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A Review of Approaches for Sleep Quality Analysis

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ABSTRACT Sleep quality is directly related to overall wellness and can reveal symptoms of several diseases. However, the term ''sleep quality'' still lacks a definitional consensus and is commonly assessed in sleep labs with polysomnography, comprising high costs, or through sleep questionnaires, a highly subjective technique. Multiple methods have been proposed to address the estimation of sleep quality, and devices were developed to conduct the examination in the subject's home. The objective of this paper is to analyze the methods and the devices presented in the literature, assessing the development of objective markers that could lead to an improvement of the subjective sleep experience understanding, leading to developments in the treatment of sleep quality deficits. A systematic review was conducted, selecting research articles published from 2000 to 2018, and two research questions were formulated, specifically, ''what methods for sleep quality assessment have been developed'' and ''what kind of measures are employed by the devices that have been developed to estimate sleep quality.'' The research trend for the assessment of sleep quality is based on the sleep macrostructure, and it was verified that despite the convenience and considerable popularity among the consumers of home health monitoring of devices, such as actigraphs, the validity of these tools regarding the estimation of sleep quality still needs to be systematically examined. A detailed resume of the key findings and the identified challenges are presented, ascertaining the main gaps in the current state of the art.

INDEX TERMS Sleep quality analysis, monitoring devices, home detection.

I. INTRODUCTION

Sleep is part of the circadian rhythm and is characterized by sequences of stages with related autonomous nervous system functions. It is a complex physiological process inherent to each individual and commonly covers nearly one third of the lifespan. The daily wear of major body systems, such as the circulatory, the respiratory, the musculoskeletal and central nervous system, is repaired during the sleep [1]. Sleep also plays a relevant role in the consolidation of memories, learning, physical development, emotion regulation and quality of life [2]. A sustained deprivation of sleep leads to a decrease in the immune system efficiency and increases the risk of cardiovascular pathologies, hypertension, obesity, metabolic deregulation and diabetes [3].

The quality of life concept was defined by the World Health Organization, reflecting the importance of each individual living conditions and the capacity of accomplishing the expectations, goals and standards in different cultural systems. Therefore, the quality of life can be seen as a subjective concept, regarding the life-satisfaction and experienced well-being, with objective desires of each individual life. The world health organization quality of life group developed a quality of life scale with four domains: physical health;

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psychological; social relationships; environment. Sleep and rest are one of the most relevant factors that affect physical health since sleep related complaints are the second most common causes for seeking medical attention, superseded only by the feel of pain [4]. Non-restorative sleep complaints are commonly associated with a variety of mental and physical conditions.

A large annual economic loss is also associated with poor sleep due to the reduction in the workplace productivity, with an estimated value ranging from $299 billion to $433 billion by the year 2020 in the United States, where more than a third of the adult population does not get enough sleep on a regular basis [5]. The estimated economic loss for Japan, United Kingdom, Germany and Canada are, respectively, $94 billion to $146 billion, $40 billion to $54 billion, $41 billion to $62 billion and $14 billion to $22 billion, with a prevision of increases in the economic loss in the following years [5].

It was estimated that nearly half of the older adults report poor sleep quality but the prevalence is lower in healthy adults, thus sleep quality may be considered as an early marker of cognitive decay in midlife [6]. With the increasingly aged population, it is expected an increase in the occurrence of neurodegenerative disorders and sleep disturbances, common symptoms in the elderly population. Therefore, it is predictable that sleep quality examination will become a major relevant analysis for the medical diagnosis. It is likely that sleep quality is a multifaceted construct that would be difficult to characterize by any single measure arising the necessity of examining sleep quality using a multivariable approach with a wide range of predictors [7] that are interpreted taking into consideration the age and gender differences [8].

Due to the current significance of this topic, a systematic literature review was conducted, analyzing the developed devices and methodologies for sleep quality analysis, thus assessing the development of objective markers that could improve the understanding of subjective sleep experience, possibly leading to improvements in the treatment of sleep quality deficits. A summary of sleep structure and metrics employed to determine the quality of sleep is presented in the second section. The employed methods are indicated in the third section and the reviewed articles are studied in the fourth and fifth sections. Discussion of the analysis was performed on the final section.

II. STRUCTURE AND QUALITY METRICS OF SLEEP

Sleep has a characteristic architecture compose by a macrostructure and a microstructure, defined by the electroencephalogram (EEG) signals, that undergoes through changes, such as sleep duration and quantity of sleep oscillations, as the person progresses into an older age [9], increasing the subjective complaints associated to poor sleep quality.

A. SLEEP MACROSTRUCTURE

Full night polysomnography (PSG) is the gold standard for sleep quality studies. PSG requires the monitoring of multiple physiological signals, including body position, respiratory movement, electrocardiogram (ECG), EEG, electrooculogram (EOG), electromyogram (EMG), breath airflow and oxygen saturation. Sleep scoring was commonly based on the visual examination of EEG signals following the Rechtschaffen and Kales's recommendations or, more recently, using the new guideline that was proposed by American Academy of Sleep Medicine (AASM). However, scoring based on visual examination has multiple difficulties since it is a slow and expensive process (needs the analysis of trained expert for multiple hours) that is prone to errors due to fatigue with an inter scorer agreement, among expert, lower than 90% [10]. Therefore, several approaches have been proposed to record sleep [11] and produce automatic sleep staging [12].

According to the AASM manual, the sleep macrostructure is composed by cycles of rapid-eye movement (REM) sleep and non-REM (NREM) sleep with three different stages in the NREM (N1, N2, N3). It is scored in 30 s epochs and comprises five phases, specifically, wake, N1, N2, N3 and REM. N1 and N2 are identified as lighter NREM stages and N3 is known as slow wave sleep (SWS). The EEG characteristic waves of each sleep stage are [13]: alpha (8–13 Hz) and beta (13–30 Hz) during wake; theta (4–8 Hz) in the N1; k-complexes (1 Hz) and sleep spindles (12–14 Hz) in the N2; delta (0.5–4 Hz) in the N3; sawtooth waves (2–6 Hz), theta (4–8 Hz), alpha (8–13 Hz) and beta (13–30 Hz) during REM.

Specific changes happen as the person advances into the fifth decade of age and beyond [9]: longer sleep-onset latency (time taken to fall asleep); higher sleep fragmentation (greater number of arousals, awakenings and transitions from deep to light sleep); advanced sleep timing (earlier rise times and bedtimes); higher probability of a feeble sleep (greater chance of awakening by external sensory stimuli); shorter total sleep duration; reduced duration of SWS with increase in the light sleep stages; increased duration of the awake periods; fewer and shorter cycles of NREM and REM sleep. The frequency of diurnal naps also increases with the progress of the age. It was verified that a significant increase in the EEG signal complexity occurs until the age of 60-year-old where it becomes stagnated or slightly decreases [14].

B. SLEEP MICROSTRUCTURE

The sleep microstructure is composed by transitional states that have a shorter duration than the conventional scoring epoch (30 s), describing the transient and phasic events in the brain electrical activity. These events can clearly be distinguishable from the background rhythm appearing as abrupt amplitude changes and (or) frequency shifts.

These periodic activities can be characterized with three parameters: repetitive elements that compose the activation phase (A phase); quiescent phase representing the return to background activity (B phases); period, characterizing the recurrence rate (the sum of the A phase and B phase duration) [15]. The cyclic alternating pattern (CAP) is a specific periodic activity in which both A and B phases

range between 2 and 60 s and is composed by the A phase and the following B phase. This pattern is only defined in the NREM sleep and a succession of two or more CAP cycles is defined as a CAP sequence. The lack of a CAP for more than 60 s is scored as non-CAP (NCAP) and concurs with a state of sustained physiological stability. The A phase waveforms include: vertex sharp waves; sleep spindle; k-complexes; delta bursts; polyphasic bursts; intermittent alpha; EEG Arousals. Three subtypes of the A phase were defined [15]: A1 is characterized by predominance of EEG synchrony with high-amplitude slow waves with a desynchrony (low-amplitude fast waves) occupying lower than 20% of phase duration; A2 has a mixture of fast and slow rhythms with desynchrony occupying between 20% and 50% of the phase; A3 is dominated by rapid low-voltage rhythms where more than 50% of the phase is occupied by desynchrony.

The EEG arousal characterizes an event that produces an awakening activity. Thus, a high presence of these events incites the sleep fragmentation and prevents the restful sleep, providing a marker of sleep disruption [16] and are related to daytime sleepiness. Since the arousals duration ranges between 3 and 15 s (AASM criteria), the person is commonly unaware of their sleep fragmentation and, despite the appearance of a continuous night sleep, the sleep stages were interrupted [17]. A disturbance in sleep, such as induced vigilance instability, produces an increase in the CAP rate, a metric defined by the ratio of the total CAP time to the total NREM time. A poorer sleep quality was associated with higher values of CAP rate indicating that CAP is a marker of sleep instability [18]. The presence of CAP has also been associated with multiple disorders including [19]: bruxism; sleep apnea; insomnia; restless leg syndrome; periodic limb movements; nocturnal frontal lobe epilepsy; idiopathic generalized epilepsy.

C. SUBJECTIVE MEASUREMENTS OF SLEEP QUALITY

As the age progresses, women are more likely to report subjective complaints of poor sleep [9]. However, the term ''sleep quality'' lacks a definitional consensus while it is widely used by clinicians, researchers and the public. This is probably due to the vague definition of what quality is [20].

A generally employed approach to measure the sleep quality is based on a self-rating index, reflecting the individual satisfaction with sleep and often involves the correlation with other measures such as the timing of sleep, environmental factors, physiologically derived indices, pharmacologic interventions, polysomnographic parameters and occurrence of sleep disorders [21]. The most used techniques regarding this approach are the Pittsburgh Sleep Quality Index (PSQI), self-report questionnaire to measure the quality of sleep quality in clinical populations with 19 question categorized into seven domains (sleep duration, sleep disturbance, sleep latency, daytime dysfunction, sleep efficiency, subjective sleep quality and use of sleep medication), the National Institutes of Health Patient-Reported Outcomes Measurement Information System (PROMIS), provides a sleep disturbance scale, and the Epworth Sleepiness Scale (ESS), assesses daytime sleepiness [22]. A new single-item Sleep Quality Scale (SQS) [23] was recently developed, where the respondent rates the sleep quality, over a 7-day recall period, considering five categories (from terrible to excellent).

The self-rating sleep and awakening quality scale (SSA) measures 20 items to produce three sub-scores (somatic complaints, subjective sleep quality and subjective awakening quality) and a total score to reflect the sleep experience [24]. However, Grandner *et al.* [25] have verified that PSQI is correlated with sleep diary variables but lack the capability to distinguish between general dissatisfaction, such as pessimistic thinking, and sleep-related disturbances.

As an example, the measured sleep complaints often are more related to general dissatisfaction than to a specific sleep-related disturbance. Rošťáková *et al.* [26] have also determined that the correspondence between objective sleep measurement and the person's subjective assessment of the sleep quality is considerably low, with a maximum correlation of 35% when considering the standard sleep characteristics and the SSA.

D. OBJECTIVE METRICS TO DEFINE SLEEP QUALITY

Basing the analysis on self-reports has a major limitation due to the fact that the subject is in a state of loss of consciousness during sleep, making the person a poor self-observer of behavior during sleep. Therefore, the accuracy of the questionnaire is subject to the individual's recall. The alternative is defining sleep quality with objective measures that have been found to closely reflect the perceived sleep quality [27] by analyzing the aspects of sleep experience that are not captured by subjective indices or metrics.

The common sleep quality indicators ([21], [26], [28]–[32]) are presented in Table 1, distributed in six groups: duration; intensity; continuity; stability; frequency; sleep episodes. A contextualization analysis of the sleep quality measures is presented in Table 2, regarding the sleep structure and the effect in the overall sleep quality.

Sleep efficiency and wake after sleep onset, continuity measures, were considered to be correlated with sleep quality by considering either signals collected from subjects [27] or the analysis of paper and pencil sleep diaries [33], such as Karolinska sleep diary (filled in the subsequent morning with questions about the previous night) [34]. However, it was verified that the measures commonly obtained by PSG (duration, intensity and continuity) have a small contribution to subjective ratings of prior-night sleep quality [8]. Consequently, the stability measures could be more relevant for future medical diagnosis [7]. A different approach was proposed by the National Sleep Foundation defining the Sleep Health Index (SHI) with a composition based in sleep quality, sleep duration and disordered sleep [22].

Multiple studies have revealed a variety of factors that can influence the sleep quality such as ([35]–[40]): existence of chronic diseases; elevated anxiety symptoms;

TABLE 1. PSG based sleep quality measures.

Group	Description	Measure	Simplified formula
Duration	Metric based in time duration	-Lights out to N1 (LN1) -Lights out to N2 (LN2) -Lights out to SWS (LSWS) -Lights out to REM (LR)* -Maximal sustained N1 (MN1) -Maximal sustained N2 (MN2) -Maximal sustained N3 (MN3) -Maximal sustained REM (MR) -Maximal sustained wake (MW) -Sleep onset latency (SOL)* -REM latency (REML) -Time attempting to sleep after the final awakening (TASAFA) episode -Time in bed (TIB) -Total sleep time (TST)* -Total wake time (TWT) -Total N1 sleep (TN1)* -Total N2 sleep (TN2)* -Total N3 sleep (TN3)* -Total NREM minutes (TNR) -Total REM minutes (TR)* -Total wake minutes (TW) -Wake after final awakening (WAFA)	- LN1 = Σ(minutes from lights out to first N1 sleep stage) - LN2 = Σ(minutes from lights out to first N2 sleep stage) - LNSWS = Σ(minutes from lights out to first N3 sleep stage) - LR = Σ(minutes from lights out to first REM sleep) - MN1 = max(sustained N1 period) - MN2 = max(sustained N2 period) - MN3 = max(sustained N3 period) - MR = max(sustained REM period) - MW = max(sustained wake period) - SOL = Σ(recording minutes)-TST - REML = TST-Σ(minutes after start first REM until final awake) - TASAFA = Σ(minutes after the final awakening) - TIB = Σ(minutes from lights out to the end of recording) - TST = Σ(sleep minutes) - TWT = Σ(wake minutes after start the sleep until final awakening) - TN1 = Σ(N1 minutes) - TN2 = Σ(N2 minutes) - TN3 = Σ(N3 minutes) - TNR = Σ(NREM minutes) - TR = Σ(REM minutes) - TW = Σ(wake minutes) - WAFA = Σ(minutes from final awakening to the end of recording)
Intensity	Percentage of time spent on a specific sleep stage	-N1 percentage (N1%)* -N2 percentage (N2%)* -REM percentage (REM%)* -REM to NREM ratio (RNR%) -Stage shift index (SSI) -SWS percentage (SWS%)* -SWS to light sleep ratio (SL%) -SWS to NREM ratio (SNR%) -SWS to REM ratio (SR%)	- N1% = Σ(N1 minutes)/TST - N2% = Σ(N2 minutes)/TST - REM% = Σ(REM minutes)/TST - RNR% = Σ(REM minutes)/ Σ(NREM minutes) - SSI = Σ(sleep stage shifts)/TST - SWS% = Σ(N3 minutes)/TST - SL%= Σ(N3 minutes)/[Σ(N1 minutes)+ Σ(N2 minutes)] - SNR%= Σ(N3 minutes)/Σ(NREM minutes) - SR%= Σ(N3 minutes)/Σ(REM minutes)
Continuity	Degree of sleep fragmentation	-Arousal index (AI)* -Awakening (A) -Awakening index (AwI) -Deep sleep efficiency (DEI) -Frequency of stage shifts (FSS) -Frequency of sights from SWS to N1 or N2 (FSN12) -Number of stage shifts (NSS) -Number of arousals (NA)* -Sleep efficiency (SE)* -Wake after sleep onset (WASO)*	AI = Σ(number of arousals)/hour of sleep - A = Σ(number of awakenings lasting more than a define period) AwI = Σ(number of awakenings)/hour of sleep - DEI = Σ(N3 minutes)/Σ(minutes in bed) - FSS = Σ(number of sleep stage shifts) - FSN12 = Σ(number of sleep stage shifts from SWS to N1 or N2) - NA = Σ(number of arousals) - NSS = Σ(number of sleep stage shifts) - SE = TST/Σ(minutes in bed) - WASO = Σ(wake minutes after start sleep)/TST
Stability	Sleep disruptive events	-A1 phase percentage (A1%) -A2 phase percentage (A2%) -A3 phase percentage (A3%)	- A1% = Σ(number of A1 phases)/ Σ(number of A phases) - A2% = Σ(number of A2 phases)/ Σ(number of A phases) - A3% = Σ(number of A3 phases)/ Σ(number of A phases)
		-A phase index (ApI) -A1 phase index (A1pI) -A2 phase index (A2pI) -A3 phase index (A3pI) -Arousals percentage (A%) -B phase index (BpI) -CAP cycle index (CAPI) -CAP rate (CAPR)	- ApI = Σ(number of A phases)/hour of NREM sleep - A1pI = Σ(number of A1 phases)/hour of NREM sleep - A2pI = Σ(number of A2 phases)/hour of NREM sleep - A3pI = Σ(number of A3 phases)/hour of NREM sleep

TABLE 1. ***(Continued.)*** **PSG based sleep quality measures.**

Group	Description	Measure	Simplified formula
		-EEG spectral indices (e.g. energy, in NREM and REM, of the frequency bands: alpha, beta, delta, high-frequency sigma, low frequency-sigma, sigma, theta) -Mean A phase duration (MAD) -Mean A1 phase duration (MA1D) -Mean A2 phase duration (MA2D) -Mean A3 phase duration (MA3D) -Mean B phase duration (MBD) -Number of CAP cycles (CAPC) -Number of periodic limb movements (NPLM)* -Periodic limb movements index (PLMI)* -Quantity or presence of pathological events -Total CAP time (CAPT) -Total number of A phases (TA) -Total number of A1 phases (TA1) -Total number of A2 phases (TA2) -Total number of A3 phases (TA3) -Total number of B phases (TB)	- A% = Σ(arousal events)/TST - BpI = Σ(number of B phases)/hour of NREM sleep - CAPI = Σ(number of CAP cycles)/hour of sleep - CAPR = Σ(CAP minutes)/Σ(NREM minutes) - MAD = Σ(A phases minutes)/ Σ(number of A phases) - MA1D = Σ(A1 phases minutes)/ Σ(number of A phases) - MA2D = Σ(A2 phases minutes)/ Σ(number of A phases) - MA3D = Σ(A3 phases minutes)/ Σ(number of A phases) - MBD = Σ(B phases minutes)/ Σ(number of B phases) - CAPC = Σ(number of CAP cycles) - NPLM = Σ(number of periodic limb movements) - PLMI = Σ(NPLM*60)/TST - CAPT = Σ(CAP minutes) - TA = Σ(number of A phases) - TA1 = Σ(number of A1 phases) - TA2 = Σ(number of A2 phases) - TA3 = Σ(number of A3 phases) - TB = Σ(number of B phases)
Frequency	Number of occurrence of a sleep stage	-Number of times in the N1 stage (NN1) -Number of times in the N2 stage (NN2) -Number of REM cycles (NR) -Number of times in the N3 stage (NS)	- NN1 = Σ(number of times in the N1 stage) - NN2 = Σ(number of times in the N2 stage) - NR = Σ(REM cycles) - NS = Σ(number of times in the SWS stage)
Sleep episodes	Description of the nap periods	-Number of naps (NN) -Nap duration (ND) -Nap frequency (NF)	- NN = Σ(number of naps in 24 h) - ND = Σ(nap minutes)/NN - NF = Σ(number of days in the past week that a nap occur)

* Recommended to be a reported parameter for polysomnography by the AASM Manual for the Scoring of Sleep and Associated Events, version 2.4, 2017.

depressive symptoms; depressive disorder; social factors; nutrition; lifestyle; mood; physical activity; obesity; mental health; age; consumption of drugs; habitual caffeine consumption; nicotine dependence (by smoking); alcohol dependence; high stress. Another major element is the presence of sleep related disorders, with more than 60 disorders already identified, divided into seven categories, by the International Classification of Sleep Disorders [41].

III. METHODS

A systematic literature review was conducted, covering papers published between the years 2000 and 2018, to address the formulated research questions: what methods for sleep quality assessment have been developed; what kind of measures are employed by the devices that have been developed to estimate sleep quality.

On the first review phase a search was conducted in the IEEE Xplore, Web of Science, ScienceDirect, PubMed and Google Scholar, covering journals that are specialized in sleep analysis and the cited literature in the included articles. The search keywords were ''sleep quality AND device'' and ''sleep quality AND method''. In total 10594 original articles were found with the presence of the keywords either on the title, keywords or abstract. The relevance of the studies for this review was assessed in the second phase considering the inclusion and exclusion criteria.

The inclusion criteria for sleep quality methods were: presentation of a method to measure sleep quality; study published in a scientific journal or a scientific conference; specifically mention the usability, for sleep quality analysis, of the method. For the sleep quality devices, the inclusion criteria were: presentation of a device for asserting sleep quality; validation of a commercial device or research project analyzing sleep quality metrics; specifically mention the usability, for sleep quality analysis, of the device. Exclusion criteria were: lack of description of the sleep quality metric or measurement method; article not written in English; presentation of an application that uses only the smartphone sensors; the developed device is not suitable for home detection.

The smartphone applications were excluded since they have been examined in a review performed by Ong and Gillespie [42]. At the end of the second phase, ninety articles (some presented both a method and a device) were selected for the review (after the duplicated results

TABLE 2. Analysis of the sleep quality measures.

Sleep structure	Higher value indicates better sleep quality	Higher value indicates low sleep quality	Specified optimal value for healthy subject	Unspecified optimal value for healthy subject
Macrostructure	DEI	LN1	NN1	FSS
	MR	LN2	NN2	FSN12
	SE*	LR*	ND	SR%
	REM%*	LSWS	NR	MN1
	RNR%	MW	NS	MN2
	SL%	N1%*	NSS	MN3
	SNR%	N2%*	TIB	
	SWS%*	NF	TN1*	
	TR*	NN	TN2*	
		REML	TN3*	
		SOL*	TNR	
		SSI	TST*	
		TASAFA		
		WASO*		
		TW		
		TWT		
		WAFA		
Microstructure		A	CAPC	A1%
		A%	MAD	A2%
		AI*		A3%
		AwI		ApI
		CAPI		A1pI
		CAPR		A2pI
		CAPT		A3pI
		NA*		BpI
		TA		MA1D
		TA1		MA2D
		TA2		MA3D
		TA3		MBD
		TB		

* Recommended to be a reported parameter for polysomnography by the AASM Manual for the Scoring of Sleep and Associated Events, version 2.4, 2017.

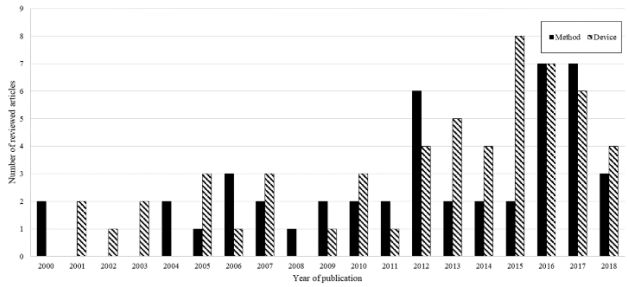

FIGURE 1. Distribution of reviewed articles by year of publication.

were removed). Forty-six articles were selected regarding the analysis of sleep quality methods and fifty-five articles were examined concerning the sleep quality devices. The articles distribution according to year of publication is presented in Figure 1. By evaluating the figure, it is possible to determine an increase in the number publications, especially in the sleep quality devices, indicating the growing importance of this topic and, therefore, reinforcing the relevance of this work.

The analysis is divided into two sections, examining first the articles that presented a method and, in the second, the devices that were developed to measure sleep quality and are suitable for home detection, since home health care is considered to be, in a near future [43], one of the most relevant wellness services, due to the low cost of diagnosis and high accessibility, providing a possible alternative to PSG. The discussion of the analysis is performed in the final section.

IV. METHODS DEVELOPED FOR SLEEP QUALITY ANALYSIS

A. BASED ON SLEEP MACROSTRUCTURE PARAMETERS

Slow-wave microcontinuity was analyzed by Kemp *et al.* [44], producing a maximum-likelihood estimator to quantify sleep depth by computing the fraction of the present slow-wave that continues to the near-future of the EEG signal. This metric is not affected by gender or anatomical parameters. The differences in duration of this metric, between consecutive nights, were correlated to changes in sleep quality. A measure to determine the sleep restorative ability was proposed by Badreldin and Morsy [45], named sleep restoration gain. This metric is evaluated every 30 s and changes according to the sleep stage. If the current epoch corresponds to SWS the current value was incremented while the opposite happens if it is N1, N2 or wake. REM stage does not affect the metric value. A transition from any sleep stage into wakefulness was highly penalized, providing a good correlation with the AI.

Chaos analysis of the heart rate variability (HRV) was proposed by Wakuda *et al.* [46], evaluating a two-dimensional map composed by the largest Lyapunov exponent (Y-axis and

related to mental fatigue) and a correlation dimension (X-axis and related to physical fatigue), to estimate the number of sleep cycles and the periodicity of the cycles based on the fact that each sleep stage presents a well-defined characteristic in the map. As a result, it was possible to verify that a low value of the largest Lyapunov exponent associated to a significant correlation dimension was correlated to feeling drowsy during the day, corroborating the sleep quality measure.

Sleep or wake detection based on an audio signal examination was also performed by Dafna *et al.* [47], examining the breathing pattern and snore properties. The repeating breathing patterns were assessed by analyzing the period (location of the first peak), intensity (peak amplitude) and consistency (how much the pattern is consistent and homogenously periodic) of the cycle (12 s interval). Snore properties were based on the maximum snore likelihood scores, within a 30 s epoch, and the snore index (SnI), number of snores per hour.

Sleep or wake classification was performed using the AdaBoost classifier, fed with features from the current and the two previous epochs (suitable approach for quasi-stationary processes). The output was employed to calculate the TST, SE, SOL, WASO and AwI. Good reliability of the proposed method was confirmed for the last three parameters. A similar approach was presented by Dafna *et al.* [48] were audio events were detected using an adaptive energy threshold and a Gaussian mixture model was employed for snore event detection. Snore likelihood score and breathing rhythmic period and intensity (determined by analyzing the audio signal energy) were used as features for the classification of sleep or wake periods based on a two-states (sleep and wake) hidden Markov model (HMM). A probability density function was estimated to produce a sleep quality score (with a 5 second resolution) by integrating the transition probability with the probability density function score of each feature.

Sound events, defined by an area where the burst level (extracted by the statistical burst extraction method) is greater than 1, were also used by Wu *et al.* [49]. Sleep-related events were clustered using the Kullback–Leibler kernel self-organizing map and categorized by hierarchical clustering. A multinomial HMM was employed to classify the data as either good or bad sleep. Highest accuracy (70%) was achieved using 5 hidden states. Time and frequency based features extracted from surrogate ECG derived respiratory (EDR) and HRV (52 from EDR and 60 from HRV) were analyzed by Bsoul *et al.* [50]. A multi-stage support vector machine (SVM) with a Gaussian radial basis function was used for the wake and sleep staging. SE and DEI were estimated from the classifier output achieving an average accuracy of 87% and 78% respectively.

Cheng and Huang [51] proposed an algorithm based on the normal to normal heart rate standard deviation average of the 5 minutes estimate. A period was considered as SWS or REM if the standard deviation was, respectively, 75% lower or 20% higher than the average. An epoch was labeled as light sleep if the standard deviation was higher, between 75% and 120% of the average value. SWS% and the ratio (TN1+TN2+TR)/TST was used as a metric for sleep quality estimation.

By analyzing the low-frequency band (LFB) power in the HRV from photoplethysmography (PPG), Tseng *et al.* [52] assessed the sleep and wake periods, analyzing the LFB power in the HRV. This analysis can then be used to estimate the TST and TWT. Body movements, from actigraphy, and PPG-derived HRV was used by Fonseca *et al.* [53] to produce features for sleep or wake classification, using linear discriminant analysis. It was verified that the estimation error of SE and SOL was small but significant in the TWT and WASO. The HRV features were also found to be better than actigraphy features for estimation of the wake state, particularly when the subject does not move.

Actigraphy signals were used by Blackwell *et al.* [54] to measure the TST, SE, WASO and SOL in a one-minute epoch. These measures were produced by analyzing three features: proportional integration (measures the vigor of motion by determining the area under the rectified conditioned transducer signal); zero crossings (indicative of the movement frequency, counting the number of times the movement single crossed the zero voltage in each epoch); time above a defined threshold (estimate the time spent in motion by summing the time above the sensitivity threshold in each epoch). Sleep and wake periods were determined by calculating a moving average taking into consideration the activity levels immediately after and prior to the current epoch.

Subject's activity was analyzed by Sathyanarayana *et al.* [55] to estimate the SE (considering a good sleep quality when the score is higher than 85%) determined through the sleep time actigraphy data and six classifiers were tested: logistic regression; multilayer perceptrons (MLP); convolutional neural network (CNN); recurrent neural network (RNN); long short-term memory RNN; time-batched long short-term memory. The highest area under the receiver operating characteristic curve was produced by the last classifier (97%), followed by the MLP and CNN (both with 95%). CNN produces the highest accuracy (93%) with filter and pooling length of 5 and 4, respectively, 25 hidden nodes and a mini-batch size of 5. However, the studied population was composed mainly by teenagers thus it is necessary to determine is the same results could be obtained with other populations.

The arterial baroreflex, a blood pressure regulatory reflex mechanism, was analyzed by Jung *et al.* [56] to estimate the SOL based in the observation that this mechanism has a marked influence on the HRV control with the onset of sleep. ECG and Ballistocardiogram (BCG) signals were used to estimate the HRV and the R–J interval, time interval between the ECG R peak the BCG J peak. SOL was defined by considering that sleep started 30 s after the presence of negative correlation coefficients, from the correlation analysis between the detrended R–J interval fluctuations and the HRV, for more than two consecutive data subsets of 120 s. BCG was also used by Park *et al.* [57] to determine the nocturnal awakening periods, through BCG peak detection, and estimate the SE.

B. USING PARAMETERS FROM SLEEP MICROSTRUCTURE

Mendonça *et al.* [19] studied eight features, generated from EEG monopolar derivations, and nine classifiers to estimate CAP. It was verified that a feed-forward neural network (FFNN) with five features (power spectral density in the beta and theta bands, Shannon entropy, Teager energy operator and autocovariance) chosen using a sequential forward selection method produced the best results with an average accuracy of 79% for CAP and A phase detection. Mariani *et al.* [58] have developed an algorithm to classify the A phases by also considering EEG monopolar derivations using specific band descriptors, differential variance and Hjorth activity to feed a FFNN, achieving an average accuracy of 82%.

A method to estimate CAP from a single-lead ECG was developed by Thomas *et al.* [59], by producing a spectrographic representation of cardiopulmonary coupling (CPC) of EDR and normal-to-normal sinus intervals. A quantitative index was defined, to measure CPC, as the product of crossspectral power and coherence. The presence of CAP was associated with the predominance of low-frequency coupling (0.01 to 0.1 Hz). Considering this method, Mendonça *et al.* [60] have developed an algorithm to estimate the CAPR considering the age-related CAPR percentages in healthy subjects as reference, classifying the NREM and CAP minutes with two deep stacked autoencoders. An improved version of the algorithms was later developed [61] analyzing multiple thresholds for CAP detection, correctly classifying 77% of the subjects regarding sleep quality (either good or bad).

C. ANALYZING A COMBINATION OF PARAMETERS FROM THE SLEEP STRUCTURE

Three machine learning approaches for measuring sleep quality were proposed by Wang *et al.* [62], specifically, discriminative graph regularized extreme learning machine (GELM), k-nearest neighbor (kNN) and SVM, using power spectral density (PSD) features extracted from the EEG signals. The analysis was made using 62-dimension PSD features from 62 different electrodes and five EEG bands, with data from 8 subjects. Sleep quality was assessed by analyzing the TST, considering 8 hours as good sleep, 6 hours as a normal (neither good or bad) and 4 hours as poor sleep quality.

A linear dynamical system was employed to decrease the EEG's feature noise and the PSD of the signal of each band was calculated. A linear kernel was used with a SVM and k equal to 1 was considered for the kNN. With 310 features the highest accuracy was achieved by GELM (62%), followed by SVM (48%) and kNN (37%) with the gamma band (31–50 Hz) producing the more relevant features. Five feature selection methods were tested to increase the accuracy, specifically, conditional infomax feature extraction, mutual information features selecting, mutual information maximization, joint mutual information and minimal-redundancy-maximal-relevance (mRMR). The best results were produced using the features selected by mRMR, with a feature dimension of 12, achieving an average accuracy of 76%, 74% and 62% for GELM, SVM and kNN, respectively.

Further improvement in the accuracy was achieved by considering the energy in the brain topographic map and mRMR to choose the best features (electrodes C6, PO3 and PZ in the beta band; electrodes C3, FCZ, FPZ and PO6 in the gamma band; electrode F1 in the delta band; electrode FCZ in the theta band). GELM achieved an average accuracy of 84%. These results are significant despite the reduced dataset. However, it is unknown if a similar performance could be achieved considering other sleep quality metrics.

A combination of multiple measures in a multivariate approach was proposed by Krystal and Edinger [7], including NREM spectral EEG indices, traditional PSG indices and CAP rate. This approach can possibly assess sleep quality with high precision if the chosen constellation of attributes of sleep, that will be used to classify the quality of sleep, does not differ significantly among individuals. Otherwise, a sub-grouping approach, based on clinical or physiological characteristics, could possibly address this issue, providing specific metrics for each subgroup (e.g. normal sleep, sleep disorder, significant pathology, addicted to substances). However, specific thresholds need to be defined for each subgroup, possibly leading to the necessity of assumptions based on statistical analysis.

Takhtsabzy and Thomsen [63] have applied crosscorrelation functions between several EEG channels to find the time of activity shift across the channels, allowing to detect the SOL, K-complexes and sleep spindles. The algorithm first finds the normalized crosscorrelation coefficients between two different times, considering the recorded potential fields and the number of electrodes, for all the samples and the values were introduced in a crosscorrelation matrix. An error function was then calculated from this matrix and the local minima represents the transition from one microstate to another since this method provides a micro segmentation of the signals. A method based in a distance measure of autocorrelation functions between a test and a moving window was also tested, providing similar results.

D. USING MODELS BASED ON SLEEP MICROSTATES

Rošáková and Rosipal [64] have developed a probabilistic sleep model (PSM) that describes sleep through posterior probabilities of 20 sleep microstates. k-means clustering was applied on the smoothed posterior curves where each cluster was characterized by an average posterior curve. It was found that microstate 19 had an 87% correlation with the wake state, providing an indicator for sleep quality since higher values of the self-rating sleep quality score (scores greater than 8 were considered as bad sleep quality) belong to the cluster associated with this microstate.

This work points to the possibility that standard sleep scoring does not allow to extract the maximum information regarding the sleep experience. This possibility was tested by Rošťáková *et al.* [26] where the PSM and the standard

hypnogram model were tested to assessed which one provides the highest correlation with subjective sleep quality measures. In total 25 standard sleep variables from PSG and 75 features for PSM were analyzed, determining the most relevant features using sequential feature selection.

PSM achieved a marginally higher average correlation when considering the most relevant features, specifically, the skewness of a moving window, the arithmetic mean, the median and the entropy for each microstructure of sleep stages. Using the PSM with 20 stages a corresponding metric to the percentage of time spent in each sleep stage, named relative time spent in a microstate, was developed by Lewandowski *et al.* [65]. A sleep fragmentation measure was also developed, indicating the number of sudden transitions between microstates that can be related to a frequency shift or arousals.

In a similar approach, Rosipal *et al.* [66] proposed a model to find correlations of sleep quality with physiological measures, subjective sleep quality ratings and neuropsychological test results. It was concluded that grouping a wider set of performance metrics into a smaller parsimonious set of commonly not directly observed latent variables should be employed to produce a robust indexing of sleep quality. However, the traditional standardize score of sleep into a finite set of discrete sleep stages may not provide enough relevant information to detect changes related to such index.

Flexer *et al.* [67] presented a probabilistic continuous sleep stager algorithm, based on HMM, using data from a single EEG signal. The method uses an unsupervised approach with a finer temporal resolution (1 s) than the commonly used 30 s epoch. A continuous model based on HMM was also proposed by Ravelo-García *et al.* [68] where sleep quality changes, between good and bad sleepers, were measured according to the SSA. A single EEG channel was employed and the hidden states of the HMM were associated with the sleep stages using 3 s epochs. Differences between groups of sleepers were found using measures that were based on probabilistic traces.

E. NON SLEEP STRUCTURE FEATURES

Choi *et al.* [69] have developed a set of rules, learning from examples based on rough sets, to qualify the sleep quality status as either good, normal or bad. These rules are based on 19 attributes and an average accuracy of 73%, on the sleep quality estimation as either good, normal or bad. The most significant detectors, from rules selected with the highest frequency, are: age; body mass index (kg/m^2), number of minutes with normal and higher heart rate during sleep and awake, average heart rate during sleep, smoking and drinking.

Estimation of sleep quality is conventionally based on EEG signals. However, other sensors can also be used to provide the estimation. A multimodality sensor system was proposed by Peng *et al.* [70], extracting features from each sensor that are fed to multiple classifiers (one SVM for each sensor). The results of each classifier are further fused together to infer the sleep quality. Movements were determined considering a motion time ratio producing a feature vector.

Detection of sleep was conducted by analyzing the spectral components of HRV in the high-frequency band (HFB), 0.15 to 0.4 Hz, and the LFB, 0.04 to 0.15 Hz. NREM is associated with a trend towards a decrease of ratio LFB/HFB while the opposite is associated with REM sleep. A Gaussian kernel was employed in the SVM for the motion classification while a linear kernel was used for the sleep classification and a normalized ensemble fusion process for the sleep or wake detection and estimation of the SOL, TST and SE. Audio signal analysis, performed using Mel-frequency cepstral coefficients, was also considered in the multimodality sensor system for the inference of the sleep or awake detection [71]. Information from a passive infrared sensor was used by Peng *et al.* [72] for motion detection using the same multimodality sensor architecture.

Alivar *et al.* [73] proposed the use of several electromechanical film sensors to assess the periodic movements during sleep and, therefore, estimate the quality of sleep. Highest accuracy in the detection of motion artifacts (95%) was achieved using a sequential detection rule formulation to determine if a sample has motion artifacts by computing the log-likelihood ratio of the binary hypothesis (sample with movement artifacts or sample without artifacts) and compare the results with a threshold to classify the sample.

F. PROPOSED NEW METRICS

Multiple sleep quality metrics have been proposed with the aim of improving the sleep analysis since metrics based on the hypnogram examination, such as TST, SE and SOL, only capture the changes in the sleep architecture. Information regarding the fragmenting behaviors and continuity of consecutive epochs can enhance the sleep quality prediction. Two sleep quality ratios were defined by Cheng and Mei [74]. The first takes into account objective measures derived from signals measured by a home monitoring device and was defined by

$$\left[TST\left(\frac{a_m}{a_p}\right)^2 + TN3\left(\frac{a_m}{a_p}\right)^2 1.5 + TR\left(\frac{a_m}{a_p}\right)^2 0.5 - TW\left(\frac{a_m}{a_p}\right)^2 0.5 - \frac{A}{a_A}\right] a_p \quad (1)$$

where a_m is the average optimal average sleep time (assumed to be 8.5), a_p is the personalized optimal sleep time and a_A is the personalized number of awakenings. The second considers subjective data that was assessed through statistical analyses of a sleep database, allowing to estimate the TN3 and TR values by considering the average values for the subject's age.

A sleep fragmentation index was proposed by Morrell *et al.* [75] calculated as

$$\frac{n_{an1}}{TST} \quad (2)$$

where n_{an1} is the number of awakenings or shifts to N1 from N2, SWS or REM. It was determined that this index was significantly related to higher levels of awake systolic blood pressure. However, Swarnkar *et al.* [76] have verified that each sleep stage has a different influence on the overall sleep quality, where some sleep transitions increase the sleep fragmentation, such as from SWS to wake, while others decrease (from N1 to N2).

Therefore, a new index was proposed, denoted weighted-transition sleep fragmentation index, where a specific weight (W) was associated with all possible sleep stage transitions and is specified by

$$\frac{\sum_{i=1}^{N-1} W_i}{mTST} \tag{3}$$

with N indicating the total number of epochs and m the median of the hypnogram time series. This index presented a significant correlation with the AI, TST and SE. Haba-Rubio *et al.* [77] have also proposed an alteration to the sleep fragmentation index considering the NSS and awakening periods, defined by

$$\frac{NSS + A}{TST} \tag{4}$$

A more complex approach, composed by a model with three variables, each having two parameters (detection threshold and weight), was presented by Bouazizi *et al.* [78] defining the mathematical diagnosis of sleep fragmentation as

$$H\left[\frac{w_X H\left(x_i - \tau_X\right) + w_Y H\left(y_i - \tau_Y\right) + w_Z H\left(z_i - \tau_Z\right) - w_X - w_Y}{w_X + w_Y + w_Z}\right] \tag{5}$$

where H is the unit step function, X is the A%, Y is the NSS, Z is A and τ and w are, respectively, the threshold and weight associated to each sleep quality metric.

Kirsch *et al.* [79] indicated that sleep fragmentation index does not capture the temporal dynamics of the underlying sleep process thus presenting two entropy-based measure that directly analyzes the hypnogram, epoch by epoch, as a categorical time series of sleep stages. The first metric was Walsh spectral entropy computed as

$$-\frac{1}{logN}\sum_{i=1}^{N}\frac{\left[\frac{1}{N}H_w\left(log_2 N\right)\cdot X\right]^2}{\sum_{i=1}^{N}\left[\frac{1}{N}H_w\left(i\right)\cdot X\right]^2} \times \log\left[\frac{\left[\frac{1}{N}H_w\left(log_2 N\right)\cdot X\right]^2}{\sum_{i=1}^{N}\left[\frac{1}{N}H_w\left(i\right)\cdot X\right]^2}\right] \tag{6}$$

where the H_w is the Walsh-Fourier transform and X is the time series (input vector with length N). The second measure was Haar spectral that was computed by replacing the Walsh-Fourier transform with the Haar transform.

It was also found that conditional entropy allows to quantify the predictability of the hypnogram by quantifying the likelihood of obtaining the pattern of length L given the existence of the pattern of length $L-1$, according to

$$-\sum_{L-1} P\left(x_{L-1}\right)\sum_{\frac{L}{L-1}} P\left(x_L|x_{L-1}\right) log\left[P\left(x_L|x_{L-1}\right)\right] \tag{7}$$

where $P(x_L|x_{L-1})$ is the conditional probability of the L^{th} sample of the pattern x_L, given the previous $L-1$ samples, and $P(x_{L-1})$ is the joint probability of the pattern x_{L-1}.

Naeck *et al.* [80] developed the sleep diversity index, based on the Shannon entropy index to model the sleep stages, specified by

$$\frac{\sum_{j>\frac{S_{max}}{2}}^{S_{max}} S_j}{\sum_{j=1}^{N} S_j} \tag{8}$$

considering N to be the number of samples (j), S the Shannon entropy of the sample and S_{max} the maximum entropy (equiprobability of occurrence of all sleep stages). Recently, Naeck *et al.* [81] proposed thresholds to define the presence of sleep fragmentation for the sleep fragmentation (14.81) and sleep diversity (20.95) indexes.

A combination of NREM sleep duration, the presence of sleeping disorders (apneic episodes) and the sleeping position was proposed by Nam *et al.* [82] to estimate sleep quality according to

$$\frac{TNR}{TST}\alpha + \left(100 - N_{AE}\right)\beta + P\gamma \tag{9}$$

where α, β and γ are tunable weights, N_{AE} is the number of apneic episodes and P is the total duration of the most chosen sleeping position. Intervals between roll-overs during sleep were analyzed by Miwa *et al.* [83] to classify light sleep (N1 and N2) and SWS if the frequency of roll-overs was, respectively, higher or lower than 20 (defined threshold). SWS% was derived from this information and it was verified that sleep quality decreases when TST rises above the average sleep duration in healthy subjects due to the fact that toward the end of sleep only light sleep increases.

Han *et al.* [84] proposed a metric based on the sleeping position and the acceleration of the movements during sleep, multiplying a weight factor associated to the measured position (0 for supine, 1 for prone and 0.5 for left or right) to the normalized value of the acceleration. Pouliot *et al.* [85] analyzed the bed occupancy, specifically the number of times the subject exit the bed during the night and the trend of the bed occupancy, as an indication of the quality of sleep.

A different approach was presented by Guettari *et al.* [86], determining the presence in bed by feeding the difference between the ambient and the radiated temperature as features for a clustering based analysis, performed by k–medoids, and classify considering a threshold. The developed sleep quality estimation algorithm operates if the subject was detected in the bed, extracting features from the difference signal using a symbolic approximation with four symbols (based in the SAX method) and detects if the subject is awake, sleeping agitated or in paradoxical sleep using a Kohonen network

(a kind of self-organizing network). Therefore, the output was used to indicate if sleep was either normal or agitated (disorder).

Norman *et al.* [87] have developed three measures of sleep continuity. The first was based on nonparametric survival curves using the Kaplan-Meier estimates of survival and the other two were based on regression analyses (one for each subject and one including the data of all the subjects). The sequence of epoch-based sleep stages was feed as input to all methods and a run starts when a change from wake to sleep was detected. In the second and third methods the distribution of the runs durations, of each subject and of all the subjects, was fitted to an exponential survival curve with the intent to determine how fast the curve drops. It was found that the longer runs were strongly related to normal sleep subjects.

V. DEVELOPED DEVICES FOR SLEEP QUALITY ESTIMATION

A. DEVICES PROPOSED BY RESEARCHERS

Multiple devices have been proposed by researchers and developed by companies with the aim of estimating sleep quality. Hamdan *et al.* [88] proposed a biofeedback system to monitor the quality of sleep and adapt the ambient environment to improve the sleeping conditions. A total sleep index was produced considering 12 metrics, including the respiratory disturbance index, to estimate the overall quality of sleep.

An approach based on a single conductive layer to measure the EEG signal was presented by Tseng *et al.* [89], using the DAQ100 (BeneGear, Taiwan) recording module, with one electrode placed under the ear (a1 location) and one on the forehead (fp1 location), to measure the value of a global minimum in the local field potential to infer the quality of sleep. A forehead EEG sensor was developed by Yu *et al.* [90], sending the measured information by Bluetooth to a computer where a developed application produces the analysis as displays the results to the user.

PPG signal was analyzed by Cheng and Huang [51] to estimate the HRV and determine the SWS% and ratio of the light sleep to TST. The algorithms were implemented in a smartphone that was connected to the PPG sensor. Bsoul *et al.* [50] analyzed a device that uses information from a single-Lead ECG to estimate the HRV and the EDR. 112 features were obtained from these signals and the sleep stage was identified using a multi-stage SVM.

A wearable actigraphy recording device was developed by Kuo *et al.* [91], defining the sleep quality metrics by analyzing the results of a wake-sleep scoring method that was based on the evaluation of movement density. The intraclass correlation coefficient between the PSG and the device scorings were 0.93, 0.84, 0.75 and 0.53 for, respectively, TST, SE, WASO and SOL, indicating that SOL was the only metric that did not achieved a good performance.

Peng *et al.* [70] developed a multimodality sensor system using a night-vision video webcam, a passive infrared sensor and a heart-rate sensor. A SVM was employed to produce the classification of the signals of each sensor and the output was fused together to deduce the sleep quality. A different configuration of the system was presented by Peng *et al.* [71] using the audio signal instead of the camera. In both systems, the sleep metrics were inferred from the sleep-awake classification. Sathyanarayana *et al.* [55] developed an actigraphy base classification of sleep periods to determine the SE, achieving a 93% accuracy using a CNN.

A combination of actigraphy and pressure sensors was proposed by Nam et al. [82] to monitor the sleeping position, activity, HRV and variations on the breathing amplitude (estimate the presence of apneic episodes). The sleep stage was determined considering the HRV and the measured activity. Park *et al.* [57] proposed a contactless approach, using polyvinylidene fluoride film sensors installed on the mattress to monitor BCG and estimate the SE.

Gaddam *et al.* [92] proposed the employment of four pressure sensors, placed under the legs of the bed, considering that during good sleep periods the sensors produce steady signals while the opposite happens during agitated periods, associated with poor sleep quality. Jung *et al.* [56] used strain gauge-based load cells, placed under the bed legs, to measure BCG and infer the HRV. A device based on pressure sensors, implemented on the bed, was developed by Pino et al. [93], measuring the body position and the number of respiratory cycles per minute. An algorithm to estimate apneic episodes and the periods out of bed was later added to the device [94].

Prakash *et al.* [95] have developed a method to measure BCG using an electromechanical film, positioned on the mattress, and load cells placed under the bed frame. These sensors were employed to measure physical activity, pulse rate and respiratory rate. A piezoelectric film sensor, placed under the mattress, was used by Paalasmaa *et al.* [96] to measure BCG signal. The sensor measures the mechanical activity of the person to estimate the HRV, measure the respiration cycle and detect the activity information. The data is sent to a web application to determine sleep metrics, including the measurement of the total amount of quiet sleep.

A Doppler radar, in the K band (24 GHz), was used by Rahman *et al.* [97] to determine the heart rate, breathing rate and the body position by transmitting a single tone on the carrier frequency, combined with phase noise from the oscillator, and analyzing the reflected signal that has information in the signal phase, according to the measured distance. The system determines sleep and wake periods using a random forest classifier (estimates the amount of sleep) and the REM or NREM periods with another a random forest classifier. The output of the classifiers was further used to produce sleep quality metrics.

An approach based on monitoring the channel state information of WiFi signals to estimate the respiration cycle and body movements was proposed by Liu *et al.* [98]. Milici *et al.* [99] have developed a device that estimates the respiration rate, movements and apnea periods by measuring variations in the earth's magnetic field using a magnetometer sensor, placed on the subject's body, detecting the

breathing movements. An indirect approach was proposed by Veiga *et al.* [100], measuring temperature, humidity, sound, luminosity and vibration with sensors implemented in a pillow that sends the information, wirelessly, to a server to estimate the sleep quality.

B. COMMERCIAL DEVICES BASED ON ACTIGRAPHY

A commercial device, Fitbit Charge HR (Fitbit, USA), was validated in a research developed by Dickinson *et al.* [101]. The device allows to measure a sleep efficiency measure based on the ratio TST/TIB, using actigraphy, a method to determine movements via an accelerometer, and it was concluded that the device overestimates sleep duration. This device was also analyzed by Choi *et al.* [69] to produce a sleep quality metric based on the heart rate analysis. However, Weatherall *et al.* [102] concluded that this device is more suitable to measure the physical activity than for sleep quality estimation by analyzing the subject self-reports. This is most likely due to errors in the measurements that define the quality of sleep since they are influenced by parameters that characterize each subject sleep and cannot be accounted for by changing the device settings.

Fitbit One (Fitbit, USA) and Beddit Pro (Beddit Ltd., Finland) were analyzed by Perez-Macias *et al.* [103]. The first uses a proprietary algorithm to estimate the sleep quality metrics from actigraphy while the second measures the temperature, sounds and light intensity and detects the presence on the bed using a piezoelectric sensor. It was verified that Beddit Pro provides more accurate results and Fitbit One overestimates the sleep quality metrics. However, both devices produced good estimations for some subjects and poor for others, indicating that a calibration for each subject may be needed. The Fitbit Ultra (Fitbit, USA) actigraph was evaluated by Meltzer *et al.* [104]. This device classifies the sleep or wake stages and can operate in the normal or sensitive modes. In the first the average accuracy, sensitivity and specificity were, specifically, 84%, 86% and 56% while in the second were 71%, 70% and 79%. Therefore, the first mode provided an overestimation of the sleep quality metrics while an underestimation was achieved in the second mode.

The Sleepwatch-O (Ambulatory Monitoring, USA) actigraph was analyzed by Blackwell *et al.* [54], measuring the movements using a piezoelectric biomorph-ceramic cantilevered beam to estimate sleep quality considering the zero crossings, a proportional integration and the time above a threshold. Merilahti *et al.* [105] have evaluated the Vivago WristCare (International Security Technology, Finland), an actigraph capable of detecting sleep or wake periods, identifying a high correlation coefficient, regarding the TST measurement, when compared with the users self-observations of their sleep time.

Two actigraphs, Fitbit (Fitbit, USA) and Actiwatch 64 (Philips Respironics, USA), were tested by Montgomery-Downs *et al.* [106] by comparing the produced analysis with a PSG. It was determined that both devices overestimate the TST and SE, having a high sensitivity (identifying sleep epochs) but a poor specificity (identifying wake epochs). The same conclusion can be achieved by analyzing the results reported by Sharif and BaHammam [107], analyzing the SenseWear Armband (BodyMedia, USA). This device uses a dual axis accelerometer and is worn over the arm instead of the common wrist an actigraph. A more recent version of the device, SenseWear Pro2 Armband (BodyMedia, USA), was analyzed by Miwa *et al.* [83] to detected roll-over movements during sleep and estimate sleep quality.

SenseWear Pro3 Armband (BodyMedia, USA) and Actiwatch 2 (Philips Respironics, USA) were studied by Shin *et al.* [108] it was found that ambient temperature can stigmatically affect the measurements of the actigraphs thus home sleep studies should be made with caution since the temperature conditions are more variable. SenseWear Pro3 Armband was also analyzed by Soric *et al.* [109]. Sheth *et al.* [110] have analyzed the feasibility of using an actigraph, Fitbit Charge 2 (Fitbit, USA) to monitor subjects with asthma, regarding sleep quality. It was verified that the device can be used as a continuous monitoring system but the results were not compared with a PSG.

Three actigraphs were tested by Weiss *et al.* [111], specifically, the Sleepwatch (Ambulatory Monitoring, USA), Actiwatch (Philips Respironics, USA) and Actical (Respironics, USA). The first two were designed to be worn on the wrist while the last should be placed around the chest. It was found that the three devices provide a good correlation with PSG in the TST estimation but had a poor performance estimating the SE, suggesting that adjustments of scoring and sensing algorithms are needed to provide more accurate classification of sleep or wake periods. Multiple actigraphs were evaluated by Keill and Lee [112], specifically Actigraph GT9X (Actigraph, USA), SenseWear Armband Mini (BodyMedia, USA), Fitbit Charge HR, Basis Peak (Intel Corp, USA), Jawbone UP3 (Jawbone, USA) and Vivosmart (Garmin, USA). It was verified that all devices produced a good correlation with the sleep diary for TST and TIB but a poor correlation for SE and WASO, concluding that the devices are not valid for the detection of wake periods during sleep.

Five actigraphs were evaluated by Mantua *et al.* [113], specifically, the Basis Health Tracker (Intel Corp, USA), the Fitbit Flex (Fitbit, USA), the Misfit Shine (MisfitWearables, USA), the Withings Pulse O2 (Withings, France) and the Actiwatch Spectrum (Philips Respironics, USA). The first two devices uploaded the data to the user website to produce the analysis while the third and fourth transmit the data by Bluetooth to a smartphone application. Best results were achieved by Actiwatch and was the only device were the mean value of SE did not differ, with significance, from PSG. Fitbit and Misfit had the highest loss of data. Actiwatch 64 and GT3X+ (Actigraph, USA) were tested by Cellini *et al.* [114] that also conclude that they provide a high sensitivity but low specificity, with GT3X+ producing better results, compared to the PSG.

Validation of the actigraph Jawbone UP (Jawbone, USA) was performed by Zambotti *et al.* [115]. The device algorithm

performs the detection of sleep or wake periods, achieving a good agreement with PSG, regarding the sleep quality metrics, but with overestimation. It was verified that the device provides a low specificity (37%, detecting wake periods) but a high sensitivity (97%, detecting sleep periods) [116]. Similar results were reported by de Souza *et al.* [117], using the Mini Motionlogger Actigraph (Ambulatory Monitoring, USA), and by Jean-Louis *et al.* [118], using the Actillume (Ambulatory Monitoring, USA). These unbalanced results could possibly question the usability of the device as a diagnostic tool. Actillume was also used by Greco *et al.* [119] to analyze the effect that psychoactive medications have in sleep quality, concluding that these drugs did not improve or reduce the quality of sleep.

The MicroMini-Motionlogger actigraph (Ambulatory Monitoring, USA) was employed by Souders *et al.* [120] to analyze children with autism spectrum disorders, using the 0-crossing mode, analyzing the mean activity, TST, SE, SOL and A (for periods longer than more than 5 minutes). It was verified that reliable measurements can be obtained from different locations, including the wrist, ankles, trunk and upper-arm, but at least seven consecutive nights of recordings should be used to attain reliable data. This conclusion was also presented by Byrom and Rowe [121]. Tworoger *et al.* [122] have evaluated the Actiwatch-16 (Mini Mitter, USA), observing that it was unreliable for measuring TST, TIB and SOL, but was acceptable to estimate TWT and SE. It was also verified that poorer actigraphic sleep measures were associated with factors such as going to bed late, increased daylight hours, use of medication and higher body mass index. An analysis of the sleep quality of totally blind subjects was conducted by Leger *et al.* [123] using the Z80-32K V1 (Gaehviler Electronic, France) for two weeks. It was verified that the subjects have lower values of TST, SE, SOL and TR, indicating poorer quality of sleep.

A combination of actigraphy, using the AW4 (Mini Mitter, USA) actighraph, and subjective reports were used by Kushida *et al.* [124] to estimate sleep metrics. It was verified that this combination produces good results in the detection of TST and SE but a poor estimation of A. A combination of objective sleep indicators, measured using the Actiwatch-L (Mini Mitter, USA), and sleep diary entries, to define the bedtime and time out of bed, was employed by McCrae *et al.* [125], verifying that actigraphy results are subjective to the gender of the user.

Da Silva Borges and Fischer [126] analyzed the differences in sleep quality and work-time alertness of subjects that work in 12 hours fixed night shift. The actigraph (Ambulatory Monitoring, USA) was used to collect the data that was analyzed using a developed algorithm to estimate the sleep or wake episodes. It was verified that these episodes were reliably estimated by comparing the predicted results with the daily logs of sleep and activity. It was also determined that the subjects napped during the shift and the self-perceived alertness systematically reduced. The daytime sleep episodes were perceived as being of poorer quality than the nighttime sleep episodes. Possibly due to the lack of synchronization between daytime sleep and circadian time structure. This conclusion is reinforced by the study of Martin *et al.* [127] that have verified that subjects with less robust circadian rhythms and disturbed sleep perform poorly on neuropsychological tests.

C. OTHER COMMERCIAL DEVICES

Paavilainen *et al.* [128] have evaluated a system that performs a continuous telemonitoring of the subject, IST Vivago (Information Security Technology, Finland), to measure the daily activity of demented subjects, verifying that they had a higher nocturnal activity but a lower daytime activity. The device is composed by a wrist unit, WristCare 3001, that measures force changes to estimate the activity and wirelessly transmits the information to a base station.

Liang and Martell [129] analyzed the difference between an actigraph, Fitbit Charge 2, and an eye mask, NeuroOn Open (inteliclinic, USA), that measures EEG, EOG, body motion, oxygen saturation and temperature. It was verified that both devices overestimated deep sleep but underestimated light sleep, with Fitbit overestimating the TR and SOL while NeuroOn underestimated A and TR. A device that uses a single-channel EEG measured by a headband, Zeo Sleep Manager Pro (Zeo, USA), transmitting the signal wirelessly to a base station for examination, was analyzed by Shambroom *et al.* [130] and Tonetti *et al.* [131]. The device allows to estimate the sleep stage and infer sleep quality measures, having an average agreement ranged from moderate to high with PSG.

De Zambotti *et al.* [132] have evaluated the Ōura ring (Oulu, Finland), a device placed on the finger measuring the subject HRV, blood volume pulse waveform and body motion to estimate the sleep and wake states. By comparing with the results provided by PSG the device achieved a 96% sensitivity (identification of sleep) and 48% specificity (identification of wake), providing a good estimate of TST but a significant difference in the overnight total WASO.

A device that computes CPC from HRV and EDR, the SleepImage (MyCardio, USA) sleep data recorder, was analyzed by Visco *et al.* [133] and Magnusdottir *et al.* [134]. This device estimates the patient's sleep quality index, a ratio of stable sleep to unstable sleep, by analyzing the duration of very low, low and high frequency coupling. The M1 (MyCardio, USA) was analyzed by Thomas *et al.* [135] and also performs sleep quality by analyzing the CPC frequency bands, defining the high-frequency coupling (0.1–0.4 Hz) as the biomarker of stable sleep. The high-frequency to low-frequency coupling ratio was also computed to produce a continuous indicator of sleep that can be used to estimate predict sleep quality or sleep related disorders.

A pressure base device, EarlySense (EarlySense, Israel), composed by a piezoelectric sensor was evaluated by Tal *et al.* [136]. The device is placed under the mattress and is capable of measuring the body movements, respiratory rate and heart rate. The information is sent to a developed

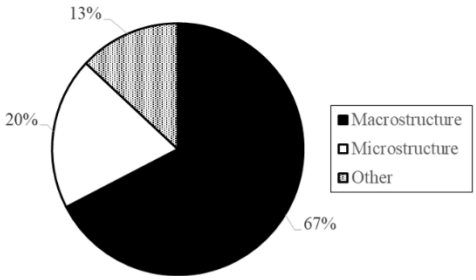

FIGURE 2. Resume of the reviewed articles on the method section.

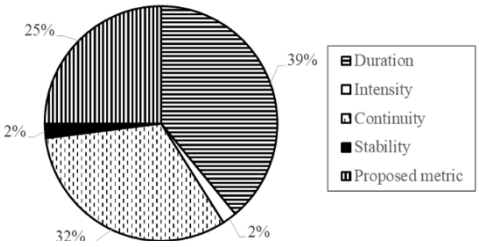

FIGURE 3. Resume of the reviewed articles on the device section.

smartphone application to perform the sleep analysis. Table 3 summarizes the analysis regarding the developed devices.

VI. DISCUSSION

A direct comparison between the reported results of the analyzed articles is not feasible due to the different databases, application conditions and employed metrics used for the experiments. Therefore, a broader analysis was performed, studying the percentage of developed methods that are based on the macro or microstructure and the percentage of devices that use a sleep quality indicator from each of the groups identified in Table 1 (or a proposed metric). The results of this analysis are presented in Figures 2 and 3.

An answer for the research question ''what methods for sleep quality assessment have been developed'' can be found by examining Figure 2, where is possible to verify that the majority of the proposed metrics (69%) are based on the examination of sleep macrostructure while 18% study the microstructure and 13% use metrics not related to the direct examination of the sleep structure. Therefore, it is conceivable to establish a tendency on the research for metrics based on the sleep macrostructure. This is probably due to the fact that more research was performed using well established sleep stage definitions to estimate the sleep quality while the microstructure is more commonly used to determine specific sleep disorder such as insomnia and periodic limb movements. However, as identified by Parrino *et al.* [18], the sleep microstructure can provide a clear indication of sleep instability thus, it could provide an estimation of the sleep quality that has a higher correlation with the subject self-rating.

Figure 3 provides an answer for the research question ''what kind of measures are employed by the devices that have been developed to estimate sleep quality''. It is possible to attest that the most common approach is the employment of metrics based on the analysis of duration (39% of cases) and continuity (31% of cases) of sleep, followed by the development of new metrics for sleep quality assessment (26% of the studied cases). Intensity and stability metrics were only used on 4% of the cases while frequency and sleep episodes' estimation were not used by any of the reviewed articles.

Only the research based devices employed the intensity and stability metrics while the commercial devices used, majorly, duration and continuity measures. This could be due to the fact that actigraphs dominate the home health care market, providing a classification of sleep or wake epochs. Consequently, it is not possible to estimate stability measures such CAPR. Actigraphs have a large employment possibly due to their simplicity to set the device and start the analysis (easy to use by the user), accessibility (commonly sold on hardware or fitness stores), and minimal invasiveness (typically they have the size of a bracelet worn on the wrist). However, as Kaplan *et al.* [8] have reported, metrics like TST or SE provide a small contribution to subjective ratings of prior-night sleep quality. Therefore, the development of devices capable of measuring stability measures could be more relevant for future medical diagnosis. Actigraphs could perhaps be used as a complement to other technologies despite the low specificity (poor detection of wake periods) of actigraphy-based devices, possibly due to the incapacity to identify periods of immobility as wake epochs, since they rely on the measurement of body movements to identify wakefulness making them more robust to the noise that certain diseases could cause in other sensors such as ECG.

Werner *et al.* [137] verified that actigraphy and sleep diaries provide similar assessments of TST, but both have a poor capability to indicate the nocturnal wake times, agreeing with the previous observation. It was also concluded that information provided by interviews or collected from questionnaires is insufficient to assess the sleep patterns. Also, Wang *et al.* [138] have concluded that actigraphs may underestimate arousals, caused by respiratory events that could lead to misleading results, especially in apnea patients. AASM have defined the practice parameters for the clinical use of actigraphy, defining guidelines to assist in the evaluation of patients with sleep disorders and circadian rhythm sleep-wake disorders [139].

A detailed review of the usability of actigraphy for the evaluation of these disorders, in adult and pediatric population was also performed by AASM [140]. It was verified that for healthy adults, actigraphy and sleep logs provide significantly different results in the estimation of TST, SOL and SE but a similar estimation of WASO. For the same population, actigraphy and PSG measures have a strong agreement estimation TST and SOL but poor estimation of SE and WASO.

Analyzing the reviewed articles, it was possible to assess a common processing flow of the developed methods, for sleep

TABLE 3. Analysis of the developed devices for sleep quality estimation.

Type of device	Name of the device	Article	Sensors	Sleep quality measurements used in the article
Proposed by researchers		[70]	Camera; passive infrared sensor; heart-rate sensor	SOL; TST; SE
		[71]	Passive infrared sensor; heart-rate sensor; Microphone	SOL; TST; SE
		[89]	EEG	Developed metric
		[90]	EEG	TN1; TN2; TN3; SE
		[51]	PPG	SWS%; developed metric
	Sleep MedAssist	[50]	ECG	Developed metric
		[88]	ECG; actigraph; oximeter; microphone	SE; SOL; A; WASO; PLMI; N1%; N2%; SWS%; REM%; REML; developed metric
		[91]	Actigraph	TST; SE; WASO; SOL
	RAHAR	[55]	Actigraph	SE
		[82]	Actigraph; pressure sensor	Developed metric
		[57]	Pressure sensor	SE
		[92]	Pressure sensor	Developed metric
		[93]	Pressure sensor	Developed metric
		[94]	Pressure sensor	TIB; developed metric
		[95]	Pressure sensor	Developed metric
		[56]	Pressure sensor	SOL
		[96]	Pressure sensor	TST; TN3; SE; developed metric
	DoppleSleep	[97]	Doppler radar	SOL; A; TST; SE
	Wi-Sleep	[98]	Transmitter and receiver antennas	Developed metric
		[99]	Magnetometer	Developed metric
		[100]	Thermometer; humidity sensor; microphone; luminosity sensor; micro-vibration sensor	Developed metric
Commercial	Actical	[111]	Actigraph	TST; SE
	Actillume	[118]	Actigraph	TST; developed metric
	Actigraph	[126]	Actigraph	Developed metric
	Actigraph GT9X	[112]	Actigraph	TST; SE; TIB; WASO
	Actiwatch	[111]	Actigraph	TST; SE
	Actiwatch 2	[108]	Actigraph	TST; SE; WASO; SOL
	Actiwatch-16	[122]	Actigraph	TST; SE; TIB; SOL; TWT
	Actiwatch 64	[114]	Actigraph	TST; SOL; WASO; SE
	Actiwatch-L	[125]	Actigraph	TST; SE; SOL; TWT
	Actiwatch Spectrum	[113]	Actigraph	TST; SE; developed metric
	AW4	[124]	Actigraph	TST; SE; A
	Basis Health Tracker	[113]	Actigraph	TST; SE; developed metric
	Basis Peak	[112]	Actigraph	TST; SE; TIB; WASO
	Fitbit	[106]	Actigraph	TST; SE
	Fitbit Charge 2	[110]	Actigraph	TST; TIB; SE
	Fitbit Charge HR	[101]	Actigraph	TST; TIB; developed metric
	Fitbit Flex	[113]	Actigraph	TST; SE; developed metric
	Fitbit One	[103]	Actigraph	TST; SE; SOL; developed metric
	Fitbit Ultra	[104]	Actigraph	TST; SE; WASO
	GT3X+	[114]	Actigraph	TST; SOL; WASO; SE
	IST Vivago	[128]	Actigraph	TIB; developed metric
	Jawbone UP	[115]	Actigraph	TST; SE; TIB; TW; SOL; WASO
	Jawbone UP3	[112]	Actigraph	TST; SE; TIB; WASO
	MicroMini-Motionlogger	[120]	Actigraph	TST, SE, SOL; A
	Mini Motionlogger	[117]	Actigraph	TST; SE; SOL; A
	Misfit Shine	[113]	Actigraph	TST; SE; developed metric
	SenseWear Armband	[107]	Actigraph	TST; TIB; SE
	SenseWear Armband Mini	[112]	Actigraph	TST; SE; TIB; WASO
	SenseWear Pro2 Armband	[83]	Actigraph	Developed metric
	SenseWear Pro3 Armband	[108]	Actigraph	TST; SE; WASO; SOL
	Sleepwatch	[111]	Actigraph	TST; SE
	Sleepwatch-O	[54]	Actigraph	TST; SE; SOL; WASO
	Vivago WristCare	[105]	Actigraph	TST
	Vivosmart	[112]	Actigraph	TST; SE; TIB; WASO
	Withings Pulse O2	[113]	Actigraph	TST; SE; developed metric
	Z80-32K V1	[123]	Actigraph	TST; SE; SOL; TR
	Ōura ring	[132]	Accelerometer; infrared sensor	TST; SOL; WASO; TN1; TN2; TN3; TR
	Zeo Sleep Manager Pro	[130]	EEG	TST; SE; SOL; WASO; A; TNR; TR; TW; REML; developed metric
	NeuroOn Open	[129]	EEG; EOG; oximeter; thermometer; accelerometer	TST; SE; A; WASO; SOL; TN1; TN2; TN3; TR
	SleepImage	[133]	ECG	Developed metric
	M1	[135]	ECG; accelerometer; vibration sensor	TST; WASO; developed metric
	Beddit Pro	[103]	Thermometer; microphone; luminosity sensor; force sensor	TST; SE; A
	EarlySense	[136]	Pressure sensor	TST

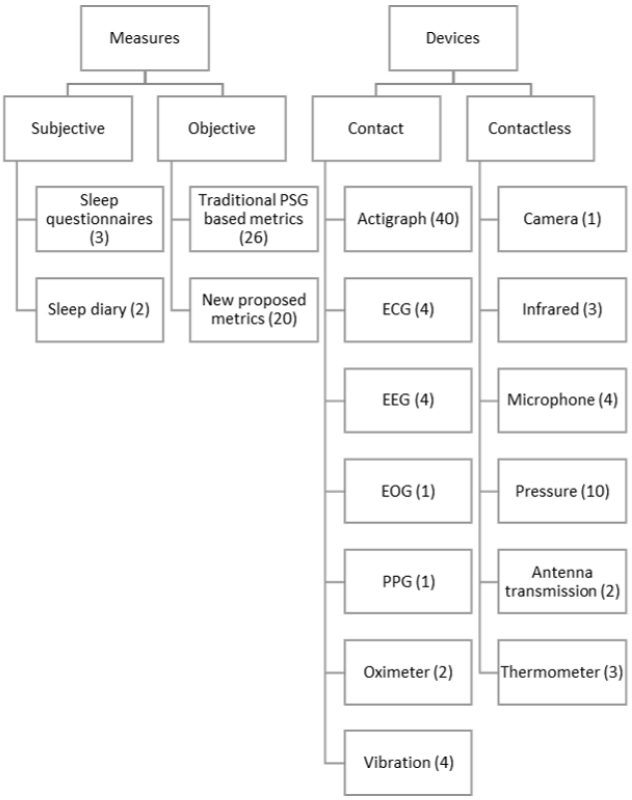

FIGURE 4. Taxonomy of sleep quality analysis. Number of studies is indicated in brackets.

quality estimation, based on a four step model. On the first step the data was collected, either from a database or from a device, and the feature-space was built on the second step, feeding the developed algorithms for the event classification (third step) and the results are presented to the user on the final step. The taxonomy of sleep quality analysis obtained through the analysis of this review is presented in Figure 4, where the number or articles analyzed in each category is indicated between brackets.

It is possible to assess that traditional PSG based metrics are the most used but there is a significant number of new proposed metrics that could possibly be considered as standard for sleep quality analysis but still need further validation. Regarding the analyzed devices, it is possible to determine a dominance of actigraphs, the few number of devices that use the traditionally employed sensors for sleep analysis, specifically EEG, ECG and EOG and the growing development of pressure based devices.

Consumer sleep trackers are growing in the home health monitoring market as the focus of health care is changing from specialty and primary care to wellness and prevention. Sleep quality analysis plays an important role in this change since it can be used as the second level control mechanism, in the fatigue error trajectory (assessment of fatigue) [141], as symptoms of diseases [7] and as an overall metric for wellness evaluation [142], indicating its potential as a preventive analysis and as a diagnostic tool.

Despite the convenience and large popularity among the consumers of home health monitoring of devices such as actigraphs, the validity of these tools for sleep quality estimation still needs to be systematically examined, especially the research devices and the commercial devices that have recently entered the market. This claim is in agreement with the agreeing with the AASM recommendation to not use consumer sleep technologies that lack the United States Food and Drug Administration clearance [143].

Independent validation of the proposed devices by research projects and repeated validation studies on commercial devices would give a higher relevance to the presented results. However, the impacts on public health regarding the introduction of sleep quality home monitoring devices as a diagnosis tool and wellness estimation still needs to be assessed and was identified as a future challenge. Despite the methodological limitations of the devices, the results are consistent. Hence a key finding of this review is that home monitoring devices can be used, at least, as an initial diagnostic tool for multiple sleep disorders and future research should emphasize on further corroborating this claim (in magnitude and significance).

A key aspect of the analyzed methods is the goal of achieving a good ratio performance-complexity, minimizing the number of required sensors and decrease the complexity of the algorithms to allow a feasible hardware implementation. However, the results achieved with the developed methods should be validated by independent research groups. Thus the relevance of using publicly available databases to allow the work reproduction. An efficient hardware implementation was the main challenge identified for the reviewed methods due to the high degree of complexity that most methods present. This claim is even more relevant for home analysis devices since they are more susceptible to data errors due to uncontrollable factors present at the subject's home.

From the general analysis of this review it can be identified as future directions for the developed methods to increase the study of metrics based on the sleep microstructure, produce more research with machine learning classifiers, with particular interest on deep learning classifiers with the capacity of self-learning features, and proceed to a hardware implementation of the algorithms. It was found that most metrics are based on the macrostructure of sleep that is currently a well-established field of research. Thus, it is recommended to increment the research in microstructure based metrics to further consolidate this field.

A new definition of sleep structure, considering more stages to better approximate the discrete measurements to the continuous process that is sleep, could possibly contribute to the development of new metrics with more time resolution. An example of such implementations is the continuous model based on the PSM. The proposal of new methods that describe the underlying physiological process of sleep can possibly be a relevant path to find new indicators of good or bad sleep. Regarding the devices, the main gap in the current state of the art is the employment of metrics based on the intensity, stability, frequency and sleep episodes estimation.

It was verified that actigraphy based analysis of sleep is the most consolidate research field, regarding the home health monitoring of devices, followed up by BCG. It is recommended the further development of home monitoring devices that employ more reliable sensors for sleep estimation, such as EEG, to produce a sleep quality estimate that can be used for clinical purposes, leading to developments in the treatment of sleep quality deficits. A more robust system should employ measurements from multiple sensors to produce the estimate, possibly combining the information into a vector of features to feed a machine learning classifier or employing ensemble methods with multiple learning algorithms.

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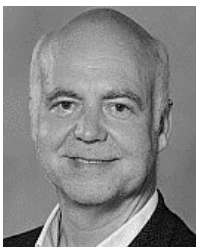

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