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TOPICAL REVIEW

The challenge in finding a simple, accurate, reliable, and affordable tool for the objective assessment of excessive daytime sleepiness (EDS)

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Keywords: excessive daytime sleepiness (EDS), photoplethysmography (PPG), wearable techniques, sleepiness, artificial intelligence (AI)

Abstract

Excessive daytime sleepiness (EDS) refers to a physiological state where individuals have difficulty remaining alert during the day. Managing EDS is particularly challenging to study and treat due to its multifaceted nature. Assessment methods include both subjective and objective approaches. Subjective evaluation often relies on simple, widely accepted, and widely used questionnaires; however, these tools are inherently limited by self-reporting bias. Objective assessment, on the other hand, primarily involves two well-known and reliable tests, but these are costly, time-consuming, and impractical for use outside of sleep units. Therefore, developing an objective tool that can quickly and accurately detect a decline in alertness, while remaining reliable, easy to use, and affordable, is of critical importance for sleep clinicians, safety organizations, and researchers. According to PRISMA guidelines, we did a systematic analysis of 95 studies that used photoplethysmography (PPG) for assessing EDS, drowsiness, and/or fatigue during the last 15 years (2010–2025). With advances in wearable technology, particularly through PPG and artificial intelligence, achieving this goal may be attainable. The next essential step is rigorous validation against established gold-standard tests to ensure the tool meets scientific and clinical standards for widespread adoption.

ABBREVIATIONS LIST

AI	Artificial intelligence
ANS	Autonomic nervous systems
AUC	Area under the curve
BFI	Brief fatigue index
BRV	Beat rate variability
CNN	Convolutional neural network
CPAP	Continuous positive airway pressure
EDS	Excessive daytime sleepiness
EEG	Electroencephalography
ESS	Epworth sleepiness scale
HF	High frequency
HRV	Heart rate variability
KSS	Karolinska Sleepiness Scale
LF	Low frequency
MSLT	Multiple Sleep Latency Test
MWT	Maintenance of Wakefulness Test

OSA	Obstructive sleep apnea
PERCLOS	Percentage of time that the eyes were closed
PSD	Power spectral density
PSG	Polysomnography
PVT	Psychomotor vigilance test
PPI	Pulse to pulse interval
PRV	Pulse rate variability
PPG	Photoplethysmography
RMSSD	Root mean square of successive differences
ROC	Receiver–operating characteristics
SpO2	Peripheral oxygen saturation
SVM	Support vector machine
SSS	Stanford Sleepiness Scale
TP	Total power
ULF	Ultra-low frequency
VLF	Very low frequency

1. Introduction

Finding an accurate, reliable, simple, and affordable tool for assessing EDS is challenging due to its multifaceted nature. EDS refers to a physiological state where individuals struggle to stay awake and alert during the day, but it manifests in various ways and can be categorized into introspective, physiological, and manifest dimensions (Carskadon and Dement 1987). Introspective sleepiness depends on self-awareness, making subjective assessments potentially unreliable. Physiological sleepiness, known as 'sleep pressure' or 'sleep intensity', is governed by homeostatic and circadian processes with specific sleep gates and wake maintenance zones (Lavie 1986). Manifest sleepiness presents as outward signs such as yawning, impaired attention, and microsleeps (Baiardi and Mondini 2020). EDS is a common symptom of sleep disorders, including OSA, narcolepsy, idiopathic hypersomnia (IH), and circadian rhythm disorders. It can also result from insufficient sleep due to insomnia or sleep deprivation, shift work, or as a medication side effect. Genetic studies of large samples further support the heterogeneity of EDS as evidenced by unique clusters of genetic variants that associate with EDS phenotypes that reflect a high sleep propensity (i.e. associated with long sleep duration and high sleep efficiency) or by sleep fragmentation (i.e. associated with short sleep duration and insomnia symptoms (Wang *et al* 2019). It is not surprising that the assessment of EDS has been a topic of great interest to the sleep research and clinical sleep community (Quan *et al* 2011). Notably, an objective tool that could readily, reliably, affordably, and accurately detect decreased levels of alertness could be of great utility for the clinical management of sleep disorders, for facilitating sleep-related research, and for utilization by public health and safety organizations for efforts related to monitoring and mitigating sleepiness in the population (Mullington *et al* 2011, Quan *et al* 2011).

1.1. An objective tool for EDS assessment in OSA

For sleep clinicians, such a tool could play a valuable role in the assessment of patients with OSA. This disease, affecting 900 million adults globally (Benjafield *et al* 2019), often presents with EDS as a cardinal symptom. EDS varies between 12%–65% of OSA patients (Léger and Stepnowsky 2020). EDS is often the most disabling daytime symptom in patients with OSA, impacting cognitive function, mood, and quality of life. In a Swedish study of 34 684 individuals with OSA, EDS prevalence was 41.4% in men and 44.6% in women (Ulander *et al* 2022), with 28% experiencing residual EDS despite CPAP treatment (Bonsignore *et al* 2021).

1.2. An objective tool for EDS assessment on public safety

EDS extends beyond clinical consequences to public safety risks, particularly drowsy driving. According to the American Automobile Association Foundation, 17.6% of fatal crashes (2017–2021) involved a drowsy driver. The National Security Council reports that fatigued drivers are three times more likely to be involved in accidents. Fatigue or sleepiness affects concentration, reaction time, and decision-making. Drowsiness- and in the extreme, falling asleep- in certain settings, such as while driving or operating dangerous equipment, may result in huge personal and societal consequences. Key contributors include sleep deprivation and underlying sleep disorders (Akerstedt 2000). Fatigue detection technologies, categorized as continuous monitoring and fit-for-duty tests, show promise for detecting at-risk situations. However, no commercially available technology meets scientifically and legally defensible standards (Dawson *et al* 2014, Cori *et al* 2021). While self-driving cars are expected to dominate or at least to show

Table 1. EDS, fatigue, alertness, and drowsiness.

Term	What it means	How it is measured	Key difference
Excessive daytime sleepiness (EDS)	A **tendency to fall asleep** during the day in situations when you should be awake (e.g. during a meeting, driving, watching TV). **It is an increased sleep propensity**, not just tiredness.	Subjective scales (example: Epworth sleepiness scale or ESS)), objective tests (MSLT, MWT).	It is about *sleepiness*- the physiological strong pressure to fall asleep,
Fatigue	A sense of low energy, weakness, or exhaustion, mental or physical, without necessarily having an urge to sleep.	Questionnaires (Fatigue severity scale (FSS)), physical exam, lab tests.	Fatigue reflects a broader sense of being tired or exhaustion, often from physical or mental exertion. You can feel fatigued **but not sleepy** (e.g. in anemia, depression, chronic illness).
Alertness	The opposite of sleepiness; a state of being awake, attentive, and ready to respond to stimuli.	Psychomotor vigilance tests, reaction-time measures.	Alertness is the ability to focus and be vigilant. Reduced alertness does not always mean EDS—
Drowsiness	A transitional state between wakefulness and sleep, with reduced mental and physical performance, but not full sleep onset yet.	Observation, EEG monitoring.	Drowsiness reflects a state of decreased alertness and tendency to fall asleep. Can happen briefly (after lunch, during boredom) without being a chronic condition.

a strong presence in specific areas or industries by 2040 (Simon 2017), a validated drowsiness detection tool could save lives across multiple settings where alertness is required to prevent injury, serious errors, or death.

EDS, fatigue, alertness, and drowsiness are concepts that share similarities but are conceptually distinct. Key differences are described in the table 1. This paper focuses on EDS, but given include studies that address the related concepts of fatigue, drowsiness, and alertness.

1.3. Examples to emphasize the differences

1. A truck driver with EDS will fall asleep at the wheel even if motivated to stay awake.
2. A cancer patient with fatigue may feel drained but still stay awake all day.
3. Someone with low alertness may miss details in a conversation without being sleepy.
4. After a big meal, most people feel drowsy for a short while, but that's not pathological.

1.3.1. Subjective vs. objective EDS assessment

Subjective tools, including the ESS (Johns 1991), SSS (Hoddes *et al* 1973), and KSS (Åkerstedt and Gillberg 1990), are widely used to screen for, or assess, sleepiness. The ESS is globally recognized but limited by self-report bias and limited repeatability (Kendzerska *et al* 2014). Many patients with OSA underestimate their sleepiness until treatment improves their condition (Guimarães *et al* 2012). For objective assessment, the MSLT remains the gold standard (Littner *et al* 2005). It measures the time taken to fall asleep under controlled conditions during 4-5 opportunities during the daytime. However, while having excellent reliability in healthy individuals (Zwyghuizen-Doorenbos *et al* 1988), it has poorer reliability in individuals with clinical disorders of hypersomnolence (Trotti *et al* 2013, 2020) and is sensitive to several contextual factors (medications, prior sleep). The MWT evaluates the ability to resist sleep in soporific settings (Mitler *et al* 1982). The MWT demonstrates moderate to good test-retest reliability in healthy subjects and in patients with conditions like narcolepsy and IH, but may not reflect the ability to stay awake in real-world situations (Doghramji *et al* 1997). These tests are costly, time-consuming, and impractical for routine use outside of specific clinical settings.

Discrepancies between self-reported and objective measures of EDS are well documented in sleep medicine. For example, a Japanese study involving 211 adolescents (aged 10–18 years) found that 35.5% reported subjective sleepiness without objective confirmation, while 10.9% exhibited objective sleepiness without subjective complaints (Munkhjargal *et al* 2022). In addition, Li *et al* (2017) demonstrated that objective, but not subjective EDS, correlates with elevated IL-6 levels, an inflammatory marker linked to

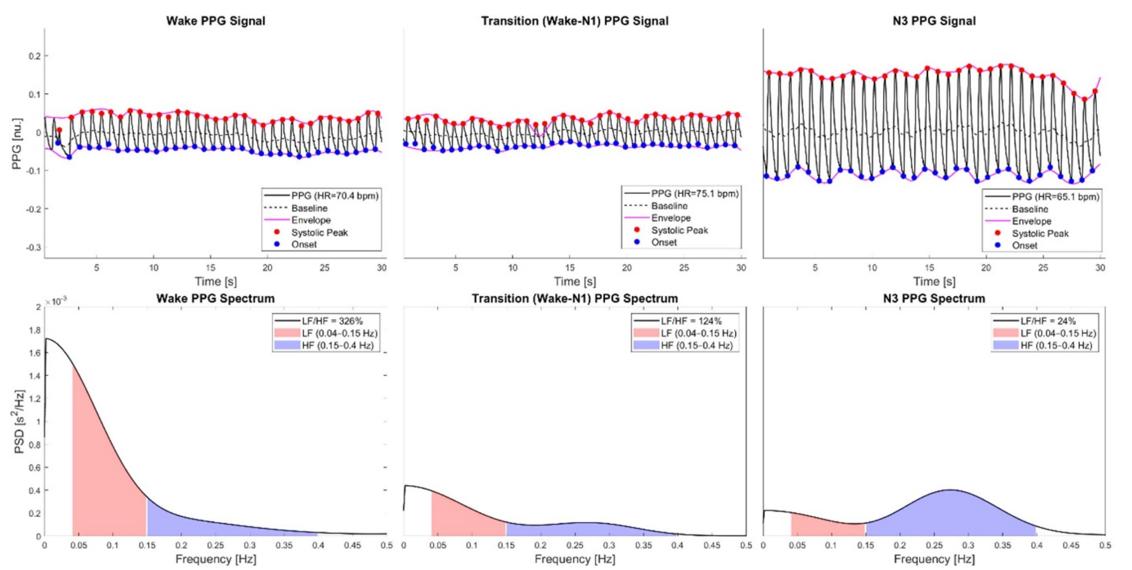

Figure 1. Showing the photoplethysmography (PPG) signal characteristics in awake, sleep-wake transition (N1), and deep sleep (N3). The PPG spectrum for each section. Typically, the low-frequency component (LF) is higher in the wake state than deep sleep stage, which indicates sympathetic control, and the high-frequency component (HF) is lower in the deep sleep stage than wake stage, which indicates parasympathetic control. Note the LF/HF ratio is decreasing during the transition from wake to sleep (N1).

cardiometabolic risk (Chrousos 2000) and mortality (Ershler and Keller 2000). This suggests that objective EDS measures better identify high-risk individuals.

1.3.2. THE PPG SIGNAL

In recent years, there have been significant advances in the use of wearable sensors capable of capturing various physiological processes, including variations in autonomic and arousal states. These advancements offer the potential to develop objective and non-invasive tools for identifying EDS in real-world settings. PPG is one promising technology that may allow for an objective, simple, and affordable assessment of EDS—and with time, may become increasingly reliable and accurate.

PPG is frequently associated with pulse oximetry, as pulse oximeters fundamentally rely on PPG signals as their raw data source (Charlton *et al* 2023). PPG can be measured using two primary techniques: transmission and reflectance. In the transmission method, an LED emits light through a body part such as a finger, and a photodetector placed on the opposite side measures the transmitted light. The amount of light absorbed by the tissue varies in response to pulsatile blood flow in the microvascular network, particularly arterial blood in the capillaries. This variation produces a waveform that is synchronized with the heartbeat (see figure 1).

The reflectance method operates on a similar principle, but both the LED and photodetector are positioned on the same side of the tissue (Charlton *et al* 2023). In this setup, the detector captures the portion of light reflected from the tissue, with signal modulation again driven by changes in arterial blood volume. Pulse oximetry builds on these principles by using two LEDs at different wavelengths to estimate SpO_2, defined as the ratio of oxygenated hemoglobin to total hemoglobin. Because this measurement involves two unknowns, the dual-wavelength approach is necessary to resolve the ratio accurately. Consequently, oximeter probes typically include at least two LEDs.

PPG technology has now become commonplace in consumer wearable devices such as smartwatches and smart rings (Charlton *et al* 2023). These devices often incorporate one or more LED-photodetector pairs on their undersides to continuously monitor cardiovascular metrics. While the fingertip remains the most common site for PPG measurement due to its strong perfusion, other locations such as the ear, foot, or even chest are also utilized in specific applications. The anatomical location significantly influences signal morphology due to varying perfusion characteristics, which must be accounted for in both clinical and wearable applications.

Preprocessing of PPG signals typically begins with signal-quality assessment and resampling to a uniform rate (Goda *et al* 2024), followed by removing low-frequency components (such as baseline wander from respiration) and high-frequency components (such as muscle noise or power line interference). Subsequent steps may include amplitude normalization, motion-artifact mitigation (e.g. adaptive filtering using accelerometry (ACC), independent component analysis, wavelet denoising, or regression against

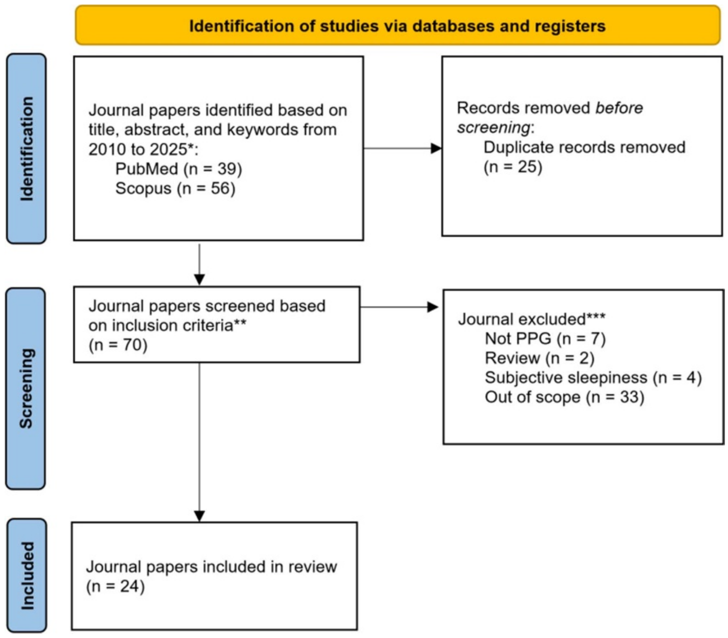

Figure 2. Systematic analysis of the selected studies.

reference channels) and beat segmentation/annotation (systolic peak and foot detection) to enable robust HR and HRV computation as well as morphological feature extraction, with quality flags and rejection criteria increasingly applied before downstream analysis.

PPG signals are influenced by several physiological factors: sympathetic activation, which alters vascular tone and blood flow, and modulates PPG amplitude and waveform morphology (Huthart *et al* 2020); respiration, which modulate the amplitude of the PPG signal (Fine *et al* 2021); blood pressure and vascular compliance, with changes related to aging or chronic hypertension resulting in arterial stiffness and between-subject differences in pulse wave velocity, with flattening of systolic peaks and altering dicrotic notch visibility (Huthart *et al* 2020); and Peripheral Perfusion, influenced by conditions such as cold exposure or vasoconstriction that reduce blood flow (hypoperfusion) and diminish PPG signal amplitude and quality (Fine *et al* 2021). Accordingly, the PPG raw waveform or derived signal, such as BRV or SpO2, can be used to monitor physiological function such as HR, arrhythmias, blood pressure, cardiac output, arterial stiffness, respiration rate and effort, sympathetic activity, thermoregulation, and SpO2 (Allen 2007, Park *et al* 2022, Charlton *et al* 2023).

1.3.3. PPG for the objective assessment of EDS

Since PPG sensors are low-cost, simple to use, and comfortable, in recent years, PPG has been considered as a valuable method to estimate several physiological metrics relevant to EDS: **HRV** (Chua *et al* 2012, Taranto Montemurro *et al* 2014, Henelius *et al* 2014, Dey *et al* 2017, Lu *et al* 2022, Yu *et al* 2024, Srinivasan *et al* 2024, Ucak *et al* 2024, Xie and Ma 2024), ***SpO2*** (Kainulainen *et al* 2019, 2020, Howarth *et al* 2023), and the ***raw PPG waveform*** (Chua *et al* 2008, Kim *et al* 2010, Koh *et al* 2017, Chen *et al* 2023a). Monitoring these parameters in individuals with EDS may provide valuable insight into the underlying physiological disturbances associated with poor sleep and sleep disorders, as well as in estimating EDS using technologies embedding PPG measurements (Allen 2007, Charlton *et al* 2023).

1.3.4. Systematic review of PPG studies

To better understand the existing literature that supports PPG for assessing EDS and related behavioral states, we conducted a systematic review of 95 studies that used PPG for assessing EDS, drowsiness, and/or fatigue. After the systematic analysis of these selected studies based on the inclusion criteria and following PRISMA guidelines , 24 studies were selected that used PPG for the objective of assessing EDS, fatigue, alertness, and drowsiness during the period from 2010–2025. (see figure 2).

These studies are summarized in a table 2, and some important characteristics are illustrated in figure 3. We subsequently provide a more detailed description of the most relevant studies, identified based on our inclusion criteria, which investigated one or more of the following physiological components derived from the PPG signal: HRV, SpO2, or the raw PPG waveform, and their associations with outcomes related to EDS, fatigue, drowsiness, and alertness. These three physiological components derived from the PPG signal are the most common parameters, and among them, HRV studies are dominant, which assessed their relationship with EDS and related phenomena.

	Scopus	**PubMed**
Keywords	**56**	**39**
Sleepiness + HRV + Psychomotor vigilance task	6	3
Fatigue estimation + photoplethysmography + HRV	4	1
Excessive daytime sleepiness + wearable + SpO2	2	2
Excessive daytime sleepiness + wearable + HRV	0	0
Excessive daytime sleepiness + SpO2 + pulse analysis	5	7
Excessive daytime sleepiness + photoplethysmography + HRV	0	0
Excessive daytime sleepiness + photoplethysmography	2	1
Excessive daytime sleepiness + HRV + ECG	5	9
Drowsiness + wearable + driver + HRV	7	3
Drowsiness + sleep onset + accident prevention	3	2
Drowsiness + PPG + multimodal	3	1
Drowsiness + photoplethysmography	18	9
Chronic sleep + HRV + Psychomotor vigilance task	1	1

**Inclusion criteria:

- Human studies that used cardiovascular metrics for the detection of sleepiness.
- Studies that used PPG, SpO2, and raw PPG for the detection of sleepiness.
- Study Populations: adult subjects, OSA patients, men, and women of any ethnicity.
- Sensors: PPG sensor in the finger, ears, and wearables.
- Only studies reported in English.
- There was no restriction regarding the research design and sample size.
- The included studies were published between 2010 and 2025.

***Exclusion criteria:

- Non-English studies
- Case reports,
- Abstracts or Conference reports
- Letters to the editor
- Editorials
- Reviews.

1.3.5. HRV or BRV in the detection of sleepiness

EDS and its underlying causes can have a profound impact on the PPG signal, reflecting disruptions in *HRV—BRV*. HRV is a good indicator of the ANSs activity, reflecting the balance between the sympathetic and parasympathetic branches. Assessment of HRV from ECG or PPG signals provides insights into how the ANS responds to various physiological and environmental factors, including fatigue and sleepiness. Changes such as reduced reaction time, changes in brain wave activity (transition from alpha to theta waves), or changes in HRV have been reported to be associated with EDS. Recently, (Ucak *et al* 2024) showed lower HRV values for root mean square successive difference, TP, absolute LF, and HF power in a group of 119 sleepy OSA patients compared to non-sleepy OSA patients, mainly in moderate—severe OSA patients, suggesting a trend toward parasympathetic withdrawal in sleepy patients with OSA. This study extends related results of a previous work showing that sleepy OSA patients have reduced baroreflex sensitivity and significantly higher low-to-HF power ratio of HRV during the different

Table 2. Detailed summary of the 24 studies selected using the PRISMA selection criteria on the use of photoplethysmography (PPG) signal for the objective assessing EDS, fatigue, alertness and drowsiness during the period from 2010-2025.

Author	Population	Device	Processing	Characteristics	Applications	Results	Limitations
(AlArnaout *et al* 2025)	Heathy male drivers, $n = 3$ (ages 28, 34, and 42 years)	Smartwatch (Fitbit Charge 5 PPG sensor)	HRV, raw signal, ML	HRV features for drowsiness	HRV-based drowsiness detection systems	Random Forest reached 86.1% accuracy (F1 = 89.0%), and SVM (RBF) F1 = 87.2% for driver drowsiness detection from HRV.	Small sample, needs real-world validation
(Aljuaid 2025)	Healthy adults, $n = 27$ (22 males and 5 females, mean ages: 32 ± 12 years)	Headband/armband (MAX30102 Sensor) + EEG	HRV, Prototype platform for neuroergonomics	Multimodal physiological signals	A multimodal platform including body temperature, HR, SpO2, EEG and HRV to detect stress and drowsiness	Females had lower RMSSD (23.5 ms) and higher LF/HF (1.5) than males (37.2 ms, 1.3); stress and drowsiness classified by HRV and EEG thresholds	Early stage, no large trials, short-term evaluation only
(Babusiak *et al* 2021)	Not reported	Finger PPG (MAX30102 Sensor) + ECG + Smart steering wheel sensors (IMU)	Fusion physiological behavioral data, HRV, PPG signal analysis	Unobtrusive health + drowsiness monitoring	Continuous drowsiness detection from HR, HRV, and SpO2, measured by an electrocardiograph and oximeter integrated into the steering wheel	Heart rate error ∼1.3 bpm, SpO2 error ∼1.6%, drowsiness detection accuracy 85.6%	Prototype tested in limited settings; participant details not reported
(Bisogni *et al* 2017)	OSA patients mild-moderate, $n = 56$(ages: 18–75 years)	Finger PPG	HRV, Sympathetic nervous system activity analysis	Sleep apnea severity and sleepiness	Correlation between subjective sleepiness (ESS) and HRV—sympathetic nervous system activation	No significant differences in HRV or arterial stiffness between groups (all $p > 0.15$)	Mild/moderate OSA only
(Bourdillon *et al* 2021)	Healthy volunteers, $n = 15$ (7 males and 8 females)	Finger PPG (Shimmer3 GSR+) + baroreflex sensitivity	HRV, PPG signal analysis	Effects of sleep deprivation on RCV signals	Changes in HRV and PPG are sensitive to partial sleep deprivation.	Sleep deprivation lowered HRV high-frequency power and PPG amplitude by ∼15%–30%, while baroreflex sensitivity stayed unchanged	Small sample size, short sleep deprivation period, and lack of long-term follow-up limit generalizability.

(Continued.)

Table 2. (Continued.)

Author	Population	Device	Processing	Characteristics	Applications	Results	Limitations
(Chang *et al* 2022)	Healthy subjects, $n = 8$ (6 males and 2 females, ages: 20–25 years)	Facial video to extract remote PPG (NIR)	HRV, PPGI signal analysis); face/eye detection; fusion rule combining for drowsiness judgment (multi-condition decision logic)	Non-contact (convenient), works in low light (NIR active); combines autonomic (LF/HF) and behavioral (PERCLOS) cues for robustness.	Real-time drowsiness detection/warning via fusion of physiological (PPGI HRV) and eyelid closure metrics; intended for in-vehicle monitoring.	92.5% overall accuracy, with 88.9% sensitivity, 93.5% specificity, and 80% PPV in detecting drowsiness, validated against EEG measurements.	Small young-adult sample, few labeled cases, and PPGI sensitive to lighting and motion; needs real-road validation
(Chen *et al* 2023a)	Healthy male adults, $n = 16$(ages: 22–24 years)	Finger PPG	Peak features extraction from PPG, HRV, brief fatigue index (BFI)	Fatigue-related physiological changes	A novel fatigue index from PPG signals, focusing on the dicrotic peak's position.	PPG-based fatigue index correlated strongly with subjective fatigue ($r = 0.907$), outperforming heart rate variability.	Limited sample diversity
(Choi *et al* 2025)	Drivers, $n = 59$ (51 males and 9 females, ages: 20–59)	Facial video to extract remote PPG	Contactless feature extraction, raw PPG, HR	Early drowsiness detection	Non-intrusive drowsiness monitoring	Accuracies of 96.7% and 75.7%, respectively in lab setting	No real-world validation
(Guo *et al* 2022)	Drivers, $n = 16$Passengers, $n = 12$	Facial video to extract remote PPG (NIR) + ECG-based Polar H10 chest strap	PPG HR + depth-based motion compensation; chest depth changes → respiration rate	Contactless, ambient-light-agnostic (active NIR), single monolithic sensor measuring HR and RR; depth allows motion compensation and RR from chest motion.	Contactless HR and RR monitoring for driver monitoring systems—drowsiness/sudden-sickness detection and broader DMS.	Depth-compensated processing achieved HR success rates of about 71.9% for drivers and 82% for passengers on highways, and reduced RR error to around ±1.4 breaths/min in road tests.	Motion/occlusion reduce accuracy; tested in limited driving scenarios
(Heydari *et al* 2022)	Healthy adults, $n = 10$	Finger PPG + EEG	HRV analysis	Drowsiness detection from finger sensors	Driver drowsiness detection based on the pulse rate variability observed at the fingertips.	Before sleep onset, PRV rises, SDNN falls, RMSSD rises, LF/HF drops, and SD1 decreases, showing PRV can detect driver drowsiness for use in smart steering wheels.	Movement artifacts affect data

(Continued.)

Table 2. (Continued.)

Author	Population	Device	Processing	Characteristics	Applications	Results	Limitations
(Hong *et al* 2018)	Healthy volunteers, $n = 16$ (12 males and 4 females, ages: 25–32 years)	Finger PPG + Ear canal EEG + ECG (BN-PPGED-T,BIOPAC Systems)	Multimodal data fusion, HRV	Intelligent drowsiness recognition, driving simulation experiment	Intelligent drowsiness detection system	The classification accuracy for PPG signals alone in drowsiness detection was significantly lower than EEG, with reported accuracies for similar setups around 64% accuracy, 71% precision, 78% recall, and 71% F-score for PPG-only features	Complex, impractical sensor setup
(Kainulainen *et al* 2020)	OSA patients, $n = 915$	Finger PPG (Nocturnal pulse oximetry)	Power spectral density analysis, SpO2, HR	Sleepiness vs spectral features	SpO2 power content increased significantly with increasing severity of EDS.	SpO_2 and HR-PSD increased with severe EDS, but the CNN detected it with only 49.5% sensitivity and 80.4% specificity.	Patient selection bias toward subjective sleepiness, lack of control for medication and comorbidities, and classification of OSA by ODI instead of AHI.
(Kundinger *et al* 2020)	Low-level driving simulator, $n = 10$High-fidelity driving simulator, n= 30	Wrist PPG (Polar smartwatch) + EDA	Feasibility analysis, HRV, PPG signal analysis	Wearables for drowsiness detection	Driver drowsiness detection	Classifiers achieved 99.9% accuracy, but age-specific heart rate patterns limit cross-age drowsiness detection, suggesting combined and individual models.	The exclusion of transitional KSS levels 5 and 6, restricting the study to binary classification of driver states without capturing intermediate drowsiness stages.
(Lee and Chung 2012)	Healthy subjects, $n = 10$ (ages: 24–40 years)	Finger PPG + ECG + eye movement	Multi-classifier ML approach, HRV, PPG signal analysis	Mobile drowsiness detection	Highly reliable drowsiness detection	Final results showed that combining information fusion with multi-classifiers achieved peak accuracy of about 97%.	Fatigue detection does not consider weather, vehicle, or environmental data.

(Continued.)

Table 2. (Continued.)

Author	Population	Device	Processing	Characteristics	Applications	Results	Limitations
(Lee *et al* 2011)	Drivers, $n = 25$	Finger PPG + vision sensors	Real-time monitoring, Face extraction, PPG drowsy signals are integrated with eyes motion	Non-intrusive detection	PPG drowsy signals are integrated with eyes motion to derive the model for drowsiness detection system. PPG drowsy signals are integrated with eyes motion to derive the final probability model for delivering valid and reliable PPG drowsy signals are integrated with eyes motion to develop a drowsiness detection system.	The system can successfully indicate the alertness of each driver with accuracy achieved up to 97%	Low practicality of sensors, vision affected by lighting/occlusion, poor model generalizability, hardware limits, and hard microsleep detection
(Lee *et al* 2015)	Healthy subjects, $n = 12$ (ages: 21–55 years, mean age = 38± 17 years)	Finger PPG + motion sensors in the smartwatch	Sensor fusion, PPG signal analysis	Driver alertness monitoring	Wearable alertness detection	The alertness index prediction accuracy can be reached up to 96.3% based on the descriptive extracted features	Pilot, small sample
(Lee *et al* 2019)	Volunteers, $n = 6$(ages: 20–35 years)	Wrist PPG (Microsoft Band 2) + Polar H7 ECG chest strap	HRV: ECG and PPG signals, extracted RR intervals, transformed them into recurrence plots, and used a CNN to classify drowsy versus awake states.	Wearable ECG/PPG; robust feature representation using recurrence plots; CNN learns RP patterns (ReLU-RP found most discriminative).	Drowsy/awake classification for driver drowsiness detection using wearable HR sensors.	Turning ECG/PPG into ReLU-based recurrence plots let a CNN detect drowsiness with ∼70% (ECG) and ∼64% (PPG) accuracy, beating older methods.	Small simulated-driving dataset (6 subjects), limited diversity, and wearable PPG/ECG signals affected by motion artifacts, so real-world performance is uncertain.
(Lee *et al* 2022)	Young woman, $n = 1$ (age: 24 years)	Palm-based PPG	HRV, PPG signal analysis	Novel measurement site	A new method for developing steering wheels that measure photoplethysmography in the palm for drowsiness detection and drunk driving.	Strong pulse count correlation (−2.43% error) suggests effectiveness for autonomous driving safety.	No drowsiness detection reported, small sample

(Continued.)

Table 2. (Continued.)

Author	Population	Device	Processing	Characteristics	Applications	Results	Limitations
(Li and Chung 2013)	Healthy subjects, $n = 4$	Finger PPG	HRV, PPG signal analysis, SVM classifier	Drowsiness detection from HRV	The combination of support vector machine-based posterior probabilistic model (SVMPPM), a EEG headband, and a wrist-worn smart device appears as an effective, simple, and inexpensive wearable solution for driver drowsiness detection.	Wavelet features achieved 95% accuracy, outperforming FFT, with a low-cost, user-friendly hardware platform.	Small sample
(Linschmann *et al* 2023)	Healthy subjects, $n = 20$	Facial video to extract remote PPG + Capacitive ECG,+ Magnetic Induction Measurement +Seismocardiography,	Multi-modal signal extraction and HR/RR algorithms, evaluated vs ECG and impedance pneumography	Unobtrusive, seat-based, redundant multi-modality (designed to improve coverage across seating positions and motion conditions); privacy-friendly vs camera.	Continuous vital-sign monitoring (HR, RR, HRV) for drowsiness/stress detection, fitness-to-drive and early cardiovascular screening.	A sensor cushion monitors drivers' heart and respiratory rates (∼70% accuracy) and can detect health risks; data is available via the UnoVis dataset.	Respiratory rate accuracy is low (∼30%), and measurement reliability may vary with movement or seating position.
(Pugliese *et al* 2022)	Healthy subjects, $n = 9$	Wrist PPG	HRV analysis, flags for drowsiness while ignoring motion-distorted data	Training-free real-time wrist-PPG, 2048-sample (∼41 s) windows, low-compute, motion-artifact sensitive	Algorithm development for processing the PPG signal and to determine the drowsiness onset.	Wrist-PPG algorithm predicts drowsiness ∼6–9 min early; validated in small studies with high accuracy (∼88% → 100% with motion-artifact handling).	Small sample sizes; sensitive to motion/artifacts; needs per-user calibration; not extensively tested in real on-road driving.
(Ryu *et al* 2018)	Healthy female, $n = 1$	Ring PPG (Flexible printed PPG sensors)	HRV analysis	Wearable sensor development	Drowsiness estimated from HRV, extracted from flexible PPG signals, using machine learning algorithms.	The flexible PPG sensor predicted drowsiness with 79.2% accuracy and 72.1% AUC, comparable to conventional sensors.	Small sample, motion artifacts, lower precision than ECG, variable signal quality, limited real-world testing

(Continued.)

Table 2. (Continued.)

Author	Population	Device	Processing	Characteristics	Applications	Results	Limitations
(Tao *et al* 2023)	Volunteers, $n = 26$	Facial video to extract remote PPG	HRV, PPG signal analysis	Fatigue driving prediction	Driver fatigue prediction. A fatigue prediction algorithm based on the fusion of improved optical flow features and microfeatures was developed.	Improved MDMO optical flow achieved 75.2% micro-expression recognition (↑7.83% vs. traditional), and microfeature fusion reached 95.24% accuracy in driver fatigue prediction	High computational demand, complex multi-modal data fusion, sensitivity to noise/environmental variability
(Tomita and Mitsukura 2018)	Male volunteer, $n = 1$	Earbud-based PPG	PPG signal analysis	Wearable monitoring system	An earbud-based PPG with noise suppression techniques for motion noises and ambient light interferences for stress and drowsiness estimation.	Estimates heart rate and detects stress/drowsiness; motion/ambient-noise suppression gave stable signals and HR vs ECG error $\approx -0.03 \pm 2.84$ BPM (best), within ± 5 BPM overall	Small sample, no real driving condition data

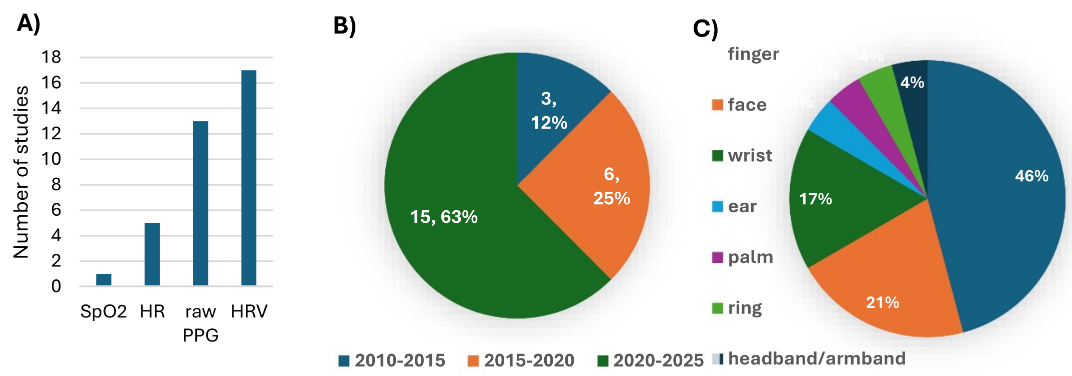

Figure 3. (A): Key PPG—derived characteristic. (B): Publication trend of selected PPG studies between 2010 and 2025. (C): Location of the PPG sensor in the selected studies.

stages of nocturnal sleep, indicating that autonomic dysregulation may be linked to EDS among patients with OSA (Lombardi *et al* 2008).

HRV is a measure of HR variations obtained from ECG data, while BRV is a similar measurement but obtained from PPG. Most studies have traditionally focused on HRV derived from ECG data rather than BRV obtained from PPG. However, research has increasingly highlighted the strong correlation between HRV measurements from ECG and PPG, making PPG a viable, non-invasive alternative for HR variability analysis. The studies by Mejía-Mejía *et al* (2020) and Singstad *et al* (2021) contribute to this growing body of evidence, reinforcing the reliability of PPG-derived HRV (PRV or BRV for various applications, from clinical diagnostics to wearable health monitoring. For example, during sleep in children, (Lázaro *et al* 2014) showed that PRV can be used to discriminate apneic from non-apneic events, which allow to avoid the need for ECG recordings. In addition, (Nitzan *et al* 1998) showed evidence that Type 2 diabetes mellitus appears to be related to lower PRV values in time, frequency, and non-linear indices. (Lan *et al* 2018) demonstrate that it is possible to detect hypertension by assessing standard deviation of normal—normal (SDNN) intervals, which is a time domain measure of PRV and has been shown to have the best predictive power.

Chua *et al* (2012) assessed changes in PVT in 24 young men who were kept awake continuously for 40 h. Every 2 h, subjects completed a 10-minute PVT to assess their ability to sustain visual attention. They used HRV, ocular (PERCLOS), and EEG measures to predict lapses in PVT. RR-interval power density performed as well as EEG power density in identifying sleepiness-related increases in PVT lapses above threshold. RR intervals—the time between successive R-peaks in an ECG—are analyzed in the frequency domain to assess autonomic regulation. Generally, the frequency bands include ULF (<0.003 Hz): Often linked to long-term physiological processes, but less commonly analyzed in short-term recordings. VLF (0.003–0.04 Hz): Associated with thermoregulatory and hormonal influences on autonomic function. LF (0.04–0.15 Hz): Thought to reflect a mix of sympathetic and parasympathetic activity. HF (0.15–0.40 Hz): Strongly linked to parasympathetic regulation and respiratory sinus arrhythmia. RR-interval power density (0.02–0.08 Hz) also classified subject performance with sensitivity and specificity that were comparable to those of PERCLOS. At the optimal classification threshold, RR-interval PSD in the 0.02- to 0.08 Hz range classified a greater than 25% increase in PVT lapses with 81% sensitivity and 85% specificity. By comparing the AUC of ROC curves, they found that RR-interval PSD and PERCLOS performed equally well at identifying a greater than 25% increase in PVT lapses relative to baseline. These results suggest that HRV monitoring, either alone or in combination with other physiologic measures, could be incorporated into safety devices to warn drowsy operators when their performance is impaired.

Taranto Montemurro *et al* (2014) studied the relationship of HRV to sleepiness (based on ESS) in severe OSA patients with and without heart failure (HF). ESS scores correlated inversely with VLF power in all ($r = -0.294$) and in HF subjects ($r = -0.468$). They found that severe OSA patients without EDS had a significantly higher VLF-HRV than those with EDS, irrespective of HF, suggesting that these patients without EDS have greater sympathetic modulation of HRV than those with EDS.

A Finnish study investigated the use of spectral HRV metrics in measuring sleepiness under chronic partial sleep restriction—4 Hours of sleep for five nights—and identified underlying relationships between HRV, KSS, and performance on the PVT in 23 young males. They found that the HRV band [0.01, 0.08] Hz showed the highest correlation for HRV–PVT (0.60, 95% confidence interval [0.49, 0.69]) and HRV–KSS (0.33, 95% confidence interval [0.16, 0.46]) for the sleep restriction group. In a three-component alertness model including circadian and homeostatic processes coupled with sleep inertia, HRV alone explained 33% of PVT variance. They concluded that HRV spectral power reflects vigilant attention in subjects exposed to partial chronic sleep restriction (Henelius *et al* 2014).

In a short communication, (Bisogni *et al* 2017) measured HRV and arterial stiffness index, as a marker of vascular damage in 56 sleepy (ESS $\geqslant$ 10) vs. non-sleepy (ESS $<$ 10) mild -moderate OSA men patients. Contrary to other studies, they found no significant association of EDS with sympathetic nervous system activation in the VLF power (VLFP), LF power, HF power, and in the LF/HF ratio, as well as in the mean arterial stiffness index in these mild-to-moderate sleepy vs. nonsleepy OSA patients.

Researchers from Spain used HRV to detect sleepy vs. non-sleepy patients during the first 3 min before sleep onset in MSLT and MWT. Non-linear dynamics of the RR rhythm were more regular in the sleepy group than in the alert group during the first wakefulness period of MSLT, but not during MWT (Guaita *et al* 2015). In the same year,(Sforza *et al* 2015) did not observe ANS differences based on HRV parameters between sleepy and non-sleepy 825 healthy elderly evaluated for unrecognized OSA. Recently, (Jeklin *et al* 2021, studied 10 subjects from the British Columbia Wildfire Service team were examined over a 14-day active fire-line period. Subjective fatigue, sleepiness, and alertness were recorded using a visual analog scale. Autonomic system modulation was assessed each morning using HRV. They found a significant inverse association between HRV and sleepiness and fatigue, but not with several parameters of reaction time. Lately, (Demareva *et al* 2023) assessed the relationship of subjective sleepiness with sympathetic activation obtained from HRV parameters using a Polar H10 sensor in 32 shift workers. They found that at evening time, high sleepiness was associated with a ‘stressed’ condition expressed by higher sympathetic activation, while later, it was associated with a ‘drowsy’ condition with higher parasympathetic activation and a decline in HRV.

A good approximation of what may be a possible tool for the objective assessment of EDS was demonstrated by Dey *et al* (2017). They proposed a smartwatch-based alertness estimation system. First, they obtained ECG signals from three public PSG databases for building the model for alertness estimation, and then deployed the model on PPG data collected from a Samsung Gear S2 smartwatch. This was possible since RR extracted from PPG and RR simultaneously acquired from ECG data had a 98.6% correlation. The novel aspect of the alertness scoring system was the use of sleep and wake utility functions to provide an assessment of the quality of sleep or wakefulness of the individual. The proposed solution uses a novel set of 43 HRV-based features obtained from PPG to provide better physiological input for the SVM-based alertness estimation model. Overall, the investigators proposed a wearable-based system that provides a detailed analysis of alertness over a determined period and were able to achieve an accuracy of 80.1%, with a specificity of 81.6% and a sensitivity of 78.6% for sleep/awake classification, along with an alertness score.

Lu *et al* (2022) did a systematic review on 18 studies that assessed HRV to estimate driver fatigue. Studies that investigated differences in HRV measures between alert and fatigued drivers provided inconsistent results—the detection performance showed a large variation, with a detection accuracy between 44% to 100%. Differences in several key aspects of the study designs may partially explain the variation of these results.

Srinivasan *et al* (2024) studied 84 young adults during simulated driving. They assessed HRV indices obtained from an ECG—i.e., the RMSSD between normal heart beats and LF/HF ratio. Other measurements were EEG (Theta power, increased during wake inattentiveness), oculography-based drowsiness, driver simulation—lane position variability, and KSS to measure fatigue. RMSSD negatively correlated with Theta power, and LF/HF ratio positively correlated with lane position variability. Structural equation modeling tested the prediction of a latent fatigue construct from HRV. RMSSD negatively predicted fatigue, explaining 6.4% of the variance, while the LF/HF ratio positively predicted fatigue, accounting for 3.7% of the variance. In summary, lower RMSSD and higher LF/HF ratio were associated with greater fatigue levels, and HRV indices exhibited significant, although modest, relationships within a multidimensional model of fatigue incorporating objective performance, ocular, and subjective measures.

A recent Australian study (Ucak *et al* 2024) of 421 OSA patients measured HRV parameters during N2 in sleepy vs. non-sleepy patients according to the ESS. Sleepy patients exhibited significantly lower HRV values for: RMSSD, TP, absolute LF, and HF power compared to non-sleepy patients. Moreover, moderate—severe OSA patients showed significantly lower HRV values for RMSSD, TP, absolute LF, and HF power. These results show a trend toward parasympathetic withdrawal—lower cardiac vagal modulation—mainly in moderate-severe sleepy OSA patients. These findings suggest that this sleepy phenotype is associated with lower cardiac adaptability—a potential explanation for heightened cardiovascular risk.

A study of Xie and Ma (2024) aimed to improve the objectivity and efficiency of HRV-based vigilance evaluation by associating HRV and behavior metrics through a sliding window approach. For this purpose, 44 healthy adults underwent PVT under both well-rested and sleep-deprived conditions, with simultaneous ECG recording. A sliding-window approach (30 s length, 10 s step) was used for HRV feature extraction and behavior assessment. A stability selection technique was applied for feature selection, and the vigilance ground truth—high (fastest 40%), intermediate (middle 20%), and low (slowest 40%)—was determined based on each participant's range of performance. Four machine-learning classifiers were trained and tested using cross-validation. SVM achieved a cross-validated accuracy of 89% for binary classification (high vs. low) vigilance epochs. For three-class classification, accuracy dropped to 72%, but SVM maintained a precision of 84% in identifying low-vigilance epochs. The authors concluded that sliding-window-based HRV metrics would effectively capture the fluctuations in vigilance during task execution, enabling more timely and accurate detection of performance decrement. In an editorial of this study (Penzel and Salanitro 2025), the authors emphasized that a key advantage of this HRV tracking vigilance approach was suggested based on its compatibility with wearable devices (smartwatches or finger rings), which provide a less intrusive alternative compared to goggles or cameras for monitoring eyelid movements. The limitations highlighted by the authors are the reliance on prerecorded data rather than real-time monitoring, which posed challenges for assessing the immediate applicability of the method. Also, they noted that the 10 s update interval may not be quick enough to alert drivers at risk of falling asleep in time to prevent accidents. The authors ended this editorial with an important message: 'as technology evolves, integrating multiple methods and improving real-time monitoring capabilities will be key to enhancing driver safety and reducing the human and economic costs of fatigue-related road accidents'.

1.4. SpO2 in the detection of sleepiness

SpO2 measurements are routinely used for assessment and management of cardio-pulmonary disorders, including OSA. For OSA, the occurrence of apneas and hypopneas produces patterns of desaturation and resaturation that are pathognomonic of the disorder. EDS is one of the most dominant daytime symptoms of OSA patients (Léger and Stepnowsky 2020). Notably, the prevalence of EDS tends to increase with OSA severity. The factors leading to the resulting EDS in OSA patients are still being debated, but hypoxemia may directly impact brain centers related to sleep-wake control as well as stimulate release of somnogenic inflammatory mediators; additionally, SpO2 desaturations may be markers for sleep fragmentation that reduces the depth and quantity of sleep (Lal *et al* 2021).

Several studies have studied associations between SpO2 and EDS Howarth *et al* 2023). In a retrospective study of 362 OSA patients, the severity of individual apneas, hypopneas, and related desaturations was evaluated in relationship to daytime sleepiness objectively assessed by MSLT. In the whole sample, a 10% increase in values of desaturation severity, obstruction severity, and time below 90% saturation (t90%) were associated with a higher risk of objectively determined EDS compared to a 10% increase in AHI. In severe OSA patients, desaturation severity had a stronger negative correlation ($\rho = -.489$) with mean daytime sleep latency compared to AHI ($\rho = -.402$) and ODI ($\rho = -.393$). Based on the general regression model, desaturation severity and male sex were the most significant factors predicting daytime sleep latency (Kainulainen *et al* 2019).

In 2020, (Kainulainen *et al* 2020) investigated the possible role of PSD features of nocturnal pulse oximetry signals in the assessment of EDS and whether a CNN could detect patients with EDS using self-learned PSD features. Data from 915 OSA patients who had a nocturnal PSG and a MSLT were assessed. PSDs were computed for SpO2, HR, and PPG, as well as power density in the 15–35 mHz band in SpO2 (PSpO2) and HR (PHR). The results showed that SpO2 power content increased significantly with increasing EDS severity. Furthermore, a significant increase in HR-PSD was found in OSA patients with severe EDS. Elevated odds of having severe EDS were found in PSpO2 (OR = 1.19 (1.05–1.35)—1.29 (1.16–1.43) and PHR (OR = 1.81 (1.33–2.46) −1.83 (1.47–2.28)). Despite these significant spectral differences, the CNN classifier reached only moderate sensitivity (49.5%) alongside high specificity (80.4%) in identifying patients with severe EDS. Therefore, while PSDs of nocturnal pulse oximetry signals contain features associated with OSA-related EDS, a CNN-based prediction model was limited.

In another study, the relationship of oxygen resaturation parameters with EDS was assessed. Since resaturation may represent increased cardiovascular fitness, the authors hypothesized that a higher resaturation rate would be protective against EDS. They studied 1629 suspected OSA patients who had a MSLT following the nocturnal PSG. Younger subjects, mainly females with larger desaturations, had significantly higher resaturation rates. In multivariable models adjusted for age, sex, body mass index, and average desaturation depth, resaturation rate showed a significant negative correlation with mean sleep latency on the MSLT (z-score standardized beta, −1.0 (95%CI −0.49, 1.52)), and significantly increased odds ratio (OR) of EDS (OR, 1.28 (95%CI 1.07, 1.53)). The study suggested that resaturation and desaturation parameters may reflect differing underlying mechanistic pathways and both be considered novel and appropriate markers for assessing sleep-disordered breathing and associated outcomes (Howarth *et al* 2023).

1.5. Raw PPG waveform in the detection of sleepiness

A pioneer study evaluated the usefulness of ECG and PPG measurements for estimating PVT in two protocols in 26 young adults. Chua *et al* (2008). The ECG and PPG signals were processed to yield the RR interval, pulse amplitude, and pulse arrival time. Features derived from ECG and PPG were entered into multiple linear regression models. Features obtained from the RR interval were found to explain approximately 34% of the PVT variation- but were suboptimal for estimating within-subject PVT changes. PVT is lower when RR is more variable and when the LF component of RR spectral variability is lower, and vice versa. This also indicates that lower alertness—higher PVT- is associated with higher LF, which may indicate an increased sympathetic autonomic activity.

Later, in a study of 10 young subjects, the PPG signal was measured on the earlobes, and PPG amplitude, PPI, and PRV were analyzed according to arousal level (but no direct measurement of sleepiness was made) (Kim *et al* 2010). The authors compared the PPG variables of rest vs. relaxation, rest vs. arousal, and relaxation vs. arousal. Relative to the rest state, PPG amplitude decreased in the relaxed state and increased in the aroused state. Relative to the rest state, PPI decreased in both states. However, a more significant decline was observed in the aroused state. The authors concluded that PPG has better usability and comfort than ECG and may be an alternative method of measuring arousal levels.

In a small Korean study, the authors proposed a method for detecting drowsy driving that utilizes the LF, HF, and LF/HF values of PPG signals measured on fingers and earlobes. Drowsiness was identified in 14 of 20 subjects through finger-based PPG signals. Eight of the 14 drivers with drowsiness were evaluated with a driving simulator and PPG signals from the earlobes. Measurement in the awake state was conducted over a period of five minutes during the daytime, and measurement in the drowsy state was made over a period of five minutes during the early morning and night hours. The study found that LF decreased, HF increased, and LF/HF decreased in the drowsy state compared with the awake state (Koh *et al* 2017).

A study from Taiwan in 16 healthy male young adults evaluated the use of the raw PPG signal for the estimation of fatigue using peak features from this signal in comparison with a subjective assessment of fatigue by using the BFI-Taiwan form. The authors proposed a novel fatigue index derived from PPG signals with a specific focus on the position of the dicrotic peak, which is utilized to replace subjective data collected through the (BFI)-Taiwan form and the HRV indices obtained from PPG signals. This index replaces subjective data from the BFI-Taiwan questionnaire and HRV indices derived from PPG signals for assessing fatigue levels (Chen *et al* 2023a).

1.5.1. Advantages and disadvantages of the PPG for the detection of EDS

PPG advantages: PPG technology has many benefits for wearable applications since it is non-invasive, simple to use, and affordable. PPG sensors are relatively inexpensive and easy to wear, making them potentially useful for long-term recordings, including for at-home sleep monitoring. In addition, compared to chest-strap electrodes used for ECG, PPG-based measurements from wrist-worn devices provide continuous monitoring with greater convenience. In addition, since PPG signals allow for assessing different physiological parameters (HRV, SpO2, respiration rate and effort, blood pressure, arrhythmias, cardiac output, arterial stiffness, sympathetic activity, and thermoregulation), this is an ideal tool for multi -modal assessment of a patient's condition.

PPG disadvantages: despite the important advantages of PPG, this technology has also several limitations. The movement of the wearer can cause motion artifacts in the PPG signal, which can lead to inaccurate measurements of the heart rate and other physiological parameters (Maity *et al* 2022). This is problematic when the wearer is engaged in physical activity. Fortunately, during sleep, this is not a major problem since, in general, most of the time during sleep, motor activity is minimal. In addition, in some cases, wearable PPG could be less accurate compared to ECG. The location of the sensor is another component that affects the accuracy of the signal and should always be taken into account. Moreover, wearable PPG devices rely on batteries, which limits their operating recording time and could be an issue in cases where continuous monitoring for long-periods is necessary. Nevertheless, the development of new data processing techniques, new sensor designs, and the development of new algorithms with the valuable use of AI and machine learning techniques are aimed to improve the quality of PPG measurements and overcoming many of these possible limitations of PPG use.

Other emerging options: EEG is considered to be the 'gold standard' method for evaluating sleep architecture, which, when disrupted, is associated with EDS. However, EEG recording requires the subject to wear scalp electrode caps, which are uncomfortable and difficult to use for long-term recording. Also, EEG systems rely on the use of many channels, rendering such systems impractical for real-world use. Their typical use over one night also introduces measurement error, including 'first-night' effects. Nevertheless, low-cost EEG systems offer the potential to record EEG over multiple nights (LaRocco *et al* 2020). These EEG-based wearables have shown high accuracy in detecting various sleep stages and could provide future options for identifying individuals with EDS. Other technologies have been used for the same purpose of detecting sleep/sleepiness/drowsiness in the real world. The Optalert system, based on eyelid tracking and searching for the blinking phenomenon, has been in the market for many years, and they have data of many subjects while driving and validation studies on their investigations on driving drowsiness (Detecting sleepiness by Optalert.pdf 2010). Pupillometry has also been assessed as a measure of alertness level and also of drowsiness (Yoss *et al* 1970), (Yamamoto *et al* 2013), and also to differentiate between IH from narcolepsy type 1 (Rach *et al* 2023).

2. Conclusion

With the widespread adoption of wearable devices incorporating PPG sensing technology, combined with advances in deep learning, there is a growing opportunity to develop and deliver accessible digital biomarkers for EDS. However, regulatory oversight and scientific validation against gold-standard tests (MSLT/MWT), conducted in the intended deployment settings—such as clinics, homes, and vehicles-will be essential to ensure the accuracy, interpretation, and appropriate use of the information provided. The unregulated use of wellness sensors carries significant risks, highlighting the need for adherence to scientifically validated and legally enforceable standards. If successful, an objective tool that is simple, affordable, reliable, and at the same time a scalable tool for assessing EDS could transform how EDS is evaluated and monitored, ultimately improving clinical care and public safety.

The reviewed literature summarized the physiological and empirical bases for utilizing data from wearable sensors, particularly from PPG and SPO2 sensors, including the use of HRV and various spectral indices of heart rate, pulse amplitude, and oxygen saturation, for use in detecting and monitoring EDS. The existing observational and experimental studies support moderate to high correlations of a range of parameters generated from these sensors using standard and advanced signal processing and machine learning methodologies. However, the clinical utility, including the predictive value of individual or combinations of markers across well-characterized and diverse populations studied in real-life situations, is lacking. There is a need to understand how various contextual factors influence potential EDS digital biomarkers, including the effects of environmental and measurement factors, such as motion artifacts, contact pressure, ambient light, skin characteristics, task-related features, and sensor placement, on the accuracy and applicability of these measurements. As such studies are designed, there is also a need to consider which sleepiness and vigilance markers are the most relevant outcomes for different populations (age, healthy individuals vs sleep disorders, etc) and tasks or settings (e.g., occupations).

Data availability statement

This is a topical review, and there is no data associated with the manuscript. The data that support the findings of this study are openly available at the following URL/DOI: https://www.bmj.com/content/bmj/suppl/2021/03/29/bmj.n71.DC1/pagm061899.w1.pdf.

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