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RESEARCH ARTICLE

Contactless System for Sleep Prediction in Drivers

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ABSTRACT Drowsy driving contributes to 10–30% of all vehicle crashes, making it a major road safety concern. Driver Monitoring Systems (DMS) aim to assess driver alertness and are typically categorized into vehicle-, behavior-, and physiology-based approaches. While physiology-based systems offer the highest accuracy, most of them rely on costly and intrusive contact-based cardiac sensors. This study demonstrates, for the first time, the feasibility of predicting driver sleep events using a fully contactless, physiology-based approach that analyzes breathing patterns in real time. Data were collected using a short-range 60 GHz standalone automotive radar in a driving-seat mockup. Crucially, sleep events were objectively validated for the first time in this context using polysomnography (PSG) data reviewed by a medical expert, following American Academy of Sleep Medicine (AASM) guidelines for the Maintenance of Wakefulness Test (MWT) — marking a departure from previous reliance on subjective behavioral observations. The proposed heuristic algorithm achieved 85% overall accuracy, with 100% (95% CI 29%–100%) specificity and 80% (95% CI 44%–97%) sensitivity. This work presents a validated, non-intrusive solution for sleep event prediction in drivers, underscoring its potential for enhancing road safety through practical, clinically supported DMS technologies.

INDEX TERMS Driver monitoring systems, driver sleep prediction, heuristic algorithm, PSG, radar, respiratory signal, safety at wheel.

I. INTRODUCTION

Road accidents result in approximately 1.35 million deaths and up to 50 million injuries per year [1], with drowsiness being the main contributing factor in 10 to 30% of the cases [2]. Most drivers have probably experienced an episode of drowsiness at least once at some point in their life, making the phenomenon more widespread than even driving under the influence of alcohol [3]. Although, since crash attribution relies largely on police and hospital reports, the impact of drowsiness is most likely underreported [4], [5]. Indeed, the incidence rate of drowsiness is estimated to be seven times higher than the data reported in the NHTSA FARS database (www.nhtsa.gov/NCSA) [6], [7]. Drowsiness becomes more probable when a fatigued and sleep-deprived driver is not actively involved in the driving task. This is common in highway scenarios with long straight paths at a constant high speed: in this context, an accident could lead to disastrous consequences not only for the drowsy driver, but also for any other involved vehicle [1], [8]. Therefore, the early detection of drowsiness through technologies able to trigger an alert/alarm promptly could be crucial in significantly reducing traffic-related injuries and deaths.

In the context of driver monitoring, the term *drowsiness* is often used as a broad descriptor of reduced alertness, despite the lack of a standardized and objective physiological definition [9]. In contrast, *sleep* [9] and *microsleep* [10], [11] events are well defined by the American Academy of Sleep

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Medicine (AASM). Accordingly, this study does not aim to detect drowsiness as a subjective state, but rather focuses on the prediction of sleep and microsleep as objectively defined events. Throughout the manuscript, the term drowsiness is therefore used only to describe the application context.

Driver monitoring systems (DMS) have made their entrance into the automotive market, trying to find an answer to society's need, and, in the past 20 years, their presence has exponentially increased [12]. DMS are commonly classified into vehicle, behavior, and physiology-based systems [13].

Vehicle-based technologies primarily exploit vehicle status and parameters, including lane departure and steering wheel movements. Their effectiveness can be influenced by external conditions such as weather and road surface, which particularly affect lane-keeping measurements. Additionally, vehicle-based features are not specific to drowsiness but could also reflect other physiological states of the driver. Moreover, this type of system presents a delayed detection capability, detecting performance alterations only once they have already manifested [14], [15], [16].

Behavior-based technologies detect drowsiness by analyzing facial features, head pose, yawning, and eye activity. These methods are usually contactless and can achieve high accuracy performances, but raise privacy concerns and can be hindered by glasses, facial hair, skin tone variations, and challenging lighting or environments, especially at night [17], [18], [19]. Moreover, behavioral indicators are not exclusively related to drowsiness, as they can also be influenced by other conditions such as alcohol consumption, sudden sickness, or the driver's level of experience. These factors may alter vehicle control dynamics (e.g., lane departure or torque variability) and visual scanning patterns of the surrounding environment, potentially leading to misclassification or reduced reliability [20].

Physiology-based technologies exploit vital signals and derived parameters of the driver to detect drowsiness, either with or without physical contact. To date, this is the most reliable approach for drowsiness detection, also enabling prediction. Physiological signals and parameters provide direct information about the driver's actual state, thereby avoiding misinterpretations and enhancing detection accuracy. Moreover, these measurements are less affected by lighting or road conditions [21]. In addition, physiological monitoring is generally harder to deceive, making it particularly suitable for automotive applications. Unlike behavior-based systems, physiological ones are less prone to false positives due to non-fatigue-related actions (e.g., singing or talking instead of yawning). However, these techniques can be intrusive, sensitive to noise and motion, and costly [22].

Among physiological signals, the photoplethysmogram (PPG) emerged thanks to its easy usability in consumer applications (e.g., smartwatches, wristbands). This signal demonstrated high performance in detecting and predicting drowsiness, particularly when leveraging derived parameters such as heart rate (HR) and heart rate variability (HRV) [23], [24], [25]. However, the studies that developed HRV-based drowsiness detection systems showed a large variation in performance, with an accuracy ranging from 44% to 100%, mainly due to differences in experimental protocols, HRV feature extraction methods, ground truth definitions, and inter-individual variability [26]. Moreover, PPG contact-based systems could cause discomfort and are not always accepted, especially from professional drivers, causing therefore reduced adherence to the intervention strategy [13]. For these reasons, contactless technologies for in-cabin driver physiological signals monitoring are considered a promising alternative.

Prediction vs. Detection in DMS

Detection-based systems identify drowsiness once vehicular, behavioral, or physiological markers have crossed a predefined threshold, triggering reactive alerts that may arrive too late to prevent an adverse event. Detection is typically applied to drowsiness, a gradual condition that still lacks a universally accepted clinical definition.

Predictive systems, in contrast, aim to anticipate the onset of well-defined sleep-related events by identifying early physiological trends preceding them. Prediction is therefore more suitable for sleep and microsleep events, which are rigorously defined in sleep medicine and can be objectively labeled via PSG scoring.

In this study, prediction denotes the ability to raise an alert before expert-labeled sleep-related events. Accordingly, the proposed system performs a physiology-based prediction—rather than detection—of sleep and microsleep events, enabling the timely prevention of adverse driving outcomes in safety-critical scenarios.

II. RELATED WORKS

A. IN-CABIN BREATHING RATE ESTIMATION

The respiratory waveform is a physiological signal that reliably reflects the driver's physiological state. In recent years, it has gained increasing attention in the literature for contactless monitoring applications. In challenging and noisy environments, such as in-cabin contactless settings, HR- and HRV-based systems often fail to provide consistent information. In such cases, the breathing pattern becomes the primary source of information about the driver's physiological and behavioral state. In particular, Breathing Rate (BR) and Breath-to-Breath Interval (BBI) are interesting respiratory parameters already explored in the literature [27].

Some recent studies have investigated different sensing technologies and signal analysis methods to estimate respiratory parameters in driving environments (Table 1). A multimodal system combining seatbelt-integrated piezoelectric sensors, seat-mounted accelerometers, and in-cabin cameras has been used to estimate BR in real driving conditions. Compared to the chest belt reference, it reported detection performances reached over 60% across urban, highway, and rural scenarios [28]. Similarly, a contactless approach based on oscillators integrated into the seat structure, which enabled estimation of BBI, was proposed. The validation

against chest belt reference showed 3% overall accuracy of 68.33% in extended highway and rural driving [29]. An alternative approach was the detection of the motion of the thorax linked to respiration using camera systems combined with plethysmography bands. High agreement with chest belt reference signals has been demonstrated, with intraclass correlation coefficients (ICC) above 0.99 [30]; however, only a stationary setting was considered. Another study employed a seat-embedded pressure sensor to monitor breathing rate across various driving conditions. Reported mean absolute error (MAE) remained within 1.5 breaths per minute, corresponding to less than 10% deviation from reference rates [31].

B. DROWSINESS DETECTION VIA IN-CABIN BREATHING RATE ESTIMATION

Given the reliability of in-cabin respiratory signals monitoring, several studies have explored the use of respiratory signals for drowsiness detection in drivers (Table 2). One approach employed an inductive plethysmography band to extract Breathing Rate Variability (BRV) during a virtual driving task. Drowsiness was assessed through observer ratings based on facial expressivity, yielding 96.6% specificity and 90.3% sensitivity on a sample of 15 participants [32]. Another study used a seatbelt-integrated force sensor to measure BR, breathing phase durations, and yawning frequency. Drowsiness ground truth was based on facial scoring (0–4) by three trained observers. A support vector machine classifier reached 88% accuracy and a 90% F1-score in tests with 20 male students in a simulated driving environment [33]. A contactless setup combining IR-UWB radar and pulse oximetry was tested in professional drivers before and after a 10-hour drive. BR served as the input to a support vector machine model, which achieved 86% classification accuracy [34]. Using the same sensing setup and experimental conditions, a convolutional neural network was trained to classify drowsiness states, improving accuracy to 96.6% [35]. These works proved the reliability of BR and BRV in driver drowsiness detection. However, despite the good performance achieved, the validation method based on facial observations by non-experts cannot be considered a robust approach for assessing drowsiness. In fact, facial observation by itself is not considered a valid method for assessing drowsiness, according to the American Academy of Sleep Medicine (AASM) [9].

C. GAPS IN THE DEFINITION AND OBJECTIVE VALIDATION OF DROWSINESS

As of July 7, 2024, Advanced Driver Assistance Systems (ADAS) have become mandatory for all newly registered vehicles in the European Union under EU Regulation 2019/2144 [36]. Considering the crucial role of drowsiness in fatal crashes [2], driver drowsiness detection has become a key research focus within ADAS development [12]. However, a standardized and objective definition of drowsiness is still lacking. The AASM classifies sleep-related behavioral states into wakefulness, sleep, and transitional states between them, such as drowsiness, fatigue, arousals, and microsleeps. While microsleeps and arousals are well characterized as brief episodes of sleep and wakefulness, respectively, the AASM and the broader sleep science community are still working to identify objective physiological markers that define drowsiness and fatigue [9].

Microsleeps are of particular relevance in the ADAS context, as they represent brief (typically 1–15 s) and involuntary intrusions of sleep during wakefulness [10], [11]. Even though their duration is very short, such episodes can cause severe driving performance degradation, leading to accidents in tasks requiring sustained attention, such as driving [37]. Furthermore, their occurrence serves as an objective indicator of excessive daytime sleepiness [38]. Despite their importance, microsleep detection and prediction in drivers remain poorly investigated, mainly due to the difficulty of reliable validation, which requires dedicated instrumentation and expert medical evaluation [39], [40]. In this work, we attempted to fill this gap.

Polysomnography (PSG) remains the gold standard for assessing sleep and microsleep events, based on the simultaneous recording and manual analysis of multiple physiological signals by a sleep specialist [41]. It typically includes EEG, electrooculography (EOG), electromyography (EMG), electrocardiography (ECG), thoracic and abdominal respiratory bands, and photoplethysmographic (PPG) sensors. This comprehensive set of physiological measurements is essential for accurate identification of microsleep episodes and other sleep-related events [9].

Nevertheless, the validation of ADAS drowsiness detection systems is commonly performed under subjective conditions. Usually, it is based on the driver's self-assessment or the opinion of an external (non-expert) observer (eur-lex.europa.eu/legal-content). Such evaluations, however, often fail to accurately reflect the actual drowsiness level, as they capture only the perceived condition of the driver [42], [43]. It was robustly demonstrated that subjective drowsiness does not correspond to objective drowsiness, both under laboratory conditions and in dynamic driving simulations [44]. In this context, the PSG data provide objective and comprehensive physiological information, yet their integration into ADAS validation frameworks within the automotive field remains largely unexplored.

In [45], a reduced PSG configuration including EOG and EEG channels was used for validation on a commercial device for drowsiness detection [45]. Nevertheless, the scoring of sleep and microsleep events was carried out by a trained scorer instead of a physician specialized in sleep medicine, which is a mandatory requirement according to AASM standards [9].

D. OUR SOLUTION

This work proposes a physiology-based [46], [47], non-contact method for sleep and microsleep prediction —rather

TABLE 1. Summary of non-invasive respiratory parameter monitoring approaches in driving-related studies.

Sensor Type	Reference	Key Metric	Test Conditions
Piezo, accelerometers, RGB camera	[28]	Accuracy: 60–63%	Urban, highway, and rural driving; 15 participants.
Seatback oscillator	[29]	Accuracy (3%BBI): 68.33%	Highway and rural driving; 12 participants.
Camera, plethysmography band	[30]	ICC: 0.991	Stationary setup; 5 participants.
Seat pressure sensor (fluid-filled)	[31]	MAE: 1.5 bpm (9.2%)	Track driving under baseline, alcohol, and impaired driver conditions; 5 participants.

Abbreviations: ICC = Intraclass Correlation Coefficient; MAE = Mean Absolute Error; BPM = Breaths Per Minute; BBI = Breath-to-Breath Interval.

TABLE 2. Summary of drowsiness detection methods using respiratory signals.

Sensor Type	Reference	Respiratory Feature	Performance and Experimental Conditions
Plethysmography band	[32]	BRV	Specificity: 96.6%; Sensitivity: 90.3%; 15 participants; virtual driving scenario.
Force belt sensor	[33]	BR, timing, yawning	Accuracy: 88%; F1-score: 90%; 20 male students; driving simulator.
IR-UWB radar, pulse oximeter	[34]	BR	Accuracy: 86%; 40 professional drivers; 5-min seated recordings before/after 10-h driving session.
IR-UWB radar (CNN-based)	[35]	BR (CNN)	Accuracy: 96.6%; same dataset and test conditions as [34].

Abbreviations: BR = Breathing Rate; BRV = Breathing Rate Variability; CNN = Convolutional Neural Network; F1 = F1-score.

than detection— by analyzing breathing pattern, acquired on-the-fly using a short-range, 60 GHz, automotive, standalone radar in a driving-seat mockup. Sleep and microsleep events were, for the first time in this context, robustly validated by a sleep expert medical doctor using the AASM guidelines. Therefore, a preliminary solution for sleep prediction of drivers via radar-acquired BR was successfully developed and validated.

III. MATERIAL AND METHODS

A. EXPERIMENTAL PROTOCOL

A driving-seat mockup was set up with a seat, seatbelt, steering wheel, and pedal. A radar module (custom FMCW radar device from IEE S.A., operating at 60 GHz with a 4-GHz bandwidth) was placed in the overhead compartment location (OHCL) (up, right position with the radar facing down and parallel to the plane of the breathing movement) at a distance of 53 cm from the participant's chest. The OHCL position represents a realistic possible position for the radar inside the vehicle. A camera was placed before the participant to monitor the scene and his/her facial expression. To avoid undesired reflections of the radar signal from the metallic structures of the experimental setup, Radio Frequency (RF) absorbing panels were placed around the mockup and the metal surfaces, such as the radar, seatbelt, and steering wheel support (Figure 1A).

This study was performed in accordance with the principles of the Declaration of Helsinki [48]; all 13 participants received detailed information about the study and freely gave their informed consent. Further explanations of the experiment were provided when asked. No coffee or tea was consumed within the three hours preceding testing. The participants completed a questionnaire focused on sleep habits. Subjective drowsiness was evaluated using the Epworth Sleepiness Scale (ESS) [49] to assess habitual daytime sleepiness, and the Karolinska Sleepiness Scale (KSS) [50], [51], administered before and after the simulated driving test on a 1–10 scale (1 = extremely alert; 10 = extremely sleepy, unable to stay awake), to quantify instantaneous drowsiness. Sleep latency, defined as the time required to fall asleep after lights out or during a Multiple Sleep Latency Test (MSLT) [52], and the total sleep time on the night preceding the test were also evaluated, considering their possible correlation with sleep and microsleep events during the driving test.

Each participant was equipped with a complete PSG setup (Figure 1B) and a Garmin smartwatch (Instinct 2 DEZL). Then the participant sat on the mockup, fastened the seatbelt, and followed the driving instructions displayed on a tablet screen positioned in front of them for 40 minutes (Figure 1C). The slow change of the driving instructions induced boredom and sleepiness. Despite the fatigue, the subject was asked to fight drowsiness as much as possible and try to perform the task.

PSG complete setup (Noxturnal A1), including the pulse oximeter (Nonin), was used for collecting vital parameters. All the signals collected through PSG and the video recording were analyzed by a sleep specialist medical doctor, who provided the categorization and distribution of sleep and microsleep events. Sleep events were scored according to the AASM guidelines for the Maintenance of Wakefulness Tests (MWT) criteria (sleep stage lasting at least 30 s) [9]. Microsleep events were scored referring to Doghramji standard (sleep stage lasting between 3 and 15 seconds) [10], [53].

B. DATA ANALYSIS

The radar BR data streams were provided as input to the sleep and microsleep prediction algorithm, and the output was compared to the ground truth provided by the sleep

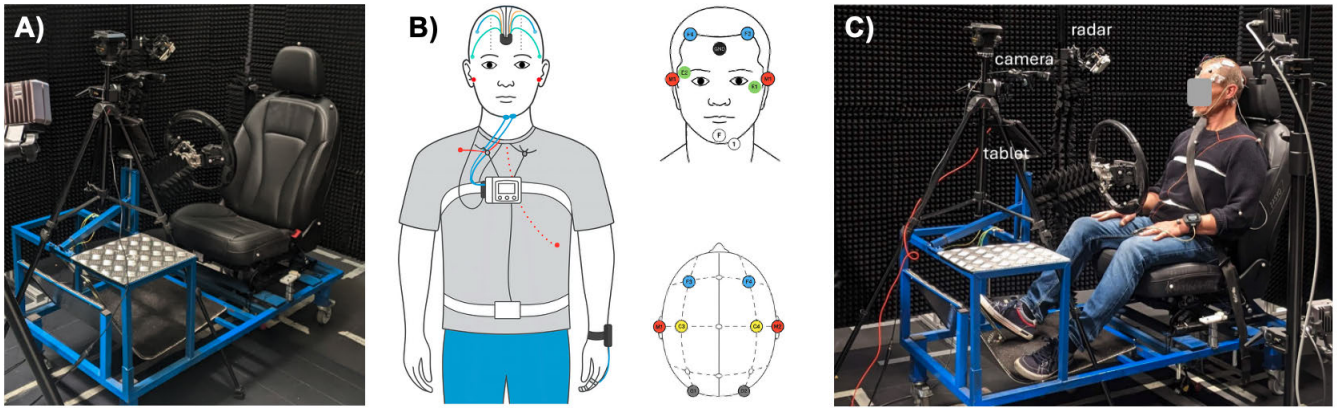

FIGURE 1. Experimental and validation setups. A) Experimental mockup of the measurement setup, including a car seat, steering wheel, radar sensor, and RF absorbing panels. B) PSG setup for sleep validation in drivers, comprising EEG (GND, F4, F3, C3, C4, O1, O2, M1, M2), EOG (E2, E1), EMG (F, I), ECG, two respiratory belts, and a PPG sensor. C) Participant equipped with the full PSG setup ready to perform the driving tasks displayed on a tablet.

TABLE 3. Definitions of evaluation metrics.

Evaluation Metric	Definition
Sensitivity	$\text{Sensitivity} = \frac{TP}{TP+FN}$
Specificity	$\text{Specificity} = \frac{TN}{TN+FP}$
Accuracy	$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$
F1-Score	$F_1 = \frac{2TP}{2TP+FP+FN}$
Time Advance	$\Delta t = t_{\text{event}} - t_{\text{alarm}}$

Abbreviations: TP = True Positives; TN = True Negatives; FP = False Positives; FN = False Negatives.

expert medical doctor. Particularly, only the first medically identified sleep event and the first alarm generated by the algorithm were considered. This choice was made because, in the driving environment, it is crucial to identify the first sleep event to avoid a crash. Any alarm triggered by the algorithm was then labeled as

- True Positive (TP): the alarm occurs before the sleep event.
- False Negative (FN): the alarm occurs after the sleep event, or the alarm does not occur even though there was a sleep event.
- False Positive (FP): the alarm is triggered, but there was no sleep event.
- True Negative (TN): the alarm was not triggered, and there was no sleep event.

The performance of the algorithm was then evaluated in terms of sensitivity, specificity, accuracy, and time advance in prediction, defined as shown in Table 3.

C. RADAR TECHNOLOGY

The proposed sleep prediction algorithm leverages the driver's vital signs, with a primary focus on real-time analysis of respiratory patterns. In this framework, non-contact monitoring of respiration via radar technology offers several advantages compared to conventional monitoring methods. Unlike wearable devices, radar systems eliminate the need for users to wear or carry supplementary equipment. Furthermore, in contrast to camera-based systems, radar signals are capable of penetrating various materials and are unaffected by factors such as skin tone or ambient lighting conditions. Additionally, radar technology inherently supports privacy preservation.

Although significant progress has been made in this field, reliably capturing vital signs in real-world settings—particularly inside a vehicle during operation—remains a significant challenge. Radar-based estimation of respiratory rate relies on analyzing backscattered signals generated by minute chest wall movements associated with cardiopulmonary activity. However, these subtle motions are often obscured by more pronounced, random body movements resulting from the act of driving. This interference, typically stronger and spectrally close to the fundamental frequency of breathing, can dominate the signal, complicating detection and impeding accurate estimation of vital signs.

To estimate the driver's breathing rate, we used the algorithm developed in [54], further validated in [55], and subsequently patented in [56]. It is based on a simple but accurate adaptive approach that explores the inherent harmonics that exist in the periodic chest wall motion. This algorithm was previously validated with real data recorded with the monitored subject performing minor movements while seated in a chair. To evaluate the performance of the radar-based BR acquisition system, a validation was carried out using PSG as the clinical reference standard. Two quantitative metrics were employed: Root Mean Square Error (RMSE) and absolute accuracy within ±3 breaths per minute (bpm).

The RMSE was calculated, as shown in Equation 1, to quantify the average magnitude of error between the radar-estimated BR $y_{\text{radar},i}$ and the reference BR $y_{\text{PSG},i}$ measured by PSG:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_{\text{radar},i} - y_{\text{PSG},i}\right)^2} \tag{1}$$

where n is the total number of samples. A lower RMSE indicates a higher agreement between the radar signal and the ground truth. In the context of respiratory monitoring, an RMSE below 2–3 bpm is generally considered acceptable for both clinical and consumer applications [57].

Absolute accuracy was computed as the percentage of radar-based respiratory rate estimates that deviated by no more than ±3 breaths per minute from the corresponding PSG reference values, as expressed in Equation 2:

$$\text{Accuracy}_{\pm 3\,\text{bpm}} = \frac{1}{n}\sum_{i=1}^{n} \mathbb{I}\left(\left|y_{\text{radar},i} - y_{\text{PSG},i}\right| \leq 3\right) \times 100 \tag{2}$$

where n is the total number of samples. This metric reflects the proportion of time windows in which the radar estimation error remained within clinically acceptable bounds.

These two metrics jointly capture both the average deviation and the proportion of clinically acceptable estimates, providing a robust evaluation of radar-based BR acquisition system performance. Most of the time, the radar provided measurements within the predefined error intervals, showing reliable estimation, especially when the driver is not actively moving, which is the critical moment for the occurrence of sleep events.

The upper plot of Figure 2 shows a portion of the chest movement obtained from the PSG chest belt (for reference), from a single measurement with 40 minutes of duration. The black vertical lines show the moments in which the driver was instructed (by the video) to perform driving actions according to the predefined protocol. The bottom plot shows the obtained breathing rate estimates from the radar (in blue), whereas the red line shows the reference values (ground truth) from the PSG chest belt. It can be seen that, most of the time, the radar estimates have a good correlation with the reference values, except for the moments in which the driver is executing the movements. For this specific measurement, the average error between radar estimates and reference values was below 3 bpm for the entire sequence (including all movements).

The BR extracted through radar was compared to the one provided by the PSG for each participant. An overall RMSE of 2.91 bpm and a 3% BPM accuracy of 74.68% were calculated and shown in Table 4. An average error of around 3 bpm for the breathing rate may seem a bit high if compared to the state-of-the-art. However, it is important to note that most research on contactless vital sign monitoring still focuses on a single-person setup under ideal conditions. The subject is typically instructed to remain relatively motionless (sitting still or lying down), in a quiet environment, and in the absence of other moving objects. This is far from the challenging environment addressed in this work. In addition, it is well known that PSG chest belts (which we used as ground truth) also do not perform well if the subject is moving [58]. This limitation can be clearly seen in Figure 2: around the black vertical lines, there are large (non-physiological) variations of the reference breathing rate during very short moments. This issue was already extensively discussed in [59].

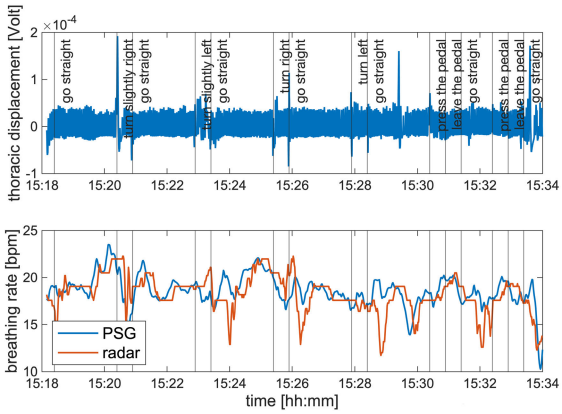

FIGURE 2. BR estimation from radar compared to the reference device (PSG). The radar-derived BR closely follows the PSG reference, demonstrating accurate respiratory pattern estimation.

TABLE 4. Mean RMSE and 3% BPM accuracy between PSG and Radar across all participants.

Metric	Mean Value
RMSE (PSG–Radar)	2.91
3% BPM Accuracy (%)	74.68

Abbreviations: RMSE = Root Mean Square Error; BPM = Breaths Per Minute; PSG = Polysomnography.

TABLE 5. List of algorithm thresholds. ***meanTh*** and ***stdTh*** are updated dynamically during script execution; ***Th*** is fixed.

Name	Definition	Unit
meanTh	Threshold for the mean Breath Rate (BR) value	Hz
stdTh	Threshold for the standard deviation of the BR	Hz
Th	Minimum duration counter threshold to trigger an alarm	Samples

Abbreviations: BR = Breathing Rate; Hz = Hertz.

D. ALGORITHM FOR SLEEP PREDICTION

The algorithm aims to predict sleep and microsleeps in advance by analyzing breathing rate. It is divided into three stages: data acquisition, data processing, and classification. The code receives as input the Breathing Rate at a sampling rate of 1 Hz. During the acquisition stage, which is the only one repeating during the first N seconds, a sufficiently high number of BR samples is acquired. During the first N seconds, the algorithm's output is "Data Acquisition". Then, during the data processing stage, the average and the differential of the standard deviation of BR are compared to thresholds to achieve dCnt. Finally, during the classification stage, dCnt is compared with another threshold to obtain the system's output, which can be "Awake" or "Alarm", when a sleep event is predicted.

The empirically derived thresholds used in the algorithm are summarized in Table 5.

These 3 stages are now described in more detail in the following sections, which are shown in the flowchart in Figure 4.

1) DATA ACQUISITION

Each second, a new BR sample is acquired. The average (*meanBR*) and standard deviation (*stdBR*) of BR are calculated within the smaller time window (n). A new value of *meanBR* and *stdBR* is computed every second.

2) DATA PROCESSING

Inside the larger time window (N), the absolute value of the differential of *stdBR* (*dsBRi*) is calculated. If $dsBRi \leq stdTh$ AND $meanBR < meanTh$, a counter variable (*cons*) is incremented; otherwise, *cons* is set to 0. *dCnt*, the maximum number of consecutive values satisfying this condition inside the large window, is stored. After the acquisition phase, an *rKSS* representing the subject's state value is computed every second.

3) CLASSIFICATION

Based on the dCnt value, the subject's state is classified as follows:

$dCnt < Th \rightarrow Awake$

$dCnt \geq Th \; AND \; meanBR < meanTh \rightarrow Alarm$

The flowchart of the algorithm is shown in Figure 4.

IV. RESULTS

A. PARTICIPANTS

13 participants were enrolled (5 females; mean age 39 ± 10 years; mean BMI 24.2 ± 4.6 kg/m^2). All subjects completed the full protocol, and 10 out of 13 exhibited at least one sleep event during the session, as validated by a sleep expert medical doctor. Table 6 summarizes their clinical characteristics and subjective drowsiness scores (ESS, KSS before and after the test). Table 7 shows the specific medication intake of the participants.

B. BR-BASED SLEEP PREDICTION ALGORITHM

Table 8 reports the performance of the proposed sleep prediction algorithm when fed with radar-derived breathing rate (BR). For each participant, the start time (Start), the ground-truth sleep event (Event), the alarm generated by the algorithm (Alarm), and the corresponding advance time (Advance) are listed together with the confusion-matrix labels. Since there is no standard agreement on the maximum acceptable advance for sleep prediction, we explicitly present the advance time for each test for the reader's consideration. A negative Advance value indicates that the algorithm detected the sleep event after it occurred, i.e., with a delay.

The BR-based algorithm achieved the following overall performance:

- Accuracy: 85%
- Sensitivity: 80%
- Specificity: 100%
- F1-score: 89%

All three participants who did not exhibit sleep events were correctly identified as true negatives, resulting in a false positive rate of 0%. Due to the limited sample size ($N = 13$), statistical uncertainty was quantified using 95% Confidence Intervals (CI) calculated via the exact Clopper–Pearson method. The analysis yielded a sensitivity of 80% (95% CI: 44%–97%) and a specificity of 100% (95% CI: 29%–100%). As expected, these intervals are wide, particularly for specificity, reflecting the scarcity of negative control subjects ($n = 3$). While the primary validation focused on detecting the initial sleep onset, a critical parameter for accident prevention, a supplementary evaluation considering all sleep events was also conducted. The results are shown in Table 10, and the performances are the following:

- Accuracy: 96%
- Sensitivity: 96% (95%CI ≈ 89%–99%)
- Specificity: 100% (95%CI ≈ 29%–100%)
- F1-score: 98%

It is worth noting the structural asymmetry in the dataset augmentation. While the number of positive instances increased by accounting for recurrent sleep events within a single session (increasing n from 10 to 80), the number of negative instances remained fixed ($n = 3$). This is because a True Negative is defined at the session level (i.e., a complete recording correctly classified as wakefulness) rather than as a discrete, recurring event. Consequently, the statistical uncertainty for specificity could not be reduced by this multi-event analysis and remains strictly bound to the number of control participants.

C. BENCHMARK AGAINST HRV-BASED SLEEP PREDICTION METHOD

To ensure a consistent comparison, the BR-based algorithm was benchmarked against a previously validated HRV-based sleep prediction method [25], tested under the same protocol and validation procedure. Table 9 reports the corresponding results.

The HRV-based method achieved identical performance:

- Accuracy: 85%
- Sensitivity: 80%
- Specificity: 100%
- F1-score: 89%

These findings confirm that a fully contactless BR-based solution can achieve performance comparable to a validated contact-based HRV method under the same testing conditions.

D. SUBJECTIVE AND OBJECTIVE DROWSINESS INDICATORS

Subjective scales (ESS, KSS before/after) did not reliably reflect the participants' actual drowsiness. Several subjects with low ESS/KSS scores still exhibited multiple sleep events

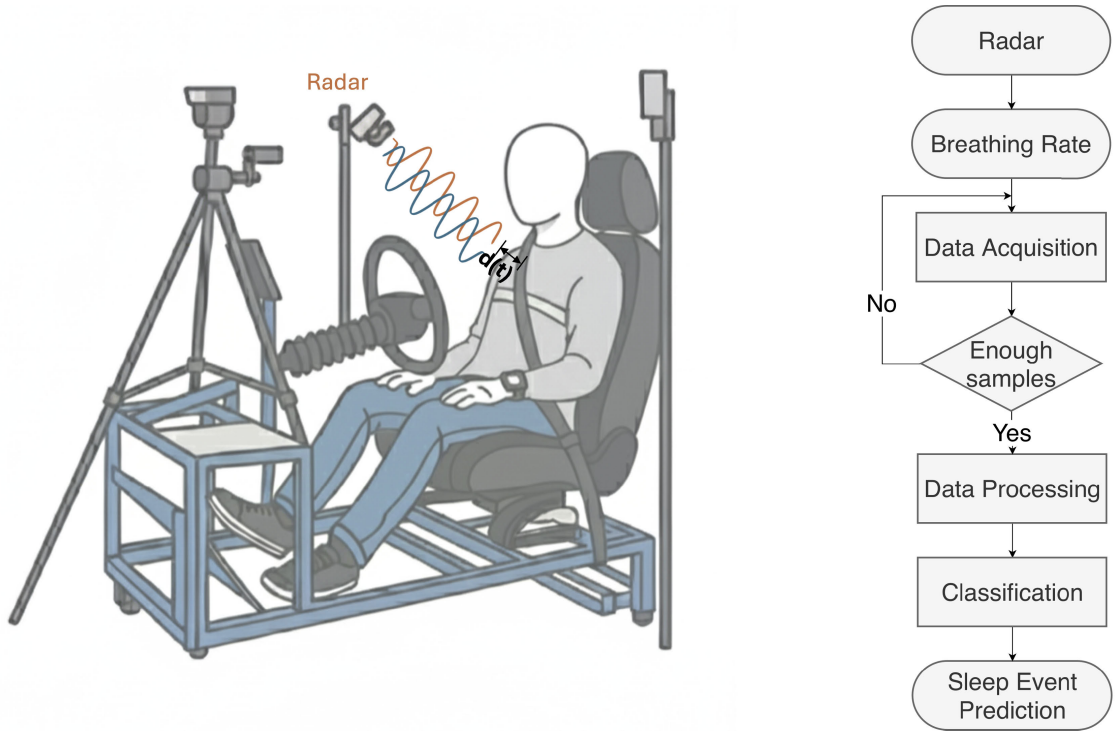

FIGURE 3. Main blocks of the algorithm. The diagram illustrates the core functional modules of the prediction algorithm.

TABLE 6. Clinical information, Sleep-related information, and subjective drowsiness metrics for all participants.

ID	Sleep Latency [min]	Medication Intake	Night Sleep [h:mm]	ESS	KSS Before	KSS After	Sleep Events
P1	<10	No	8:00	3	3	3	4
P2	10–30	No	7:00	6	5	6	0
P3	<10	Yes	6:30	12	3	5	3
P4	<10	No	7:00	3	2	4	0
P5	<10	Yes	7:00	5	3	6	1
P6	<10	No	7:00	6	5	6	0
P7	>30	No	6:30	10	5	6	16
P8	<10	No	6:00	7	3	5	12
P9	10–30	No	7:00	12	3	3	5
P10	<10	No	6:00	9	6	7	1
P11	<10	No	7:00	7	4	7	3
P12	>30	No	6:30	1	5	6	20
P13	<10	Yes	5:30	10	6	7	27

Abbreviations: ESS = Epworth Sleepiness Scale; KSS = Karolinska Sleepiness Scale.

(P1, P3, P8, P9), whereas others with higher scores showed none.

Similarly, sleep latency and total sleep time from the previous night did not correlate consistently with daytime sleep events, highlighting the need for objective physiological validation.

E. ADVANCE TIME ANALYSIS

Prediction advance times varied across subjects. Short advance times (P8, P9, P12, P13) were primarily associated with sleep events occurring within the first minute from the start of the test, limiting the algorithm's ability to analyze pre-event behavior.

Conversely, longer advance times (P5, P10) indicate anticipatory detection but may require refining the definition of a meaningful prediction window for real-world applications.

V. DISCUSSION

The proposed BR-based sleep prediction algorithm demonstrated high specificity and good overall accuracy when validated against medical-grade PSG scoring. In particular, it achieved a false positive rate of 0%, an essential

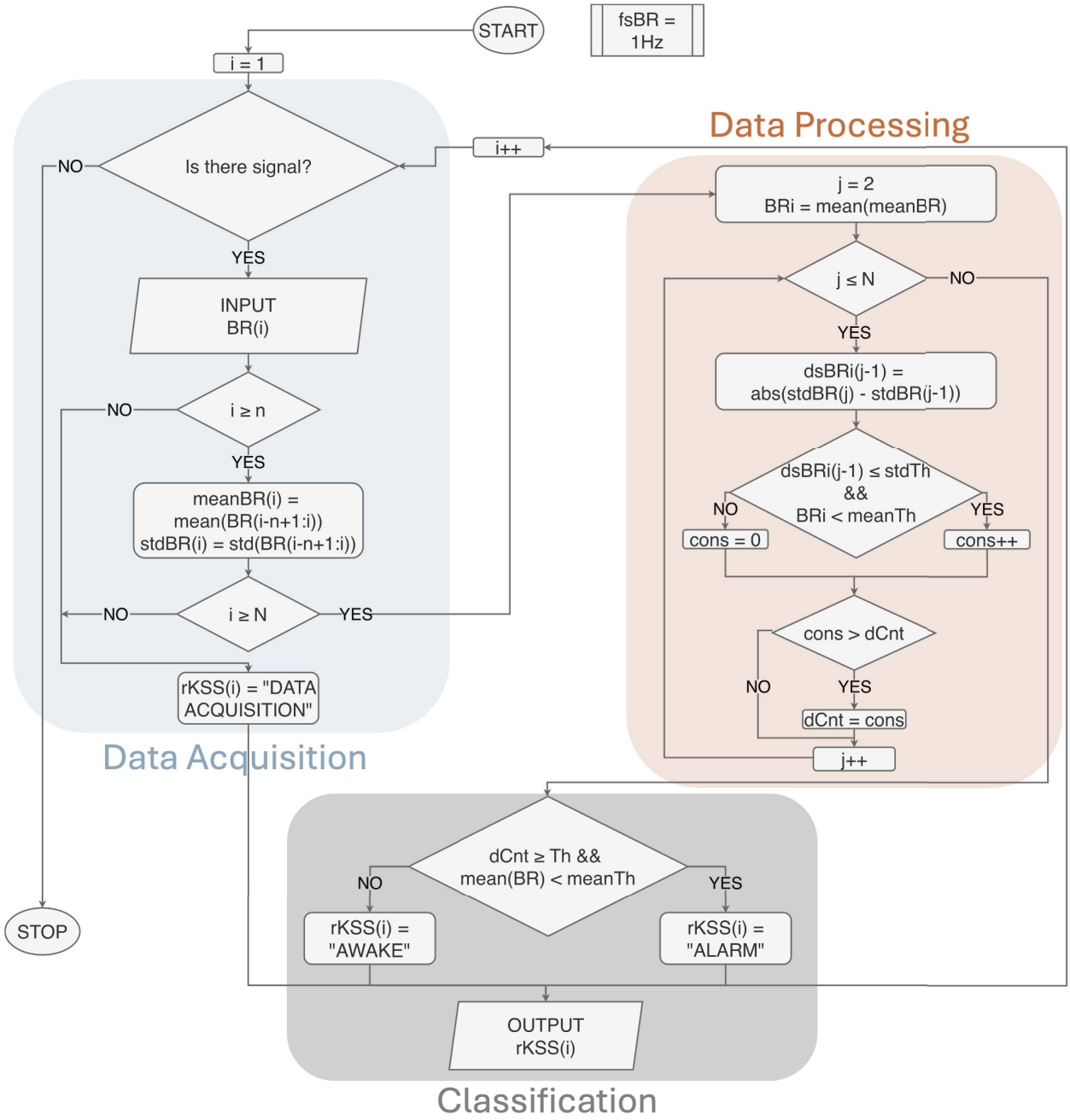

FIGURE 4. Algorithm flowchart. The block diagram illustrates the proposed respiratory monitoring framework, including data acquisition, signal processing, and classification stages. The algorithm computes sliding-window statistics of the breathing rate (BR(i)) using the arithmetic mean (mean) and the standard deviation (std). The absolute difference (abs) between consecutive standard deviation values is then used to assess signal stability and to perform the final state classification.

requirement for real-world applications where excessive or inaccurate alerts may compromise user trust.

When compared with existing non-invasive respiratory monitoring approaches in driving-related studies (Table 11), the radar-based BR estimation achieved higher accuracy under controlled conditions. Similarly, the performance metrics reported in Table 12 indicate that the proposed method is comparable to or better than state-of-the-art drowsiness detection systems, despite relying on a more rigorous validation framework grounded on PSG scoring.

A direct comparison with a previously validated HRV-based sleep prediction algorithm was also performed under identical experimental conditions. As shown in Table 13, the BR-based algorithm achieved identical sensitivity, specificity, and accuracy, confirming the feasibility of a fully contactless radar-based approach for sleep prediction.

The convergence of these performance metrics stems from a strong physiological alignment between the two modalities, as both HRV and BR are modulated by the same Autonomic Nervous System (ANS) shift during

TABLE 7. Selected participants medication profile: Autonomic and cardiorespiratory focus.

ID	Medication	Clinical Indication	Autonomic/Cardiorespiratory Impact
P3	Candesartan Cilexetil	Hypertension / Heart Failure	**RAAS Inhibition:** Reduces systemic vascular resistance; lowers BP without significant reflex tachycardia.
P3	Tolterodine	Overactive Bladder	**Antimuscarinic:** Blocks M_2/M_3 receptors; may increase heart rate and decrease Heart Rate Variability (HRV).
P5	L-Thyroxin	Hypothyroidism	**Metabolic Stimulant:** Increases myocardial oxygen demand; can induce palpitations, tachycardia, and elevated cardiac output.
P5	Folic Acid	Vitamin Deficiency	**Minimal/Indirect:** Necessary for erythropoiesis; no acute autonomic or cardiorespiratory effect at standard doses.
P13	Lorazepam	Anxiety / Insomnia	**CNS Depressant:** Potentiates GABA; causes respiratory depression (reduced rate) and blunts autonomic arousal.

Abbreviations: RAAS = Renin-Angiotensin-Aldosterone System; BP = Blood Pressure; HRV = Heart Rate Variability; CNS = Central Nervous System; GABA = Gamma-Aminobutyric Acid.

TABLE 8. BR-based sleep prediction results with True/False Positive/Negative outcomes and advance time.

ID	Start	Event	Alarm	Advance	TP	FN	TN	FP
P1	12:11:05	12:16:10	12:17:18	−00:01:08	0	1	0	0
P2	14:33:53	–	–	–	0	0	1	0
P3	10:22:05	10:45:33	–	–	0	1	0	0
P4	13:46:18	–	–	–	0	0	1	0
P5	14:32:47	15:00:00	14:33:13	00:26:47	1	0	0	0
P6	14:51:05	–	–	–	0	0	1	0
P7	15:33:02	15:37:42	15:35:02	00:02:40	1	0	0	0
P8	14:59:45	15:00:10	15:00:01	00:00:09	1	0	0	0
P9	11:04:37	11:05:28	11:04:57	00:00:31	1	0	0	0
P10	15:22:17	15:44:44	15:26:42	00:18:02	1	0	0	0
P11	14:27:22	14:28:56	14:27:28	00:01:28	1	0	0	0
P12	14:34:36	14:36:45	14:36:06	00:00:39	1	0	0	0
P13	14:42:55	14:43:11	14:43:09	00:00:02	1	0	0	0
Total					**8**	**2**	**3**	**0**

Abbreviations: TP = True Positives; FN = False Negatives; TN = True Negatives; FP = False Positives. The advance time indicates the anticipation between the alarm and the actual sleep event.

TABLE 9. HRV-based sleep prediction results with True/False Positive/Negative outcomes and advance time.

ID	Start	Event	Alarm	Advance	TP	FN	TN	FP
P1	12:11:05	12:16:10	12:22:32	−00:06:22	0	1	0	0
P2	14:33:53	–	–	–	0	0	1	0
P3	10:22:05	10:45:33	–	–	0	1	0	0
P4	13:46:18	–	–	–	0	0	1	0
P5	14:32:47	15:00:00	14:42:13	00:17:47	1	0	0	0
P6	14:51:05	–	–	–	0	0	1	0
P7	15:33:02	15:37:42	15:23:32	00:14:10	1	0	0	0
P8	14:59:45	15:00:10	14:59:50	00:00:20	1	0	0	0
P9	11:04:37	11:16:57	11:13:31	00:03:26	1	0	0	0
P10	15:22:17	15:44:44	15:22:52	00:21:52	1	0	0	0
P11	14:27:22	14:28:56	14:27:22	00:01:34	1	0	0	0
P12	14:34:36	14:36:45	14:34:36	00:02:09	1	0	0	0
P13	14:42:55	14:43:11	14:42:55	00:00:16	1	0	0	0
Total					**8**	**2**	**3**	**0**

Abbreviations: HRV = Heart Rate Variability; TP = True Positives; FN = False Negatives; TN = True Negatives; FP = False Positives. The advance time indicates the anticipation between the alarm and the actual sleep event.

the wake-to-sleep transition. This phenomenon, known as cardiorespiratory coupling, explains why both algorithms identified the same true positives and failed on the same edge cases (e.g., atypical sleep onsets), leading to identical classification outcomes. It should also be noted that the relatively small sample size (13 participants) may further accentuate this convergence; in a limited dataset, stochastic variations between the two signals are less likely to result in different categorical outcomes compared to large-scale populations. Consequently, the primary distinction between the two approaches lies not in their categorical accuracy, but in their temporal lead time (Advance time, as detailed in Tables 8 and 9) and the inherently non-obtrusive nature of radar-based acquisition.

From a physiological perspective, the proposed heuristic prediction approach is supported by well-established evidence showing that the transition from wakefulness to sleep is preceded by progressive changes in autonomic regulation and respiratory control. As cortical arousal decreases and parasympathetic activity increases, breathing patterns become more variable and less tightly regulated. Importantly, these changes occur even before sleep onset is identified according to AASM criteria [46], [47]. Alterations in BR, BRV, and cardio-respiratory coupling have been reported during the pre-sleep period. These changes reflect a gradual disengagement of wake-related control mechanisms and provide a plausible mechanistic basis for anticipating sleep and microsleep events using BR dynamics. This physiological evidence supports the use of BR-based predictors for low-latency, real-time applications.

Two false negatives were observed. For participant P1, the first sleep event occurred only five minutes after the data acquisition phase. This early prediction suggests that the subject may have already been drowsy during data acquisition, thus preventing the algorithm from establishing a stable wakeful baseline. This highlights the need for an improved data acquisition strategy.

For participant P3, the absence of detected sleep events appears to be related to medication. Specifically, candesartan

TABLE 10. BR-based sleep prediction results considering all the sleep events.

ID	TP	FN	TN	FP
P1	3	1	0	0
P2	0	0	1	0
P3	0	2	0	0
P4	0	0	1	0
P5	1	0	0	0
P6	0	0	1	0
P7	18	0	0	0
P8	7	0	0	0
P9	4	0	0	0
P10	1	0	0	0
P11	3	0	0	0
P12	12	0	0	0
P13	28	0	0	0
Total	**77**	**3**	**3**	**0**

Abbreviations: TP = True Positives; FN = False Negatives; TN = True Negatives; FP = False Positives.

TABLE 11. Comparison with literature of non-invasive respiratory parameter monitoring approaches in driving-related studies.

Reference	Key Metric	N
[28]	Accuracy: 60–63%	15
[29]	Accuracy (3%BBI): 68.33%	12
This study	Accuracy (3%BPM): 74.68%	13

Abbreviations: BBI = Breath-to-Breath Interval; BPM = Breaths Per Minute; N = number of subjects.

cilexetil and tolterodine, which are known to modulate autonomic balance, may have altered respiratory dynamics, making sleep events more difficult to detect from BR patterns alone. Other medicated participants (P5, P13) also showed atypical advance times, suggesting a broader impact of pharmacological agents on BR-based sleep prediction.

Short advance times observed in P8, P9, P12, and P13 were attributable to extremely early sleep onset, often within the first minute of the test, leaving the algorithm with limited pre-event data. Conversely, very early alarms (e.g., P5, P10) emphasize the need to define an optimal prediction window to ensure meaningful and user-acceptable alerts. In participant P10, the reported advance time (18 minutes) corresponds to the earliest validated alarm preceding sleep onset. Alternative alarm-selection criteria (e.g., considering later alarms closer to the event) would yield shorter advance times, in this case 6 minutes and 7 seconds, highlighting the dependence of advance-time metrics on the adopted alarm-validation strategy.

In this first study, the aim was not to define an optimal prediction advance time for sleep or microsleep events, but rather to assess the feasibility of anticipating sleep onset and to characterize inter-individual variability in prediction advance times. From an operational standpoint, a meaningful advance time should be sufficient to allow either the driver or the autonomous vehicle to safely initiate a stopping maneuver. Determining such an optimal prediction window requires dedicated studies explicitly linking advance times to intervention strategies and safety constraints and will be explored in future work.

TABLE 12. Comparison with literature of drowsiness detection.

Reference	Sensitivity (%)	Specificity (%)	Accuracy (%)	N
[32]	90.3	96.6	–	15
[33]	–	–	88	20
[34]	–	–	86	40
[35]	–	–	96.6	40
This study	80	100	85	13

Abbreviations: Sensitivity = True Positive Rate; Specificity = True . Negative Rate. The proposed method achieves comparable or superior performance among non-invasive approaches; N = number of subjects

TABLE 13. Comparison of sleep prediction algorithm performance based on HRV and BR.

Method	Sensitivity (%)	Specificity (%)	Accuracy (%)
HRV-based heuristic	80	100	85
BR-based heuristic	80	100	85

Abbreviations: HRV = Heart Rate Variability; BR = Breathing Rate. Both methods achieved identical performance metrics under the same test conditions.

Beyond the driver monitoring application, the proposed system aligns with key principles of the Healthcare 5.0 paradigm, including human-centric design, continuous physiological sensing, and preventive intervention. In this context, hyper-personalized risk assessment is enabled by assessing sleep and microsleep risk relative to individual-specific physiological baselines, rather than relying on population-level thresholds [60]. Accordingly, the proposed subject-specific and adaptive prediction framework allows the anticipation of well-defined sleep-related events before their onset, supporting preventive intervention in safety-critical scenarios.

Subjective indicators (ESS, KSS) and common objective indicators (sleep latency, total sleep time) did not correlate reliably with actual sleep events, reinforcing the importance of a validation approach based on comprehensive PSG scoring rather than visual observation or self-reports. The validation methodology adopted in this study—based on expert analysis of full PSG signals—represents one of its main strengths and differentiates it from existing approaches in the literature.

In addition to the single-event analysis, an all-events analysis was performed. Notably, the results of this extended analysis were found to be consistent with those of the previous single-event evaluation. While the increased number of events (from 8 to 77 TP) led to a refinement of the sensitivity (from 80% to 96.3%), the specificity remained constant at 100%, with zero false positives recorded despite the massive increase in the number of analyzed physiological transitions. This confirms that the model's performance and its perfect precision are highly stable and not subject to degradation even when the dataset is significantly expanded to include all recurrent sleep episodes.

Finally, although the dataset was unbalanced, with 10 out of 13 participants exhibiting sleep events, the algorithm correctly identified all true-negative cases. Expanding the dataset and including more balanced populations will be important future steps to improve robustness and generalization.

A limitation of this study is that experiments were conducted under controlled laboratory conditions with a relatively small sample size (13 participants). While this setting enabled rigorous validation against medical-grade PSG scoring, it does not fully capture the complexity of real-world driving, where steering activity, vehicle vibrations, and increased cognitive load may affect breathing-rate estimation and sleep event prediction, potentially reducing the signal-to-noise ratio (SNR). Nevertheless, sleep and microsleep events typically occur during prolonged, monotonous driving, where steering demands and driver motion are limited. Future work will therefore focus on validating the proposed method in real-world driving scenarios and on larger, more diverse populations to assess robustness and generalizability.

Overall, the results demonstrate the potential of radar-derived breathing rate for contactless sleep prediction and provide a solid foundation for further development and deployment in real driving scenarios.

VI. CONCLUSION

In this study, a new approach for predicting sleep and microsleep events in drivers was introduced. Rather than relying on traditional behavioral- or vehicle-based drowsiness indicators, the method focused on forecasting sleep onset using a breathing-rate (BR)-based heuristic algorithm fed by BR signals acquired on-the-fly from a short-range 60 GHz automotive radar integrated into a driving-seat mockup. The radar-derived BR was validated against medical-grade thoracic and abdominal belts from the polysomnography (PSG) system, while all sleep and microsleep events were annotated by a sleep medicine expert based on EEG, EOG, EMG, ECG, PPG, respiratory signals, and synchronized video recordings, in accordance with the current AASM gold-standard procedures.

Using this framework, the BR-based heuristic algorithm achieved an accuracy of 85%, a specificity of 100%, and a sensitivity of 80%, evaluated on 13 participants (5 females, mean age 39 ± 10 years) during 40-minute simulated driving sessions. Although the method demonstrated performance comparable to or exceeding that reported in the literature, a direct comparison remains difficult due to differences in objectives, protocols, and validation methodologies.

To provide a fairer evaluation, the algorithm was benchmarked against a previously developed heart-rate-variability (HRV)-based heuristic model, tested under the same experimental conditions and using identical PSG-based ground truth. The BR-based algorithm achieved equivalent overall performance, with reduced prediction capability only for participants taking medications known to influence autonomic and respiratory behavior.

Future work will involve expanding the dataset, conducting studies in more realistic driving environments, and systematically including participants taking medications that may alter respiratory dynamics. Overall, this work demonstrates a promising and fully contactless solution for sleep prediction and establishes a rigorous validation pipeline based on medical-grade PSG scoring within a simulated driving context.

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CONFLICTS OF INTEREST AND FUNDING

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REFERENCES

[1] M. E. Shaik, "A systematic review on detection and prediction of driver drowsiness," *Transp. Res. Interdiscipl. Perspect.*, vol. 21, Sep. 2023, Art. no. 100864.

[2] M. Gonçalves, R. Amici, R. Lucas, T. Åkerstedt, F. Cirignotta, J. Horne, D. Léger, W. T. McNicholas, M. Partinen, J. Téran-Santos, P. Peigneux, and L. Grote, "Sleepiness at the wheel across Europe: A survey of 19 countries," *J. Sleep Res.*, vol. 24, no. 3, pp. 242–253, Jun. 2015.

[3] J. S. Higgins, J. Michael, R. Austin, T. Åkerstedt, H. P. A. V. Dongen, N. F. Watson, C. A. Czeisler, A. I. Pack, and M. R. Rosekind, "Asleep at the wheel—The road to addressing drowsy driving," *Sleep*, vol. 40, no. 2, 2017.

[4] National Highway Traffic Safety Administration (NHTSA), "Traffic safety facts: 2011 Data-overview," U.S. Dept. Transp., Washington, DC, USA, Tech. Rep. DOT HS 811 753, Apr. 2013, pp. 1–12.

[5] R. R. Knipling and J.-S. Wang, "Crashes and fatalities related to driver drowsiness/fatigue," Nat. Highway Traffic Safety Admin., U.S. Dept. Transp., Washington, DC, USA, Tech. Rep. DOT HS 808 707, Nov. 1994.

[6] B. C. Tefft, "Prevalence of motor vehicle crashes involving drowsy drivers, United States, 1999–2008," *Accident Anal. Prevention*, vol. 45, pp. 180–186, Mar. 2012.

[7] S. V. Masten, J. C. Stutts, and C. A. Martell, "Predicting daytime and nighttime drowsy driving crashes based on crash characteristic models," in *Proc. 50th Annu. Assoc. Advancement Automot. Med.*, 2006.

[8] M. E. Shaik, M. M. Islam, and Q. S. Hossain, "A review on neural network techniques for the prediction of road traffic accident severity," *Asian Transp. Stud.*, vol. 7, Nov. 2021, Art. no. 100040, doi: 10.1016/j.eastsj.2021.100040.

[9] R. B. Berry et al., *The AASM Manual for the Scoring of Sleep and Associated Events: Rules, Terminology and Technical Specifications, ver. 2.2*, Darien, IL, USA: American Academy of Sleep Medicine, 2015.

[10] K. Doghramji et al., "A normative study of the maintenance of wakefulness test (MWT)," *Electroencephalogr. Clin. Neurophysiology*, vol. 103, no. 5, pp. 554–562, Nov. 1997, doi: 10.1016/S0013-4694(97)00010-2.

[11] A. Hertig-Godeschalk, J. Skorucak, A. Malafeev, P. Achermann, J. Mathis, and D. R. Schreier, "Microsleep episodes in the borderland between wakefulness and sleep," *Sleep*, vol. 43, no. 1, Jan. 2020, Art. no. zsz163, doi: 10.1093/sleep/zsz163.

[12] F. Guo, Y. Zhou, X. Wang, W. Li, and J. Cai, "Literature review of driving fatigue research based on bibliometric analysis," *J. Traffic Transp. Eng. (English Edition)*, vol. 11, no. 6, pp. 1401–1419, Dec. 2024.

[13] A. Sahayadhas, K. Sundaraj, and M. Murugappan, "Detecting driver drowsiness based on sensors: A review," *Sensors*, vol. 12, no. 12, pp. 16937–16953, Dec. 2012.

[14] D. Das, S. Zhou, and J. D. Lee, "Differentiating alcohol-induced driving behavior using steering wheel signals," *IEEE Trans. Intell. Transp. Syst.*, vol. 13, no. 3, pp. 1355–1368, Sep. 2012.

[15] P. M. Forsman, B. J. Vila, R. A. Short, C. G. Mott, and H. P. A. Van Dongen, "Efficient driver drowsiness detection at moderate levels of drowsiness," *Accident Anal. Prevention*, vol. 50, pp. 341–350, Jan. 2013.

[16] C. J. de Naurois, C. Bourdin, A. Stratulat, E. Diaz, and J.-L. Vercher, "Detection and prediction of driver drowsiness using artificial neural network models," *Accident Anal. Prevention*, vol. 126, pp. 95–104, May 2019.

[17] S. Martin, A. Tawari, and M. M. Trivedi, "Toward privacy-protecting safety systems for naturalistic driving videos," *IEEE Trans. Intell. Transp. Syst.*, vol. 15, no. 4, pp. 1811–1822, Aug. 2014.

[18] M. Ngxande, J.-R. Tapamo, and M. Burke, "Driver drowsiness detection using behavioral measures and machine learning techniques: A review of state-of-art techniques," in *Proc. Pattern Recognit. Assoc. South Afr. Robot. Mechatronics (PRASA-RobMech)*, Nov. 2017, pp. 156–161.

[19] K. Kumar, S. Dhamija, and M. Kaur, "Head movement-based driver drowsiness detection: A review of state-of-art techniques," in *Proc. IEEE Int. Conf. Eng. Technol. (ICETECH)*, Coimbatore, India, Mar. 2016, pp. 903–908.

[20] M. S. Al-Quraishi, S. S. A. Ali, M. Al-Qurishi, T. B. Tang, and S. Elferik, "Technologies for detecting and monitoring drivers' states: A systematic review," *Heliyon*, vol. 10, no. 20, Oct. 2024, Art. no. e39592.

[21] E. Perkins, C. Sitaula, M. Burke, and F. Marzbanrad, "Challenges of driver drowsiness prediction: The remaining steps to implementation," *IEEE Trans. Intell. Vehicles*, vol. 8, no. 2, pp. 1319–1338, Feb. 2023.

[22] M. Ramzan, H. U. Khan, S. M. Awan, A. Ismail, M. Ilyas, and A. Mahmood, "A survey on state-of-the-art drowsiness detection techniques," *IEEE Access*, vol. 7, pp. 61904–61919, 2019.

[23] K. Fujiwara, E. Abe, K. Kamata, C. Nakayama, Y. Suzuki, T. Yamakawa, T. Hiraoka, M. Kano, Y. Sumi, F. Masuda, M. Matsuo, and H. Kadotani, "Heart rate variability-based driver drowsiness detection and its validation with EEG," *IEEE Trans. Biomed. Eng.*, vol. 66, no. 6, pp. 1769–1778, Jun. 2019.

[24] J. Vicente, P. Laguna, A. Bartra, and R. Bailón, "Drowsiness detection using heart rate variability," *Med. Biol. Eng. Comput.*, vol. 54, no. 6, pp. 927–937, Jun. 2016.

[25] L. Pugliese, M. Violante, and S. Groppo, "A novel algorithm for detecting the drowsiness onset in real-time," *IEEE Access*, vol. 10, pp. 42601–42606, 2022.

[26] K. Lu, A. Sjörs Dahlman, J. Karlsson, and S. Candefjord, "Detecting driver fatigue using heart rate variability: A systematic review," *Accident Anal. Prevention*, vol. 178, Dec. 2022, Art. no. 106830.

[27] A. Nicolò, C. Massaroni, E. Schena, and M. Sacchetti, "The importance of respiratory rate monitoring: From healthcare to sport and exercise," *Sensors*, vol. 20, no. 21, p. 6396, Nov. 2020.

[28] J. M. Warnecke, J. Lasenby, and T. M. Deserno, "Robust in-vehicle respiratory rate detection using multimodal signal fusion," *Sci. Rep.*, vol. 13, no. 1, Nov. 2023, Art. no. 20435.

[29] A. Radomski and D. Teichmann, "On-road evaluation of unobtrusive in-car respiration monitoring," *Sensors*, vol. 24, no. 14, p. 4500, 2024.

[30] J. Solaz, J. Laparra-Hernández, D. Bande, N. Rodríguez, S. Veleff, J. Gerpe, and E. Medina, "Drowsiness detection based on the analysis of breathing rate obtained from real-time image recognition," *Transp. Res. Procedia*, vol. 14, pp. 3867–3876, 2016.

[31] S. Jain and M. A. Perez, "On-road evaluation of an unobtrusive in-vehicle pressure-based driver respiration monitoring system," *Sensors*, vol. 25, no. 9, p. 2739, Apr. 2025.

[32] F. Guede-Fernández, M. Fernández-Chimeno, J. Ramos-Castro, and M. A. García-González, "Driver drowsiness detection based on respiratory signal analysis," *IEEE Access*, vol. 7, pp. 81826–81838, 2019.

[33] F. Khanehshenas, A. Mazloumi, A. Nahvi, A. Nickabadi, A. Aghamal-izadeh, and A. Keihani, "Evaluation of driver drowsiness based on respiratory metrics," *Work*, vol. 78, no. 3, pp. 747–760, Jul. 2024.

[34] H. U. R. Siddiqui, A. A. Saleem, R. Brown, B. Bademci, E. Lee, F. Rustam, and S. Dudley, "Non-invasive driver drowsiness detection system," *Sensors*, vol. 21, no. 14, p. 4833, Jul. 2021.

[35] H. U. R. Siddiqui, A. Akmal, M. Iqbal, A. A. Saleem, M. A. Raza, K. Zafar, A. Zaib, S. Dudley, J. Arambarri, Á. K. Castilla, and F. Rustam, "Ultra-wide band radar empowered driver drowsiness detection with convolutional spatial feature engineering and artificial intelligence," *Sensors*, vol. 24, no. 12, p. 3754, Jun. 2024.

[36] European Parliament and the Council of the European Union, "Regulation (EU) 2019/2144 of 27 November 2019 on type-approval requirements for motor vehicles and their trailers, and systems, components and separate technical units intended for such vehicles," Official J. Eur. Union, Brussels, Belgium, 2019.

[37] P. Tondo, C. Pronzato, I. Risi, C. Perretti, L. De Gennaro, M. R. Bonsignore, A. Malovini, and F. Fanfulla, "The role of microsleeps to estimate sleepiness at the wheel and near-miss accidents in obstructive sleep apnea," *J. Clin. Sleep Med.*, 2024, doi: 10.5664/jcsm.11376.

[38] M. A. Carskadon, *Encyclopedia of Sleep and Dreaming*. New York, NY, USA: Macmillan, 1993.

[39] C. Wang, B. Guragain, A. K. Verma, L. Archer, S. Majumder, A. Mohamud, E. Flaherty-Woods, G. Shapiro, M. Almashor, M. Lenné, R. Myers, J. Kuo, S. Yang, N. Wilson, and K. Tavakolian, "Spectral analysis of EEG during microsleep events annotated via driver monitoring system to characterize drowsiness," *IEEE Trans. Aerosp. Electron. Syst.*, vol. 56, no. 2, pp. 1346–1356, Apr. 2020.

[40] G. Lenis, P. Reichensperger, D. Sommer, C. Heinze, M. Golz, and O. Dössel, "Detection of microsleep events in a car driving simulation study using electrocardiographic features," *Current Directions Biomed. Eng.*, vol. 2, no. 1, pp. 283–287, Sep. 2016.

[41] J. V. Rundo and R. Downey III, "Polysomnography," in *Handbook of Clinical Neurology*, vol. 160, Amsterdam, The Netherlands: Elsevier, 2019, pp. 381–392, doi: 10.1016/B978-0-444-64032-1.00025-4.

[42] C. Anderson, A. W. T. Cai, M. L. Lee, W. J. Horrey, Y. Liang, C. S. O'Brien, C. A. Czeisler, and M. E. Howard, "Feeling sleepy? Stop driving—Awareness of fall asleep crashes," *SLEEP*, vol. 46, no. 11, Nov. 2023, Art. no. zsad136.

[43] A. W. T. Cai, J. E. Manousakis, T. Y. T. Lo, J. A. Horne, M. E. Howard, and C. Anderson, "I think I'm sleepy, therefore i am–awareness of sleepiness while driving: A systematic review," *Sleep Med. Rev.*, vol. 60, Dec. 2021, Art. no. 101533.

[44] S. Groppo, M. Guagnano, L. Pugliese, J. Sini, and M. Violante, "To be or not to be... awake? A comparison of subjective and objective methods for drowsiness detection in drivers," in *Proc. IEEE 22nd Medit. Electrotechnical Conf. (MELECON)*, Jun. 2024, pp. 684–688.

[45] C. François, T. Hoyoux, T. Langohr, J. Wertz, and J. Verly, "Tests of a new drowsiness characterization and monitoring system based on ocular parameters," *Int. J. Environ. Res. Public Health*, vol. 13, no. 2, p. 174, Jan. 2016.

[46] F. Snyder, J. A. Hobson, D. F. Morrison, and F. Goldfrank, "Changes in respiration, heart rate, and systolic blood pressure in human sleep," *J. Appl. Physiol.*, vol. 19, no. 3, pp. 417–422, 1964.

[47] T. Penzel, J. W. Kantelhardt, R. P. Bartsch, M. Riedl, J. F. Kraemer, N. Wessel, C. Garcia, M. Glos, I. Fietze, and C. Schöbel, "Modulations of heart rate, ECG, and cardio-respiratory coupling observed in polysomnography," *Frontiers Physiol.*, vol. 7, p. 460, Oct. 2016.

[48] W. M. Association, "World medical association declaration of Helsinki: Ethical principles for medical research involving human subjects," *JAMA*, vol. 310, no. 20, pp. 2191–2194, 2013.

[49] M. W. Johns, "A new method for measuring daytime sleepiness: The Epworth sleepiness scale," *Sleep*, vol. 14, no. 6, pp. 540–545, Nov. 1991.

[50] A. Shahid, K. Wilkinson, S. Marcu, and C. M. Shapiro, "Karolinska sleepiness scale (KSS)," in *STOP, THAT and One Hundred Other Sleep Scales*. New York, NY, USA: Springer, 2011, pp. 209–210, doi: 10.1007/978-1-4419-9893-4_47.

[51] A. Å. Miley, G. Kecklund, and T. Åkerstedt, "Comparing two versions of the Karolinska sleepiness scale (KSS)," *Sleep Biol. Rhythms*, vol. 14, no. 3, pp. 257–260, Jul. 2016.

[52] S. S. Sullivan and C. A. Kushida, "Multiple sleep latency test and maintenance of wakefulness test," *Chest*, vol. 134, no. 4, pp. 854–861, 2008.

[53] A. M. Anniss, A. Young, and D. M. O'Driscoll, "Microsleep assessment enhances interpretation of the maintenance of wakefulness test," *J. Clin. Sleep Med.*, vol. 17, no. 8, pp. 1571–1578, Aug. 2021.

[54] G. Beltrão, W. A. Martins, B. Shankar M. R., M. Alaee-Kerahroodi, U. Schroeder, and D. Tatarinov, "Adaptive nonlinear least squares framework for contactless vital sign monitoring," *IEEE Trans. Microw. Theory Techn.*, vol. 71, no. 4, pp. 1696–1710, Apr. 2023.

[55] G. Beltrão, M. Alaee-Kerahroodi, U. Schroeder, D. Tatarinov, and B. S. M. R., "Nonlinear least squares estimation for breathing monitoring using FMCW radars," in *Proc. 18th Eur. Radar Conf. (EuRAD)*, Apr. 2022, pp. 241–244.
[56] G. T. Beltrao, W. A. Martins, B. S. M. R. Rao, M. Alaee-Kerahroodi, U. Schroeder, and D. Tatarinov, "Method and system for contactless vital sign monitoring via calculating displacement signal by applying adaptive nonlinear least squares method," U.S. Patent U.S. 12 465 234 B2, Nov. 11, 2025.
[57] M. Weenk, H. van Goor, M. van Acht, L. J. Engelen, T. H. van de Belt, and S. J. H. Bredie, "A smart all-in-one device to measure vital signs in admitted patients," *PLoS ONE*, vol. 13, no. 2, Feb. 2018, Art. no. e0190138.
[58] K. Montazeri, S. A. Jonsson, J. S. Agustsson, M. Serwatko, T. Gislason, and E. S. Arnardottir, "The design of RIP belts impacts the reliability and quality of the measured respiratory signals," *Sleep Breathing*, vol. 25, no. 3, pp. 1535–1541, Sep. 2021.
[59] G. Beltrão, R. Stutz, F. Hornberger, W. A. Martins, D. Tatarinov, M. Alaee-Kerahroodi, U. Lindner, L. Stock, E. Kaiser, S. Goedicke-Fritz, U. Schroeder, and M. Zemlin, "Contactless radar-based breathing monitoring of premature infants in the neonatal intensive care unit," *Sci. Rep.*, vol. 12, no. 1, pp. 1–13, Mar. 2022.
[60] M. J. T. Tan, H. R. Kasireddy, A. B. Satriya, H. A. Karim, and N. AlDahoul, "Health is beyond genetics: On the integration of lifestyle and environment in real time for hyper-personalized medicine," *Frontiers Public Health*, vol. 12, Jan. 2025, Art. no. 1522673.

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