other aspects of synucleinopathies by up to half a century. *Neurology* **2011**, *77*, 1155–1155. [CrossRef]
27. Magrinelli, F.; Picelli, A.; Tocco, P.; Federico, A.; Roncari, L.; Smania, N.; Zanette, G.; Tamburin, S. Pathophysiology of motor dysfunction in Parkinson's disease as the rationale for drug treatment and rehabilitation. *Parkinsons Dis.* **2016**, *2016*, 9832839. [CrossRef] [PubMed]
28. Lajoie, A.C.; Lafontaine, A.L.; Kaminska, M. The spectrum of sleep disorders in Parkinson disease: A review. *Chest* **2021**, *159*, 818–827. [CrossRef]
29. Lin, J.Y.; Zhang, L.Y.; Cao, B.; Wei, Q.Q.; Ou, R.W.; Hou, Y.B.; Liu, K.C.; Xu, X.R.; Jiang, Z.; Gu, X.J.; et al. Sleep-related symptoms in multiple system atrophy: Determinants and impact on disease severity. *Chin. Med. J.* **2020**, *134*, 690–698. [CrossRef]
30. Ferman, T.J.; Smith, G.E.; Dickson, D.W.; Graff-Radford, N.R.; Lin, S.C.; Wszolek, Z.; Van Gerpen, J.A.; Uitti, R.; Knopman, D.S.; Petersen, R.C.; et al. Abnormal daytime sleepiness in dementia with Lewy bodies compared to Alzheimer's disease using the Multiple Sleep Latency Test. *Alzheimer Res. Ther.* **2014**, *6*, 76. [CrossRef]
31. Duncan, M.J.; Veasey, S.C.; Zee, P. Editorial: Roles of sleep disruption and circadian rhythm alterations on neurodegeneration and Alzheimer's disease. *Front. Neurosci.* **2021**, *15*, 737895. [CrossRef]
32. Herzog-Krzywoszanska, R.; Krzywoszanski, L. Sleep disorders in Huntington's disease. *Front. Psychiatry* **2019**, *10*, 221. [CrossRef]
33. Boentert, M. Sleep disturbances in patients with amyotrophic lateral sclerosis: Current perspectives. *Nat. Sci. Sleep* **2019**, *11*, 97–111. [CrossRef]

34. Corben, L.A.; Ho, M.; Copland, J.; Tai, G.; Delatycki, M.B. Increased prevalence of sleep-disordered breathing in Friedreich ataxia. *Neurology* **2013**, *81*, 46–51. [CrossRef]
35. Mollayeva, T.; Thurairajah, P.; Burton, K.; Mollayeva, S.; Shapiro, C.M.; Colantonio, A. The Pittsburgh sleep quality index as a screening tool for sleep dysfunction in clinical and non-clinical samples: A systematic review and meta-analysis. *Sleep Med. Rev.* **2016**, *25*, 52–73. [CrossRef]
36. Kohnen, R.; Allen, R.P.; Benes, H.; Garcia-Borreguero, D.; Hening, W.A.; Stiasny-Kolster, K.; Zucconi, M. Assessment of restless legs syndrome—Methodological approaches for use in practice and clinical trials. *Mov. Disord.* **2007**, *22*, S485–S494. [CrossRef] [PubMed]
37. Skorvanek, M.; Feketeova, E.; Kurtis, M.M.; Rusz, J.; Sonka, K. Accuracy of rating scales and clinical measures for screening of rapid eye movement sleep behavior disorder and for predicting conversion to Parkinson's disease and other synucleinopathies. *Front. Neurol.* **2018**, *9*, 376. [CrossRef] [PubMed]
38. McWhirter, D.; Bae, C.; Budur, K. The assessment, diagnosis, and treatment of excessive sleepiness: Practical considerations for the psychiatrist. *Psychiatry* **2007**, *4*, 26–35.
39. Riek, L.D. Healthcare robotics. *Commun. ACM* **2017**, *60*, 68–78. [CrossRef]
40. Sivaparthipan, C.B.; Muthu, B.A.; Manogaran, G.; Maram, B.; Sundarasekar, R.; Krishnamoorthy, S.; Hsu, C.H.; Chandran, K. Innovative and efficient method of robotics for helping the Parkinson's disease patient using IoT in big data analytics. *Trans. Emerg. Telecommun. Technol.* **2020**, *31*, e3838. [CrossRef]
41. Moro, C.; Štromberga, Z.; Raikos, A.; Stirling, A. The effectiveness of virtual and augmented reality in health sciences and medical anatomy: VR and AR in Health Sciences and Medical Anatomy. *Anat. Sci. Educ.* **2017**, *10*, 549–559. [CrossRef]
42. Walper, S.A.; Lasarte Aragonés, G.; Sapsford, K.E.; Brown, C.W., 3rd; Rowland, C.E.; Breger, J.C.; Medintz, I.L. Detecting biothreat agents: From current diagnostics to developing sensor technologies. *ACS Sens.* **2018**, *3*, 1894–2024. [CrossRef] [PubMed]
43. Wang, Y.; Lai, F.; Vespa, P. Enabling technologies facilitate new healthcare delivery models for acute stroke. *Stroke* **2010**, *41*, 1076–1078. [CrossRef] [PubMed]
44. Guillodo, E.; Lemey, C.; Simonnet, M.; Walter, M.; Baca-García, E.; Masetti, V.; Moga, S.; Larsen, M.; HUGOPSY Network; Ropars, J.; et al. Clinical applications of mobile health wearable-based sleep monitoring: Systematic review. *JMIR mHealth uHealth* **2020**, *8*, e10733. [CrossRef] [PubMed]
45. Rune Labs Secures FDA Clearance for Parkinson's Disease Monitoring through StrivePD Ecosystem on Apple Watch. 2022. Available online: https://www.prnewswire.com/news-releases/rune-labs-secures-fda-clearance-for-parkinsons-disease-monitoring-through-strivepd-ecosystem-on-apple-watch-301566472.html (accessed on 16 December 2022).
46. Ben-Sadoun, G.; Manera, V.; Alvarez, J.; Sacco, G.; Robert, P. Recommendations for the design of serious games in neurodegenerative diseases. *Front. Aging Neurosci.* **2018**, *10*, 13. [CrossRef] [PubMed]
47. Alves, M.L.M.; Mesquita, B.S.; Morais, W.S.; Leal, J.C.; Satler, C.E.; Dos Santos Mendes, F.A. Nintendo Wii™ versus Xbox Kinect™ for assisting people with Parkinson's Disease. *Percept. Mot. Skills* **2018**, *125*, 31512518769204. [CrossRef]
48. Amprimo, G.; Masi, G.; Priano, L.; Azzaro, C.; Galli, F.; Pettiti, G.; Mauro, A.; Ferraris, C. Assessment tasks and virtual exergames for remote monitoring of Parkinson's disease: An integrated approach based on Azure Kinect. *Sensors* **2022**, *22*, 8173. [CrossRef]
49. Fino, E.; Mazzetti, M. Monitoring healthy and disturbed sleep through smartphone applications: A review of experimental evidence. *Sleep Breath.* **2019**, *23*, 13–24. [CrossRef] [PubMed]
50. Sun, X.; Qiu, L.; Wu, Y.; Tang, Y.; Cao, G. SleepMonitor: Monitoring respiratory rate and body position during sleep using smartwatch. In Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies, Association for Computing Machinery (ACM), New York, NY, USA, 2017; Volume 1, pp. 1–22.
51. Giannakopoulou, K.M.; Roussaki, I.; Demestichas, K. Internet of Things technologies and machine learning methods for Parkinson's disease diagnosis, monitoring and management: A systematic review. *Sensors* **2022**, *22*, 1799. [CrossRef]
52. Sheikhtaheri, A.; Sabermahani, F. Applications and outcomes of Internet of Things for patients with Alzheimer's disease/dementia: A scoping review. *Biomed. Res. Int.* **2022**, *2022*, 6274185. [CrossRef] [PubMed]
53. Simonet, C.; Noyce, A.J. Domotics, smart homes, and Parkinson's disease. *J. Parkinsons. Dis.* **2021**, *11*, S55–S63. [CrossRef] [PubMed]
54. Alberdi, A.; Weakley, A.; Schmitter-Edgecombe, M.; Cook, D.J.; Aztiria, A.; Basarab, A.; Barrenechea, M. Smart home-based prediction of multidomain symptoms related to Alzheimer's Disease. *IEEE J. Biomed. Health Inform.* **2018**, *22*, 1720–1731. [CrossRef] [PubMed]
55. ROSETTA. 2012. Available online: http://www.aal-europe.eu/projects/rosetta/ (accessed on 16 December 2022).
56. Home. 2014. Available online: https://www.neurodegenerationresearch.eu/ (accessed on 16 December 2022).
57. Cooray, N.; Andreotti, F.; Lo, C.; Symmonds, M.; Hu, M.T.M.; De Vos, M. Proof of concept: Screening for REM sleep behaviour disorder with a minimal set of sensors. *Clin. Neurophysiol.* **2021**, *132*, 904–913. [CrossRef]
58. Rechichi, I.; Zibetti, M.; Borzì, L.; Olmo, G.; Lopiano, L. Single-channel EEG classification of sleep stages based on REM microstructure. *Healthc. Technol. Lett.* **2021**, *8*, 58–65. [CrossRef] [PubMed]
59. Park, K.S.; Choi, S.H. Smart technologies toward sleep monitoring at home. *Biomed. Eng. Lett.* **2019**, *9*, 73–85. [CrossRef] [PubMed]
60. Nochino, T.; Ohno, Y.; Kato, T.; Taniike, M.; Okada, S. Sleep stage estimation method using a camera for home use. *Biomed. Eng. Lett.* **2019**, *9*, 257–265. [CrossRef] [PubMed]

61. Chen, Z.; Lin, M.; Chen, F.; Lane, N.; Cardone, G.; Wang, R.; Li, T.; Chen, Y.; Choudhury, T.; Cambell, A. Unobtrusive Sleep Monitoring using Smartphones. In Proceedings of the Proceedings of the ICTs for improving Patients Rehabilitation Research Techniques, Venice, Italy, 5–8 May 2013.
62. Ya-Ti Peng.; Ching-Yung Lin.; Ming-Ting Sun.; Landis, C.A. Multimodality sensor system for long-term sleep quality monitoring. *IEEE Trans. Biomed. Circuits Syst.* **2007**, *1*, 217–227. [CrossRef]
63. Kwon, S.; Kim, H.; Yeo, W.H. Recent advances in wearable sensors and portable electronics for sleep monitoring. *iScience* **2021**, *24*, 102461. [CrossRef]
64. Tran, V.P.; Al-Jumaily, A.A.; Islam, S.M.S. Doppler radar-based non-contact health monitoring for obstructive sleep apnea diagnosis: A comprehensive review. *Big Data Cogn. Comput.* **2019**, *3*, 3. [CrossRef]
65. Ma, L.; Liu, S.Y.; Cen, S.S.; Li, Y.; Zhang, H.; Han, C.; Gu, Z.Q.; Mao, W.; Ma, J.H.; Zhou, Y.T.; et al. Detection of motor dysfunction with wearable sensors in patients with idiopathic rapid eye movement disorder. *Front. Bioeng. Biotechnol.* **2021**, *9*, 627481. [CrossRef]
66. Febriana, N.; Rizal, A.; Susanto, E. Sleep monitoring system based on body posture movement using Microsoft Kinect sensor. In *AIP Conference Proceedings*; AIP Publishing LLC: New York, NY, USA, 2019.
67. Lee, J.; Hong, M.; Ryu, S. Sleep monitoring system using Kinect sensor. *Int. J. Distrib. Sens. Netw.* **2015**, *2015*, 1–9. [CrossRef]
68. Jakkaew, P.; Onoye, T. Non-contact respiration monitoring and body movements detection for sleep using thermal imaging. *Sensors* **2020**, *20*, 6307. [CrossRef]
69. Veauthier, C.; Ryczewski, J.; Mansow-Model, S.; Otte, K.; Kayser, B.; Glos, M.; Schöbel, C.; Paul, F.; Brandt, A.U.; Penzel, T. Contactless recording of sleep apnea and periodic leg movements by nocturnal 3-D-video and subsequent visual perceptive computing. *Sci. Rep.* **2019**, *9*, 16812. [CrossRef]
70. Ancona, S.; Faraci, F.D.; Khatab, E.; Fiorillo, L.; Gnarra, O.; Nef, T.; Bassetti, C.L.A.; Bargiotas, P. Wearables in the home-based assessment of abnormal movements in Parkinson's disease: A systematic review of the literature. *J. Neurol.* **2022**, *269*, 100–110. [CrossRef] [PubMed]
71. Breasail, M.Ó.; Biswas, B.; Smith, M.D.; Mazhar, M.K.A.; Tenison, E.; Cullen, A.; Lithander, F.E.; Roudaut, A.; Henderson, E.J. Wearable GPS and accelerometer technologies for monitoring mobility and physical activity in neurodegenerative disorders: A systematic review. *Sensors* **2021**, *21*, 8261. [CrossRef] [PubMed]
72. Channa, A.; Popescu, N.; Ciobanu, V. Wearable solutions for patients with Parkinson's disease and neurocognitive disorder: A systematic review. *Sensors* **2020**, *20*, 2713. [CrossRef]
73. Mughal, H.; Javed, A.R.; Rizwan, M.; Almadhor, A.S.; Kryvinska, N. Parkinson's disease management via wearable sensors: A systematic review. *IEEE Access* **2022**, *10*, 35219–35237. [CrossRef]
74. Woodberry, E.; Browne, G.; Hodges, S.; Watson, P.; Kapur, N.; Woodberry, K. The use of a wearable camera improves autobiographical memory in patients with Alzheimer's disease. *Memory* **2015**, *23*, 340–349. [CrossRef]
75. Lussier, M.; Lavoie, M.; Giroux, S.; Consel, C.; Guay, M.; Macoir, J.; Hudon, C.; Lorrain, D.; Talbot, L.; Langlois, F.; et al. Early detection of mild cognitive impairment with in-home monitoring sensor technologies using functional measures: A systematic review. *IEEE J. Biomed. Health Inform.* **2019**, *23*, 838–847. [CrossRef]
76. Saner, H.; Schütz, N.; Botros, A.; Urwyler, P.; Buluschek, P.; du Pasquier, G.; Nef, T. Potential of ambient sensor systems for early detection of health problems in older adults. *Front. Cardiovasc. Med.* **2020**, *7*, 110. [CrossRef]
77. Varatharajan, R.; Manogaran, G.; Priyan, M.K.; Sundarasekar, R. Wearable sensor devices for early detection of Alzheimer disease using dynamic time warping algorithm. *Cluster Comput.* **2018**, *21*, 681–690. [CrossRef]
78. Mc Ardle, R.; Del Din, S.; Galna, B.; Thomas, A.; Rochester, L. Differentiating dementia disease subtypes with gait analysis: Feasibility of wearable sensors? *Gait Posture* **2020**, *76*, 372–376. [CrossRef]
79. Kourtis, L.C.; Regele, O.B.; Wright, J.M.; Jones, G.B. Digital biomarkers for Alzheimer's disease: The mobile/wearable devices opportunity. *NPJ Digit. Med.* **2019**, *2*, 9. [CrossRef]
80. Sigcha, L.; Domínguez, B.; Borzì, L.; Costa, N.; Costa, S.; Arezes, P.; López, J.M.; De Arcas, G.; Pavón, I. Bradykinesia detection in Parkinson's disease using smartwatches' inertial sensors and deep learning methods. *Electronics* **2022**, *11*, 3879. [CrossRef]
81. Casciola, A.A.; Carlucci, S.K.; Kent, B.A.; Punch, A.M.; Muszynski, M.A.; Zhou, D.; Kazemi, A.; Mirian, M.S.; Valerio, J.; McKeown, M.J.; et al. A deep learning strategy for automatic sleep staging based on two-channel EEG headband data. *Sensors* **2021**, *21*, 3316. [CrossRef] [PubMed]
82. Shustak, S.; Inzelberg, L.; Steinberg, S.; Rand, D.; David Pur, M.; Hillel, I.; Katzav, S.; Fahoum, F.; De Vos, M.; Mirelman, A.; et al. Home monitoring of sleep with a temporary-tattoo EEG, EOG and EMG electrode array: A feasibility study. *J. Neural Eng.* **2019**, *16*, 026024. [CrossRef] [PubMed]
83. Yi, R.; Enayati, M.; Keller, J.M.; Popescu, M.; Skubic, M. Non-Invasive In-Home Sleep Stage Classification Using a Ballistocardiography Bed Sensor. In Proceedings of the IEEE EMBS International Conference on Biomedical and Health Informatics (BHI), Chicago, IL, USA, 19–22 May 2019.
84. Ko, Y.F.; Kuo, P.H.; Wang, C.F.; Chen, Y.J.; Chuang, P.C.; Li, S.Z.; Chen, B.W.; Yang, F.C.; Lo, Y.C.; Yang, Y.; et al. Quantification analysis of sleep based on smartwatch sensors for Parkinson's disease. *Biosensors* **2022**, *12*, 74. [CrossRef]
85. Mahoney, E.L.; Mahoney, D.F. Acceptance of wearable technology by people with Alzheimer's disease: Issues and accommodations. *Am. J. Alzheimer Dis. Other Demen.* **2010**, *25*, 527–531. [CrossRef]

86. Bate, G.; Richardson, S.; Taylor, J.P.; Burn, D.; Allan, L.; Yarnall, A.; Guan, Y.; Del-Din, S.; Lawson, R. Feasibility of using wearable sensors to monitor activity and sleep patterns in inpatients with delirium and Parkinson's disease. *Mov. Disord.* **2022**, *37*, S365–S366.
87. Lazarou, I.; Karakostas, A.; Stavropoulos, T.G.; Tsompanidis, T.; Meditskos, G.; Kompatsiaris, I.; Tsolaki, M. A novel and intelligent home monitoring system for care support of elders with cognitive impairment. *J. Alzheimer Dis.* **2016**, *54*, 1561–1591. [CrossRef]
88. Stavropoulos, T.G.; Meditskos, G.; Tsompanidis, T.; Andreadis, S.; Kompatsiaris, I. Dem@Home: Ambient Monitoring and Clinical Support for People Living with Dementia. In Proceedings of the 13th European Semantic Web Conference (ESWC) Crete, Greece, 29 May–2 June 2016; Volume 9989, pp. 26–29.
89. Andreadis, S.; Stavropoulos, T.G.; Meditskos, G.; Kompatsiaris, I. Dem@Home: Ambient Intelligence for Clinical Support of People Living with Dementia. In Proceedings of the 13th European Semantic Web Conference (ESWC), Crete, Greece, 29 May–2 June 2016.
90. Lazarou, I.; Stavropoulos, T.G.; Meditskos, G.; Andreadis, S.; Kompatsiaris, I.Y.; Tsolaki, M. Long-term impact of intelligent monitoring technology on people with cognitive impairment: An observational study. *J. Alzheimer Dis.* **2019**, *70*, 757–792. [CrossRef]
91. Thomas, N.W.D.; Beattie, Z.; Marcoe, J.; Wright, K.; Sharma, N.; Mattek, N.; Dodge, H.; Wild, K.; Kaye, J. An Ecologically Valid, longitudinal, and Unbiased Assessment of Treatment Efficacy in Alzheimer disease (the EVALUATE-AD trial): Proof-of-concept study. *JMIR Res. Protoc.* **2020**, *9*, e17603. [CrossRef]
92. Kikhia, B.; Stavropoulos, T.G.; Meditskos, G.; Kompatsiaris, I.; Hallberg, J.; Sävenstedt, S.; Melander, C. Utilizing ambient and wearable sensors to monitor sleep and stress for people with BPSD in nursing homes. *J. Ambient Intell. Humaniz. Comput.* **2018**, *9*, 261–273. [CrossRef]
93. Rose, K.M.; Lach, J.; Perkhounkova, Y.; Gong, J.; Dandu, S.R.; Dickerson, R.; Emi, I.A.; Fan, D.; Specht, J.; Stankovic, J. Use of body sensors to examine nocturnal agitation, sleep, and urinary incontinence in individuals with Alzheimer's disease. *J. Gerontol. Nurs.* **2018**, *44*, 19–26. [CrossRef] [PubMed]
94. Hayes, T.L.; Riley, T.; Mattek, N.; Pavel, M.; Kaye, J.A. Sleep habits in mild cognitive impairment. *Alzheimer Dis. Assoc. Disord.* **2014**, *28*, 145–150. [CrossRef] [PubMed]
95. Au-Yeung, W.T.M.; Miller, L.; Beattie, Z.; May, R.; Cray, H.V.; Kabelac, Z.; Katabi, D.; Kaye, J.; Vahia, I.V. Monitoring behaviors of patients with late-stage dementia using passive environmental sensing approaches: A case series. *Am. J. Geriatr. Psychiatry* **2022**, *30*, 1–11. [CrossRef] [PubMed]
96. Rawtaer, I.; Mahendran, R.; Kua, E.H.; Tan, H.P.; Tan, H.X.; Lee, T.S.; Ng, T.P. Early detection of mild cognitive impairment with in-home sensors to monitor behavior patterns in community-dwelling senior citizens in Singapore: Cross-sectional feasibility study. *J. Med. Internet Res.* **2020**, *22*, e16854. [CrossRef]
97. Abbate, S.; Avvenuti, M.; Light, J. MIMS: A minimally invasive monitoring sensor platform. *IEEE Sens. J.* **2012**, *12*, 677–684. [CrossRef]
98. Branco, D.; Bouça, R.; Ferreira, J.; Guerreiro, T. Designing free-living reports for Parkinson's disease. In Proceedings of the Extended Abstracts of the 2019 CHI Conference on Human Factors in Computing Systems—CHI EA '19 Glasgow, Scotland, UK, 4–9 May 2019; ACM Press: New York, NY, USA, 2019.
99. Silva de Lima, A.L.; Hahn, T.; de Vries, N.M.; Cohen, E.; Bataille, L.; Little, M.A.; Baldus, H.; Bloem, B.R.; Faber, M.J. Large-scale wearable sensor deployment in Parkinson's patients: The Parkinson@home study protocol. *JMIR Res. Protoc.* **2016**, *5*, e172. [CrossRef] [PubMed]
100. van Wamelen, D.J.; Sringean, J.; Trivedi, D.; Carroll, C.B.; Schrag, A.E.; Odin, P.; Antonini, A.; Bloem, B.R.; Bhidayasiri, R.; Chaudhuri, K.R.; et al. Digital health technology for non-motor symptoms in people with Parkinson's disease: Futile or future? *Parkinsonism Relat. Disord.* **2021**, *89*, 186–194. [CrossRef]
101. Boroojerdi, B.; Ghaffari, R.; Mahadevan, N.; Markowitz, M.; Melton, K.; Morey, B.; Otoul, C.; Patel, S.; Phillips, J.; Sen-Gupta, E.; et al. Clinical feasibility of a wearable, conformable sensor patch to monitor motor symptoms in Parkinson's disease. *Parkinsonism Relat. Disord.* **2019**, *61*, 70–76. [CrossRef]
102. Klingelhoefer, L.; Rizos, A.; Sauerbier, A.; McGregor, S.; Martinez-Martin, P.; Reichmann, H.; Horne, M.; Chaudhuri, K.R. Night-time sleep in Parkinson's disease - the potential use of Parkinson's KinetiGraph: A prospective comparative study. *Eur. J. Neurol.* **2016**, *23*, 1275–1288. [CrossRef]
103. Xue, F.; Wang, F.Y.; Mao, C.J.; Guo, S.P.; Chen, J.; Li, J.; Wang, Q.J.; Bei, H.Z.; Yu, Q.; Liu, C.F. Analysis of nocturnal hypokinesia and sleep quality in Parkinson's disease. *J. Clin. Neurosci.* **2018**, *54*, 96–101. [CrossRef]
104. Bhidayasiri, R.; Sringean, J.; Taechalertpaisarn, P.; Thanawattano, C. Capturing nighttime symptoms in Parkinson disease: Technical development and experimental verification of inertial sensors for nocturnal hypokinesia. *J. Rehabil. Res. Dev.* **2016**, *53*, 487–498. [CrossRef] [PubMed]
105. Mirelman, A.; Hillel, I.; Rochester, L.; Del Din, S.; Bloem, B.R.; Avanzino, L.; Nieuwboer, A.; Maidan, I.; Herman, T.; Thaler, A.; et al. Tossing and turning in bed: Nocturnal movements in Parkinson's disease: Nocturnal movement in pd. *Mov. Disord.* **2020**, *35*, 959–968. [CrossRef] [PubMed]
106. Gavriel, C.; Thomik, A.A.C.; Lourencco, P.R.; Nageshwaran, S.; Athanasopoulos, S.; Sylaidi, A.; Festenstein, R.; Faisal, A.A. Kinematic body sensor networks and behaviourmetrics for objective efficacy measurements in neurodegenerative disease drug

trials. In Proceedings of the 2015 IEEE 12th International Conference on Wearable and Implantable Body Sensor Networks (BSN), Cambridge, MA, USA, 9–12 June 2015.
107. Gavriel, C.; Thomik, A.A.C.; Lourenco, P.R.; Nageshwaran, S.; Athanasopoulos, S.; Sylaidi, A.; Festenstein, R.; Faisal, A.A. Towards neurobehavioral biomarkers for longitudinal monitoring of neurodegeneration with wearable body sensor networks. In Proceedings of the 2015 7th International IEEE/EMBS Conference on Neural Engineering (NER), Montpellier, France, 22–24 April 2015.
108. Wei, J.; Boger, J. Sleep detection for younger adults, healthy older adults, and older adults living with dementia using wrist temperature and actigraphy: Prototype testing and case study analysis. *JMIR mHealth uHealth* **2021**, *9*, e26462. [CrossRef] [PubMed]
109. Cesari, M.; Kohn, B.; Holzknecht, E.; Ibrahim, A.; Heidbreder, A.; Bergmann, M.; Brandauer, E.; Hogl, B.; Garn, H.; Stefani, A. Automatic 3D video analysis of upper and lower body movements to identify isolated REM sleep behavior disorder: A pilot study. *Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.* **2021**, *2021*, 7050–7053. [PubMed]
110. Waser, M.; Stefani, A.; Holzknecht, E.; Kohn, B.; Hackner, H.; Brandauer, E.; Bergmann, M.; Taupe, P.; Gall, M.; Garn, H.; et al. Automated 3D video analysis of lower limb movements during REM sleep: A new diagnostic tool for isolated REM sleep behavior disorder. *Sleep* **2020**, *43*, zsaa100. [CrossRef]
111. Högl, B.; Stefani, A.; Videnovic, A. Idiopathic REM sleep behaviour disorder and neurodegeneration—An update. *Nat. Rev. Neurol.* **2018**, *14*, 40–55. [CrossRef]
112. Filardi, M.; Stefani, A.; Holzknecht, E.; Pizza, F.; Plazzi, G.; Högl, B. Objective rest-activity cycle analysis by actigraphy identifies isolated rapid eye movement sleep behavior disorder. *Eur. J. Neurol.* **2020**, *27*, 1848–1855. [CrossRef]
113. Hjelm, N.M. Benefits and drawbacks of telemedicine. *J. Telemed. Telecare* **2005**, *11*, 60–70. [CrossRef]
114. Dhanvijay, M.M.; Patil, S.C. Internet of Things: A survey of enabling technologies in healthcare and its applications. *Comput. Netw.* **2019**, *153*, 113–131. [CrossRef]
115. Smith, M.T.; McCrae, C.S.; Cheung, J.; Martin, J.L.; Harrod, C.G.; Heald, J.L.; Carden, K.A. Use of Actigraphy for the Evaluation of Sleep Disorders and Circadian Rhythm Sleep-Wake Disorders: An American Academy of Sleep Medicine Clinical Practice Guideline. *J. Clin. Sleep Med.*. **2018**, *14*, 1231–1237. [CrossRef]
116. Conti, M.; Orcioni, S.; Madrid, N.M.; Gaiduk, M.; Seepold, R. A review of health monitoring systems using sensors on bed or cushion. In *Bioinformatics and Biomedical Engineering*; Springer International Publishing: Cham, Switzerland, 2018; pp. 347–358.

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