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Gaëtan Perrotte, Clément Bougard, Arthur Portron, Jean-Louis Vercher. Monitoring driver drowsiness in partially automated vehicles: Added value from combining postural and physiological indicators. *Transportation Research Part F: Traffic Psychology and Behaviour*, 2024, 100, pp.458-474. 10.1016/j.trf.2023.12.010 . hal-04372802

HAL Id: hal-04372802

<https://amu.hal.science/hal-04372802v1>

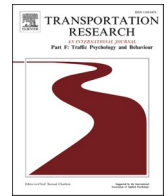
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Contents lists available at [ScienceDirect](https://www.sciencedirect.com)

Transportation Research Part F: Psychology and Behaviour

journal homepage: www.elsevier.com/locate/trf

Monitoring driver drowsiness in partially automated vehicles: Added value from combining postural and physiological indicators

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ARTICLE INFO

Keywords:

Monitoring
Drowsiness
Postural indicators
Physiological indicators
Partially autonomous driving

ABSTRACT

Drowsiness at the wheel is one of the leading causes of road fatalities. Driver monitoring systems (DMS) mainly rely on vehicle-based data and drivers' facial information to detect drowsiness. However, the introduction of partially autonomous driving will change the way we drive, letting the vehicle manage the driving task while drivers may be free to engage in non-driving tasks. This calls for new ways of detecting drowsiness, and even sleeping, at the wheel. Here, 22 participants drove for 100 min in a static simulator under level-2 automation on a 2 × 2 motorway. Postural (i.e., pressure and movements) and physiological (i.e., cardiac and respiratory) indicators were continuously recorded, while PERCLOS70 was used to classify drowsiness. The results reveal different physiological and postural signatures for the different states of drowsiness defined. While slight drowsiness is mainly associated with a higher heart rate, slower breathing, and an increased number of movements on the seat, being asleep is characterized by a lower heart rate and a slouched position on the seat. This study points to the relevance of using postural indicators in combination with physiological data to detect driver drowsiness. Focusing on the partially automated vehicle, it explores not only resistance to drowsiness but also sleeping at the wheel.

1. Introduction

Drowsiness at the wheel and fatigue are a major cause of road accidents, particularly on highways (de Mello et al., 2013; Horne & Reyner, 1995; ONISR, 2019). To prevent such accidents, car manufacturers have integrated driver monitoring systems (DMS) into vehicles. Most of these DMSs use two types of data: the driver's facial features and vehicle-based data. However, the emergence of partially autonomous vehicles (i.e., levels 2 and 3 of automation, SAE International, 2016) is bound to change drivers' behavior and attitudes. Drivers will become supervisors, with the driving task performed by the car, and will be able to engage in non-driving related tasks (NDRT). This means that the data underlying the DMS, developed principally for manual driving, will lose relevance. The DMS will have to be adapted to this new way of driving, i.e., capable of determining at any moment whether the driver can take control of the vehicle. New DMSs operating on a different, non-intrusive basis will be required to detect altered driver states such as drowsiness at the wheel.

Drowsiness is considered as a transition between wakefulness and sleep. It is driven by the central nervous system, particularly the brainstem, where the nuclei responsible for sleep-wake transitions are located (Saper & Fuller, 2017). When it occurs, physiological, cognitive, and behavioral changes can be observed. These were traditionally used to detect drowsiness at the wheel by DMSs, initially

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<https://doi.org/10.1016/j.trf.2023.12.010>

Received 19 June 2023; Received in revised form 16 November 2023; Accepted 14 December 2023

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developed for manual driving. Vehicle-based data was used to assess the driver's performance and facial information was gathered through video-image processing (see Halin et al., 2021 for a review) because of the reliability and ease of recording offered by these two types of indicators. For instance, ocular parameters are affected by drowsiness and show various modifications such as increased blink duration and blink frequency, as well as a higher percentage of eye closure (PERCLOS) (see Cori et al., 2019 for a review). These changes appear to be independent of the tasks performed, as revealed by experiments with a large number of tasks of varying complexity (Cori et al., 2019). Thus, camera-based video acquisition was used to record the above ocular behaviors typical of a drowsy driver, or facial features indicative of drowsiness (e.g. yawning or head movements) (Ramzan et al., 2019). In terms of vehicle-based data, falling asleep at the wheel dangerously reduces the driver's control of the vehicle, leading to greater variability in speed, lane deviations or even lane crossings (Bougard et al., 2021; Ma et al., 2018; Philip et al., 2005). Thus, features such as standard deviation of lane position (SDLP) and steering wheel movements were commonly used to detect drowsiness at the wheel (see Liu et al., 2009 for a review).

Partially autonomous vehicles have recently been developed to assist with driving tasks, notably featuring the "Highway driver assist" function. In these modes, the driving task is carried out by the vehicle itself, turning the driver into a supervisor, either free to engage in NDRTs (level-3) or not (level-2). Nevertheless, according to the SAE definition, even if drivers do not control the lateral and longitudinal movements of the car, they must maintain cognitive awareness of the driving environment (especially in level 2) and be able to intervene in any safety-critical event where the automation does not respond properly (McWilliams & Ward, 2021). Ironically, drowsiness is more likely to occur in these autonomous modes than in manual driving (Jamson et al., 2013), especially when drivers are not engaged in NDRTs (Schömig et al., 2015; Vogelwohl et al., 2019). To ensure that drivers are able to take over their vehicle at any time, a DMS needs to detect such altered states. However, with the trajectory controlled by the vehicle and the driver no longer obliged to look at the road (and therefore not necessarily facing the camera, usually located in front of the driver's head), current DMSs will become at least partially irrelevant. This new type of driving calls for the DMS to be adapted to include alternative features.

One of these alternatives could be the use of physiological data. The first stages of sleep are associated with both a decrease in heart rate (HR) (Berg et al., 2005; Burgess et al., 1999) and a decrease in ventilation (Douglas et al., 1982; Trinder et al., 1992). These physiological functions are mainly driven by the activity of both branches of the autonomic nervous system. While the sympathetic nervous system (SNS) is principally involved in the "fight or flight" reaction, the parasympathetic nervous system (PNS) is involved in the "rest and digest" reaction (Rea, 2014). These branches seem to work in an opposite manner, but are related in a complex, not linear, way (Billman, 2013). More subtle indicators can be derived from overall measurements. HR modulation leads to changes in interbeat intervals and is responsible for heart rate variability (HRV). The power spectrum of HRV signals, particularly the Low-Frequency (LF: 0.04–0.15 Hz) and High-Frequency (HF: 0.15–0.4 Hz) domains, are often used as indicators of sympathetic and parasympathetic activation, respectively. Thus, the LF/HF ratio is considered as an indicator of sympatho-vagal balance (Billman, 2013; Pagani et al., 1984, 1986). The LF band is mainly driven by both SNS and PNS activation, whereas the HF band is mainly driven by PNS activity (Billman, 2013; Shaffer & Ginsberg, 2017).

These data are increasingly being explored as a way of detecting drowsiness in manual driving; recent work has examined HR, HRV or respiration rate (RespR) (e.g., Buendia et al., 2019; Fujiwara et al., 2019; Jacobé de Naurois et al., 2018; Li & Chung, 2013). However, contrary to laboratory conditions, a driver who falls asleep at the wheel is not in a relaxed position before sleep onset and may fight it when it appears. Although decreased HR (Buendia et al., 2019; Persson et al., 2021) and RespR (Kiasari et al., 2018) have been reported in sleepy drivers, results concerning power spectrum analysis are more divergent and inconclusive (Lu et al., 2022; Persson et al., 2021). Actually, in LF, absolute power increases with level of drowsiness (Buendia et al., 2019; Persson et al., 2021) and distance driven (Egelund, 1982), whereas in HF, absolute power either increases (Buendia et al., 2019) or shows no significant difference (Persson et al., 2021). Vicente et al., (2016) hypothesized that this might lead to SNS activation and PNS deactivation when drivers need to wake up. In addition, one of the main challenges for road safety lies in identifying early stages of drowsiness, before fatal accidents can occur. Such intermediate states of drowsiness are rarely addressed in studies where classifiers are used to detect deeper states of drowsiness; in one attempt, adding an intermediate state of drowsiness induced a drop of approximately 20 % in the classifier's accuracy (Persson et al., 2021). Finally, these physiological indicators are very sensitive to inter-individual differences (Jacobé de Naurois et al., 2018; Persson et al., 2021), which suggests that the algorithm would need to be adapted to each driver (Jacobé de Naurois et al., 2019).

In addition to physiological changes, drivers beginning to fall asleep exhibit behavioral changes. There is a wide range of early signs of drowsiness at the wheel, such as yawning, self-centered gestures or even changing position (Nordbakke & Sagberg, 2007; Rogé et al., 2001). This latter is observed in more than 60 % of drivers experiencing signs of drowsiness (Watling et al., 2015) and increases with time spent driving (Rogé et al., 2001). These observations were confirmed in an experiment conducted by Itoh et al., (2015), where the number of movements increased in intermediate states of drowsiness. Not only movements, but also position and posture on the seat (i. e., center of pressure), are used for drowsiness detection in simulated manual driving studies (Gwak et al., 2020; Murata et al., 2018; Sunagawa et al., 2020). Overall, these studies show that postural features hold promise as a way to detect drowsiness at the wheel, with seat-based sensors providing usable (non-invasive) and relevant driver monitoring. Seat-based sensors such as pressure sensors have been tested in distraction monitoring systems (Zhao et al., 2021), as well as to record physiological signals (e.g., Wusk & Gabler, 2018) without recourse to conventional recording involving skin contact with electrodes or sensors, which is not always possible in real driving conditions.

With a view to driver monitoring under future autonomous vehicle functioning, our primary objective was to explore the potential of using both postural and physiological features to characterize the full spectrum of drowsiness (from fully alert to asleep at the wheel). Consistent with the above, level-2 partially autonomous vehicles were used to induce drowsiness in well-rested drivers. Although such vehicles on the market feature alarms when the driver's hands are no longer on the steering wheel (Autopilot and Full

Self-Driving Capability | Tesla Support France, 2023) or when the driver’s eyes are no longer on the road (Super Cruise: Hands-Free Driving, Cutting Edge Technology, 2023), we chose not to set any alarm. Our aim was to prevent drivers from waking up, and thus to be able to consider the whole spectrum of drowsiness. To our knowledge, this study is the first to explore the use of postural and physiological indicators in partially autonomous driving to characterize drowsiness at the wheel. Our hypothesis was that these indicators could provide information about levels of drowsiness that would be valuable from a safety perspective.

2. Material and methods

2.1. Participants

Twenty-two participants (the drivers) were included in the study (12 females, 10 males; mean age: 23.1 ± 3.7 years old; weight: 63.5 ± 7.7 kg; height: 171.7 ± 10.2 cm). Recruitment criteria included holding a valid driver’s license for at least 6 months, without visual impairment or with vision corrected by contact lenses for driving. Based on Baiardi et al. (2018), who found that drowsiness episodes at the wheel and near-miss accidents were correlated with a mean Epworth Sleepiness Scale (ESS; Johns, 1991) score of 5.9 ± 3.1 and 6.9 ± 3.1 , respectively, the ESS score required was 7 or above. This made it more likely that drivers would experience drowsiness at the wheel. The following participant information was collected: quality of the previous night’s sleep (on a scale from 1 to 10), driving frequency (number of times per week), average distance (kilometers) driven per year, and score on the Horne and Östberg morning/evening questionnaire (Horne & Ostberg, 1976). All participants received information about the experiment and agreed to participate. An ethical committee (agreement IRB00012476-2020–15-07–63) approved the protocol. The participants were not allowed to smoke nor to drink coffee or tea on the day of the experimental session.

2.2. Subjective and objective tests

Subjective sleepiness was determined using the Karolinska Sleepiness Scale (KSS; Akerstedt & Gillberg, 1990), a 9-point scale based

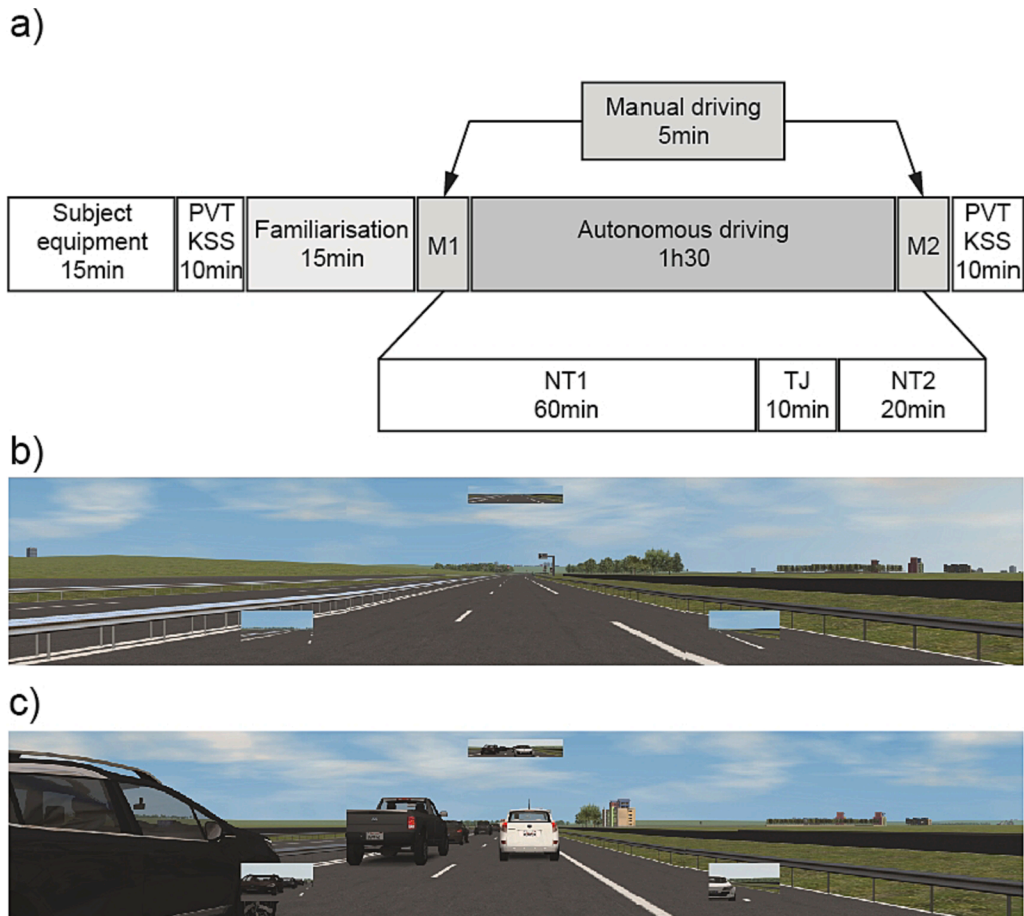


Fig. 1. The experimental scenario and the driving session (a). Simulated driving environments for the no-traffic (NT) and the traffic-jam (TJ) periods are illustrated (b and c, respectively).

on a self-reported, subjective assessment of the subject's level of alertness. Ratings were graded: 1 = extremely alert, 3 = alert, 5 = neither alert nor sleepy, 7 = sleepy (but not fighting sleep), 9 = very sleepy (fighting sleep).

To reproduce the Psychomotor Vigilance Task (PVT-B; Basner et al., 2012), a 3-min simple reaction time test (SRTT) was performed by the participants using PEBL Toolbox (Mueller & Piper, 2014). A stimulus (a yellow circle on a black computer screen) was displayed at randomized (1–4 s) intervals over 3 min. Participants faced the computer screen, and were instructed to press the spacebar of the keyboard with the preferred hand as quickly as possible after appearance of the visual stimulus. In response to the key press, the screen displayed the participant's time reaction for 0.5 s, providing trial-by-trial performance feedback. The screen returned to black for 0.5 s after providing the performance feedback, ready for the next block. In short, each block lasted 2 to 5 s. Mean reaction time (RT), number of lapses (RT > 355 ms), and number of anticipations (RT < 150 ms) were calculated for each session. Both KSS and SRTT were performed before and after the driving procedure.

2.3. Driving procedure

This study was performed on a static driving simulator at the Mediterranean Center of Virtual Reality. The static simulator was composed of three UHD screens (43 in.), each forming with its neighbor a 130-degree angle. The front screen was located approximately 140 cm from the steering wheel regardless of the adjustments made by the driver, who was then allowed to make forward and backward adjustments to the seat but not the recline (reclined angle $\approx 105^\circ$ degree). Only the gas and brake pedals were activated, to mimic an automatic gearbox. The driving environment was developed via SCANer Studio® 1.8, simulating a 2×2 highway. After vigilance tests, participants became familiar with the simulator and the autonomous mode during a 15-min familiarization phase. This consisted of four runs of approximately 3 mins each: the first involved only manual driving, while during the others, the autonomous mode was activated and deactivated, to train participants in using this mode.

The autonomous mode was activated by pressing a button on the left of the steering wheel and deactivated by pushing either the gas or the brake pedal. Once activated, the test session was conducted under level-2 automation: in this mode, the participants were not allowed to engage in an NDRT which might keep them alert, but had to monitor the road environment around them. The drivers were not informed of the duration of the autonomous phase. The session proceeded as follows (see Fig. 1): participants drove under manual mode for 5 min (M1). At the end of M1, the system sent a manual-to-autonomous request to activate the "Highway driver assist" function. Once this was activated, drivers were instructed to monitor the environment and to take over vehicle control as soon as possible after receiving a visuo-auditory signal. The run under autonomous mode lasted 90 min, with three alternating phases: (i) 60 min at 110 km/h without any traffic (NT1), (ii) 10 min in a traffic jam (TJ), and (iii) 20 min under the same conditions as the first phase (NT2). Following this, a take-over request (TOR) was sent and an obstacle on the road had to be avoided. Once they had taken over vehicle control, drivers had to continue driving for approximately 5 min under manual mode (M2).

The traffic-jam phase proceeded as follows: after one hour with no traffic in NT1, 20 vehicles were added ahead of and 20 behind the ego-vehicle such that participants could not see them appear. Then, the speed of the two leading vehicles ahead of the ego-vehicle was regulated so as to range between 10 and 30 km/h and readjusted every 10 s to create an accordion effect. At the end of the 10 min, the vehicles disappeared from the participants' field of view: the front vehicles moved away from the ego-vehicle at a speed of 140 km/h and the back vehicles at 80 km/h. The objective of using two traffic-free phases of different lengths was to observe both resistance and severe drowsiness in the first and in the second, to induce resistance only. The traffic jam phase was intended to reactivate the drivers. Our focus was on resistance to drowsiness, the most difficult state to detect.

2.4. Data acquisition and processing

2.4.1. Ocular indicators

During the driving session, ocular data (i.e., PERCLOS70, blink frequency and blink duration) were recorded using a Drowsimeter R100 (Phasya®). This device is equipped with a 120 Hz camera, an infrared illumination source, and a hot mirror (François et al., 2016). A 60-sec calibration was performed before the driving procedure, with participants instructed to look straight ahead, keeping their eyes open in a normal way (Stawarczyk et al., 2020).

2.4.2. Physiological indicators

Physiological data (i.e., heart rate and respiration rate) were recorded using a BIOPAC® MP150 system at 500 Hz sampling rate. Electrocardiograms (ECG) were recorded using three silver-silver chloride (Ag/AgCl) electrodes (EL-504, BIOPAC®) and respiration was recorded with a chest belt sensor. Physiological parameters were extracted via the Neurokit-2 Python toolbox (Makowski et al., 2021). ECG signals were pre-processed using a 0.5 Hz high-pass butterworth filter (order = 5), followed by powerline filtering (powerline = 50). The peak detection algorithm employed by the Neurokit2 method is based on QRS complex detection using the absolute gradient of the ECG signal (Brammer, 2020). The R peaks were then detected as local maxima in the QRS complexes (Brammer, 2020) and R-R interval series were calculated. Power Spectral Density of the preceding time series was computed via a Fast Fourier Transform to obtain the frequency band.

Respiration signals were pre-processed using a linear detrending function followed by a fifth-order 2 Hz low-pass IIR Butterworth filter. Pre-process and breathing detection followed procedures used in Khodadad et al., (2018). All the physiological features extracted are listed in Table 1.

2.4.3. Postural indicators

Body-seat pressure distribution was recorded with two textile pressure sensor mats from XSENSOR® Technology (Xsensor, Inc., Calgary, Alberta, Canada). A 36x36 sensor cell matrix (model LX100:36.36.02; sensing area: 45.7 cm × 45.7 cm; range of pressure: 5–200 mmHg) was used for the seat cushion and a 40 × 64 sensor cell matrix (model PX100:40.64.02; sensing area: 50.8 cm × 81.2 cm; range of pressure: 14–200 mmHg) for the backrest and the headrest. Both mats' spatial resolution is 12.7 mm per cell. All pressure measurements were acquired via XSENSOR Pro V8 software at 30 Hz to guarantee the acquisition of movements on the seat and high frequency features. After signals examination, they were down-sampled to 5 Hz due to the absence of high frequency features. Spatial cutting was performed using the average COP of the first manual driving phase (M1) as baseline to define several areas on the seat cushion and backrest. Overall, 5 zones were defined: Anterior (Ant) and Posterior (Post) zones of the seat, Top and Bottom (Bot) zones of the backrest, and Headrest (Head) zone (Fig. 2).

Contact surface (CS; cm²), contact pressure (CP; mmHg), and the y-coordinate of the COP (mm) were computed from data extracted for each area using the provided software. Each cell is 12.7 mm × 12.7 mm. Since the software only provides contact surface as the number of activated cells and COP coordinates as the number of cells from the origin (right, posterior corner relative to the participant), the contact surface was calculated by multiplying this number by the surface area of a single cell, while the y-coordinate is obtained by multiplying the number of cells by the width of a single cell. Use of the headrest (pHead) was measured by the time spent with head touching it per analysis window. For the computation, frames when the headrest CS had more than four cells activated were considered as indicating use of the headrest. Less than four cells activated in the zone were considered as artifacts. Finally, the number of frames revealing contact on was divided by the number of frames in the analysis window. COP movement (COPm) signals were obtained by calculating the Euclidean distance between the (n-1)th COP and nth COP coordinates. On this signal, peaks represent a large variation in COP during a short period of time, which can be considered as a movement on the seat or backrest (as illustrated in the Fig. 4). Peak detection was thus performed on this signal to determine the number of movements. A threshold of 0.5 was used, roughly representing a movement of the y-COP of 30 mm per sec. All the postural features extracted are listed in Table 1.

2.5. Classification and rescaling

Test sessions were cut by 150-s epochs for all participants. PERCLOS70 was used to classify drowsiness based on the classifications of Chang et al., (2022) and Feldhütter et al., (2019). Since higher PERCLOS has been observed in automated driving (Arefnezhad et al., 2022), additional states were added to the existing scale. Five classes were defined based on the mean of PERCLOS70 during the time window: Alert (A; 0–7.5 %), Slightly Drowsy (SD; 7.5–15 %), Drowsy (D; 15–25 %), Extremely Drowsy (ED; 25–50 %) and Asleep (Asl; 50–100 %). Time window length was chosen to ensure computational consistency, notably for frequency-domains of HRV metrics (Shaffer et al., 2020). Overall, 21 epochs were removed from the analysis due to hardware acquisition failure. In the end, a total of 859 epochs were used: 527 for A, 158 for SD, 75 for D, 60 for ED, and 39 for Asl. There was a final rescale for each participant, where the mean of A state was subtracted from all features (Persson et al., 2021) to limit inter-individual variability.

2.6. Statistical analysis

All statistical analyses were performed using R software® (R Core Team, 2022). Paired-t tests were used to compare dependent measures before and after (KSS and SRTT results) the driving session, with a 0.05 level of confidence. Postural and physiological features were compared via an ANOVA with one fixed factor (i.e., Drowsiness: Alert, Slightly Drowsy, Drowsy, Extremely Drowsy and Asleep) resulting to 4 degrees of freedom. For all features, results of the ANOVA were reported with F-Value, p-value and η². Post-hoc analysis was performed using a pairwise-t test with a Bonferroni correction. The pairs reported in tables are those between the alert

Table 1

All features computed for each participant, as presented in the Results section.

| | Abbreviation | Signification |
|------------------------------------|--------------|---|
| Oculomotor features | / | Duration of blinks |
| | / | Frequency of blinks |
| Cardiac features | HR | Heart rate (bpm) |
| | LFn | Normalize power of LF |
| | HFn | Normalize power of HF |
| | LF/HF | Ratio between LF and HF bands |
| Respiratory features | RespR | Respiratory rate (rpm) |
| | RespAmp | Respiratory amplitude |
| | SDBB | Standard deviation of breath-to-breath interval |
| | I-time | Mean of duration of inspiration phase |
| | E-time | Mean of duration of expiration phase |
| Respiratory Sinus Arrhythmia (RSA) | P2T | Difference between HRmax-HRmin for each breathing cycle |
| Postural features | y-COP | y-coordinate of the center of pressure of the zone |
| | CS | Contact surface over the zone |
| | CP | Contact pressure over the zone |
| | Mov | Number of movements (seat or backrest) |
| | pHead | Percentage of time using the headrest |

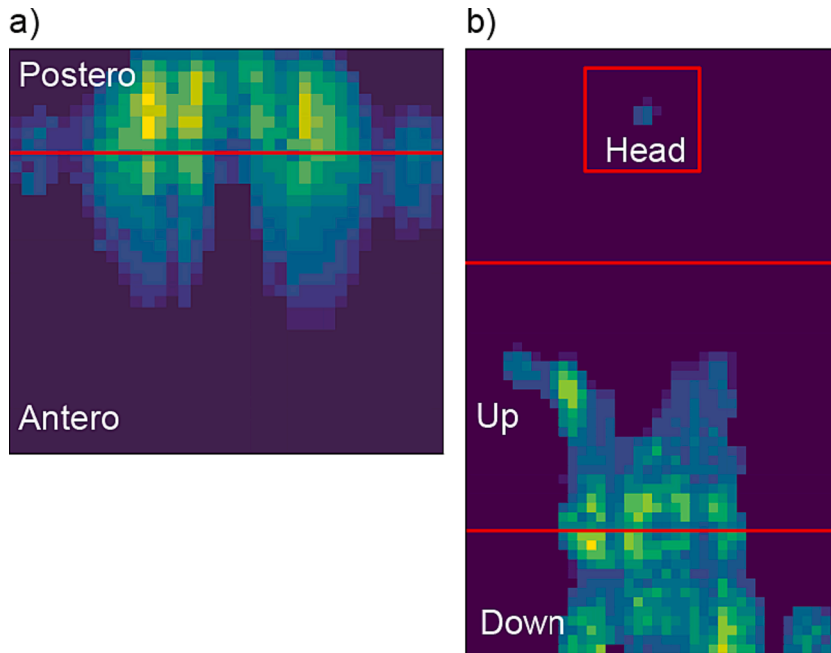


Fig. 2. Sensor mats for the seat cushion (a; 36 × 36 cells) and the backrest (b; 40 × 64 cells). Red lines illustrate the demarcation between zones. Seat cushion mat was sliced into 2 zones: posterior and anterior. Backrest mat was sliced into three zones: head, upper and lower back. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

state (i.e., A) and each drowsiness levels (i.e., SD, D, ED and Asl) mimicking a Dunnett procedure. Significance levels were defined as * $p < 0.05$, ** $p < 0.01$ and *** $p < 0.001$. Absolute value of Cohen’s d coefficient (Cohen, 1988) was computed to provide further information about the effect size between pairs comparisons. This coefficient was only calculated between pairs that were significantly different and are reported directly in tables. The following thresholds can be used as indicators of small, moderate and large effects: 0.2 to < 0.6, 0.6 to < 1.2 and greater than 1.2, respectively (Hopkins et al., 2009).

3. Results

All participants completed the full driving task, approximately 100 min of driving. None of them experienced motion sickness due to the static simulator. Using the oculometer appeared to generate some discomfort.

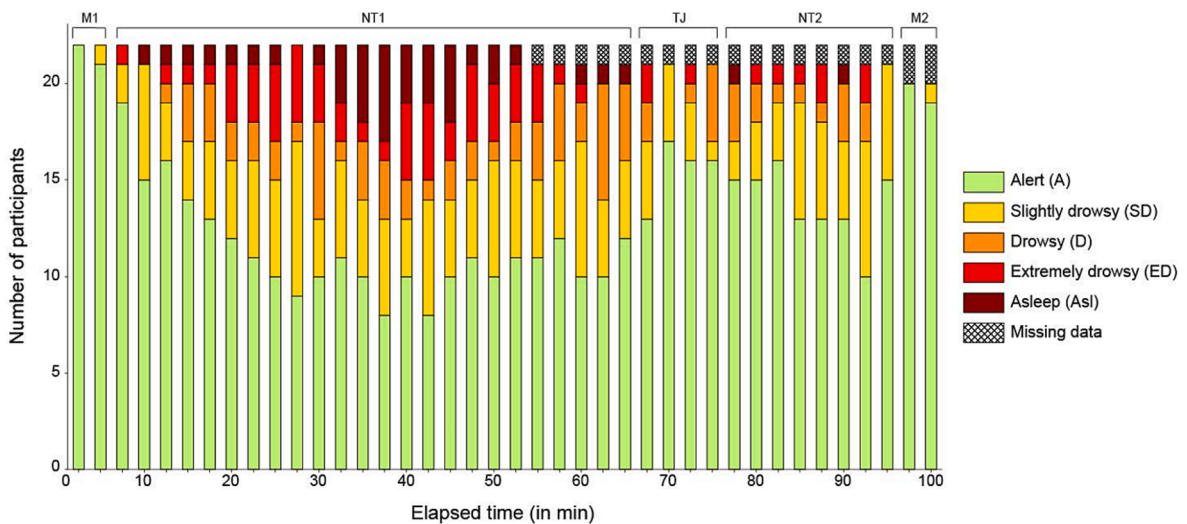


Fig. 3. Occurrence of each state (A, SD, D, ED and Asl) during the driving session. Each bar represents a period of 2.5 min. The different phases of the driving scenario (M1, NT1, TJ, NT2, M2) are indicated at the top of the graph.

3.1. Drowsiness

As expected, level-2 automation can induce several levels of drowsiness; all five states were observed throughout the driving session (Fig. 3). As depicted, on average the peak of the deepest states of drowsiness (i.e., ED and Asl) occurred between 25 and 45 min into the driving session. This peak was followed by a natural decrease without modification of the driving environment (still in NT1), so that at the beginning of the traffic jam (i.e., at 65 min into the driving session), none of the drivers was in ED or Asl. After this 10 min TJ phase, there was an increase in drowsiness, with a higher proportion of deeper drowsiness states. At the end of the automated driving, 90 % of participants were in an alert state during the second manual driving phase. Although deeper drowsiness states were observed during the driving session, only 36 % of drivers reached these states.

As an example, Fig. 4 presents some signals (PERCLOS70, HR, RespR and COPm) for two participants (Fig. 4). Periods of high drowsiness are highlighted in red. Episodes of drowsiness can be seen to occur at different times, with very different dynamics. For the first subject, this drowsiness progressed gradually through all the states to reach Asl, while the second participant went directly from a slightly drowsy state to eventually falling asleep.

3.2. Physiological and postural indicators

Since there is not necessarily temporal continuity regarding the different states of drowsiness (i.e., a driver can go from A to D without passing through SD), all features in the results section will be compared only to the alert (A) state. The rescaling performed also means that the average of each feature is equal to zero in the alert (A) state. Figures illustrate a trend in drowsiness states, while tables present statistical analyses.

3.3. Physiological indicators

3.3.1. Oculomotor features

Driver drowsiness level had a significant effect on eye-blinks both in frequency ($F_{(4,854)} = 82.03$; $p < 0.001$; $\eta^2 = 0.277$) and duration ($F_{(4,854)} = 136.9$; $p < 0.001$; $\eta^2 = 0.391$). Results are summarized in Table 2. Post-hoc analyses revealed that SD and D were associated with significantly higher values than A for blinks frequency. ED was associated with significantly higher values than A for both duration and frequency. Asl was associated with significantly higher values for blinks duration and a significantly lower value for blinks frequency in comparison with A.

3.3.2. Cardiac features

Predictably, and in line with the literature, driver drowsiness has a significant effect on all cardiac features i.e., HR ($F_{(4,854)} = 43.06$; $p < 0.001$; $\eta^2 = 0.168$), HFn ($F_{(4,854)} = 25.82$; $p < 0.001$; $\eta^2 = 0.108$), LFh ($F_{(4,854)} = 8.26$; $p < 0.001$; $\eta^2 = 0.037$) and LFHF ($F_{(4,854)} =$

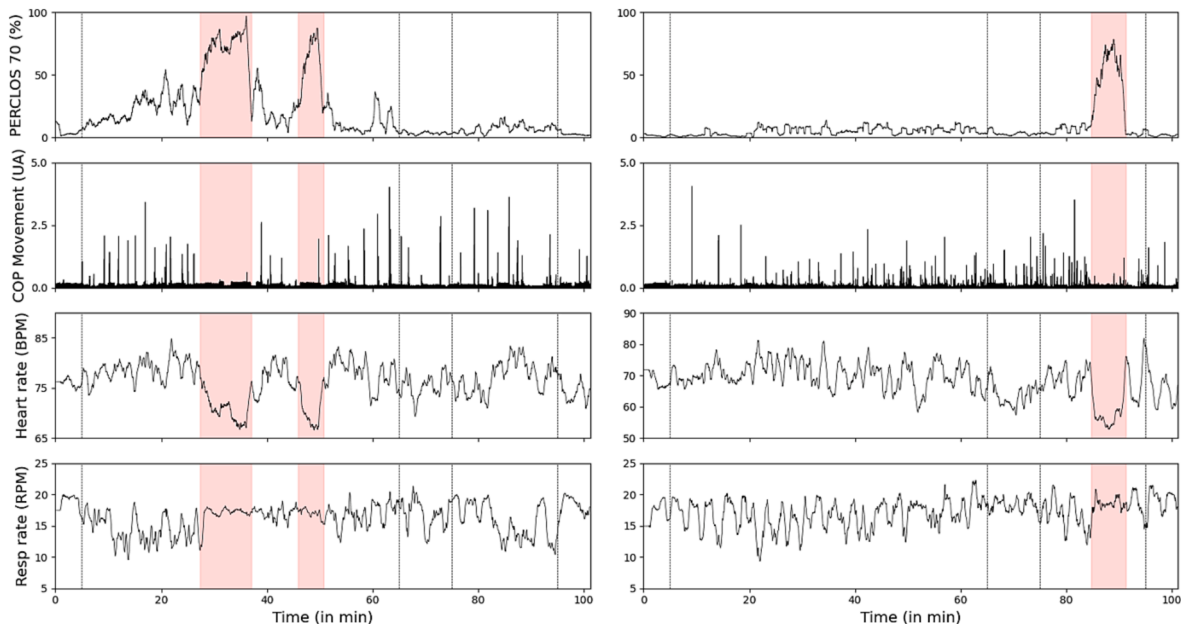


Fig. 4. Dynamics time-course of PERCLOS70, COP movement on the seat cushion, HR and RespR during the test session for two participants. The red areas represent periods of high drowsiness (PERCLOS > 50 %). The dotted line represents the different phases of the driving sessions (i.e. M1, NT1, TJ, NT2 and M2). M = manual; NT = no traffic; TJ = traffic jam. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 2

Values of ocular features (mean ± SEM, n = 22) for each state of drowsiness. Values in bold show a significant difference compared to Alert. Significant differences are represented by * (p < 0.05), ** (p < 0.01), and *** (p < 0.001) and Effect Size (ES) was indicated by the Cohen's d coefficient.

| | A | SD | D | ED | Asl |
|----------------|---------------|-------------------------------------|-------------------------------------|--|---|
| Blinks (Hz) | 0.000 ± 0.004 | 0.134 ± 0.008 *** (ES = 14.) | 0.132 ± 0.015 *** (ES = 1.3) | 0.139 ± 0.024 *** (ES = 1.3) | -0.089 ± 0.023 *** (ES = 0.9) |
| Blinks (msecs) | 0.00 ± 3.35 | 167.24 ± 17.46 | 529.04 ± 50.31 | 1140.64 ± 105.55 *** (ES = 4.2) | 9417.60 ± 1841.81 *** (ES = 3.2) |

8.92; p < 0.001; η² = 0.040). Results are summarized in Table 3 and Fig. 5. Most of these features displayed a U-Shape (i.e., for HR, LFn, and LFHF) or an inverted U-shape (i.e., for HFfn). Post-hoc analyses showed that SD was associated with significantly higher values of HR and of LFn and a significantly lower value of HFfn compared to A. D was only associated with a significantly lower HFfn value. In contrast, Asl was associated with a significantly higher HFfn value and significantly lower HR, LFn, and LFHF values compared to A.

3.3.3. Respiratory features

Driver drowsiness also has a significant effect on most respiratory features such as RespR (F_(4,854) = 35.246; p < 0.001; η² = 0.142), SDBB (F_(4,854) = 25.23; p < 0.001; η² = 0.106), inspiratory time (F_(4,854) = 29.93; p < 0.001; η² = 0.123), expiratory time (F_(4,854) = 13.37; p < 0.001; η² = 0.06) and P2T (F_(4,854) = 15.351; p < 0.001; η² = 0.067). Results are summarized in Table 4 and Fig. 6. As for the HRV features, some respiratory features displayed a U-Shape (i.e., for SDBB, inspiratory and expiratory time) or an inverted U-shape (i.e., for RespR). Post-hoc analyses indicated that SD was associated with a significantly lower value for RespR and significantly higher values for inspiratory and expiratory time, SDBB, and P2T. D was associated with significantly higher values for inspiratory time and P2T, ED with a significantly lower value for expiratory time, and Asl with a significantly lower SDBB value and a higher P2T value.

3.4. Postural indicators

Driver drowsiness level has a significant effect on all static and dynamic postural features, summarized in Table 5 and Fig. 7. For the seat cushion, driver drowsiness level has a significant effect on y-COP_{seat} (F_(4,854) = 18.297; p < 0.001; η² = 0.079), CS_{postero} (F_(4,854) = 4.57; p < 0.001; η² = 0.02), CS_{antero} (F_(4,854) = 9.97; p < 0.001; η² = 0.045), CP_{postero} (F_(4,854) = 21.32; p < 0.001; η² = 0.091), CP_{antero} (F_(4,854) = 13.91; p < 0.001; η² = 0.061). Also, for the backrest, driver drowsiness level has a significant effect on y-COP_{backrest} (F_(4,854) = 23.16; p < 0.001; η² = 0.098), CS_{up} (F_(4,854) = 7.695; p < 0.001; η² = 0.035), CS_{down} (F_(4,854) = 23.545; p < 0.001; η² = 0.099), CP_{up} (F_(4,854) = 10.60; p < 0.001; η² = 0.047), CP_{down} (F_(4,854) = 29.60; p < 0.001; η² = 0.122). For the headrest, driver drowsiness level has a significant effect on pHead (F_(4,854) = 27.125; p < 0.001; η² = 0.113), CS_{head} (F_(4,854) = 23.096; p < 0.001; η² = 0.098), CP_{head} (F_(4,854) = 15.825; p < 0.001; η² = 0.069). Lastly, driver drowsiness level has a significant effect on dynamic features represented by Mov_{seat} (F_(4,854) = 20.639; p < 0.001; η² = 0.088), Mov_{backrest} (F_(4,854) = 35.110; p < 0.001; η² = 0.141).

The post-hoc analysis of postural indicators showed that all the drowsiness states were associated with a higher value for y-COP on the seat than in A, and significantly higher for SD, D, ED and Asl. These higher values indicate a shift of the center of pressure toward the anterior position and are in line with the CS and CP measured over the seats: significantly higher CS and CP were observed over the anterior zone for D, ED, and Asl. Over the posterior zone, however, CP values were lower for SD, D, ED, and Asl, while CS only showed lower values for D. In the same manner, the y-COP of the backrest was significantly higher in ED and Asl, reflecting a shift in the upper direction.

Once again, this result is supported by the values obtained for the lower part of the backrest: a significant decrease in CP for SD, D, ED, and Asl and a significant decrease in CS for SD, D, ED, and Asl. In contrast, for the upper part of the backrest, there was a significant increase in CP for ED and Asl. Finally, over the headrest, both CS and CP increased significantly for D, ED, and Asl. This result is further supported by the percentage of time spent using the headrest, significantly higher for ED and Asl. Taken together, the postural information obtained here suggests that states of deep drowsiness led to the body sagging more in the seat, as compared to more alert states. Moreover, seat and back movements exhibited an inverted U-Shape (Yerkes & Dodson, 1908), with significantly

Table 3

Values of cardiac features (mean ± SEM, n = 22) for each state of drowsiness. Values in bold show a significant difference compared to Alert. Significant differences are represented by * (p < 0.05), ** (p < 0.01), and *** (p < 0.001) and Effect Size (ES) was indicated by the Cohen's d coefficient.

| | A | SD | D | ED | Asl |
|--------------------|-------------|-------------------------------------|------------------------------------|----------------|------------------------------------|
| HR (bpm) | 0.00 ± 0.13 | 3.75 ± 0.45 *** (ES = 0.9) | 1.05 ± 0.41 | -0.20 ± 0.49 | -3.7 ± 0.74 *** (ES = 1.2) |
| LFn (a.u. x 10-3) | 0.00 ± 4.54 | 33.35 ± 7.69 * (ES = 0.3) | 30.14 ± 13.7 | 28.74 ± 13.13 | -59.0 ± 23.34 * (ES = 0.5) |
| HFfn (a.u. x 10-3) | 0.00 ± 4.50 | -50.07 ± 7.63 *** (ES = 0.5) | -48.99 ± 9.52 ** (ES = 0.5) | -31.74 ± 14.34 | 123.5 ± 28.1 *** (ES = 1.1) |
| LF/HF (a.u.) | 0.00 ± 0.09 | 0.44 ± 0.12 | 0.51 ± 0.21 | 0.48 ± 0.39 | -1.55 ± 0.4 *** (ES = 0.7) |

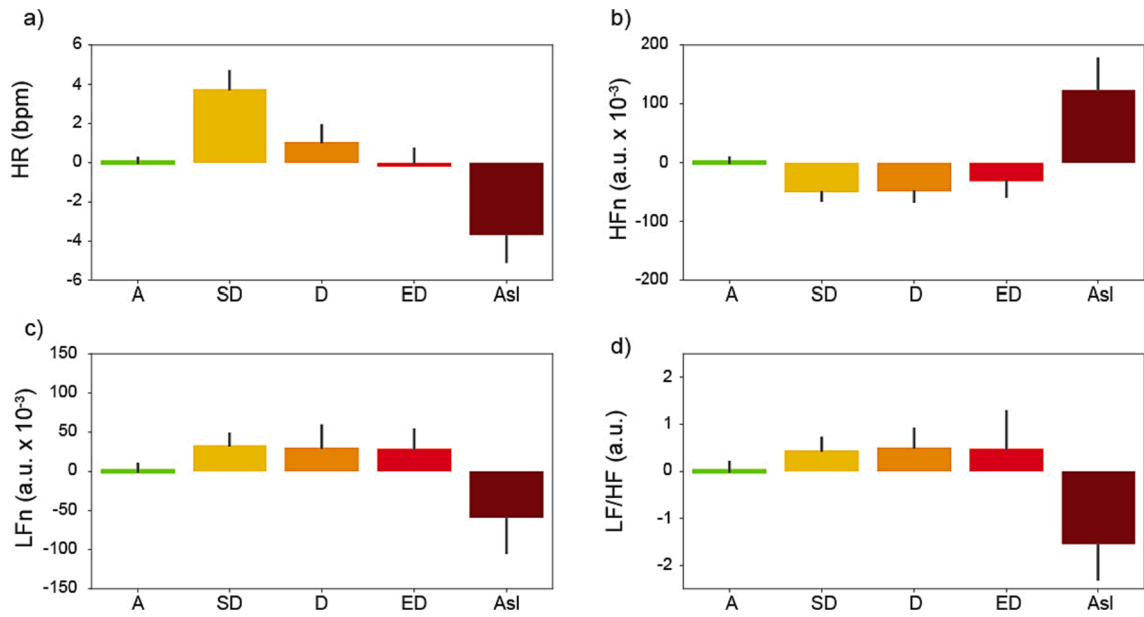


Fig. 5. Bar plots representing cardiac features (mean ± SEM, n = 22) for each state of drowsiness: HR (a), HFn (b), LFn (c) and LF/HF ratio (d).

Table 4

Values of respiratory features and RSA (mean ± SEM, n = 22) for each state of drowsiness. Values in bold show a significant difference compared to Alert. Significant differences are represented by * (p < 0.05), ** (p < 0.01), and *** (p < 0.001) and Effect Size (ES) was indicated by the Cohen's d coefficient.

| | A | SD | D | ED | Asl |
|----------------|--------------|--|-------------------------------------|---------------------------------------|--|
| RespR (rpm) | 0.00 ± 0.07 | -1.94 ± 0.22*** (ES = 1.0) | -0.47 ± 0.18 | -0.09 ± 0.25 | -0.09 ± 0.21 |
| RespAmp (a.u.) | 0.00 ± 0.02 | 0.06 ± 0.04 | 0.04 ± 0.05 | 0.10 ± 0.08 | -0.07 ± 0.10 |
| I-Time (msecs) | 0.00 ± 8.56 | 245.28 ± 30.58*** (ES = 1.0) | 90.13 ± 28.32* (ES = 0.4) | 75.55 ± 39.84 | -20.1 ± 25.78 |
| E-Time (msecs) | 0.00 ± 11.86 | 144.38 ± 25.11*** (ES = 0.5) | -13.22 ± 39.84 | -140.74 ± 50.43* (ES = 0.5) | -98.54 ± 33.96 |
| SDBB (msecs) | 0.00 ± 30.35 | 581.71 ± 79.39*** (ES = 0.7) | 231.31 ± 104.19 | -177.89 ± 160.28 | -663.22 ± 145.19*** (ES = 0.9) |
| P2T (msecs) | 0.00 ± 0.55 | 9.29 ± 1.48*** (ES = 0.7) | 5.68 ± 1.86* (ES = 0.4) | 1.85 ± 2.30 | 9.85 ± 2.6*** (ES = 0.8) |

higher values for SD and D. Backrest movements also showed lower values for Asl.

3.5. Subjective and objective tests

Results of the KSS scores confirmed an effect of the driving session on perceived drowsiness, indicated by a significant increase in KSS score between pre- (4.09 ± 1.27) and post-session measurements (6.55 ± 1.34) ($t_{(21)} = -6.84, p < 0.05$). Only two drivers had a lower KSS score after the driving session. However, for the PVT-B test, no significant difference was observed in any indicator between pre- and post-session values.

4. Discussion

The results of the study highlight the severe drowsiness or even sleep onset that can be induced by partially autonomous driving. It also identified a non-linearity between drowsiness states and some postural and physiological indicators, with a tipping point at slight drowsiness. Finally, this study finds evidence of the relevance of postural indicators for the detection of drowsiness at the wheel.

Partially automated driving is a paradigm in which the driving task is operated by the car but drivers still have to monitor and supervise the driving environment (SAE International, 2016). This particularly applies to level-2 automation, where drivers are not allowed to engage in NDRTs (SAE International, 2016). In this mode, therefore, drivers must continuously check how well the vehicle is monitoring the environment and managing the driving task, to ensure that they detect any potential failure or take-over request. Driver drowsiness is more common under partial automation than in manual driving, especially when drivers are not engaged in

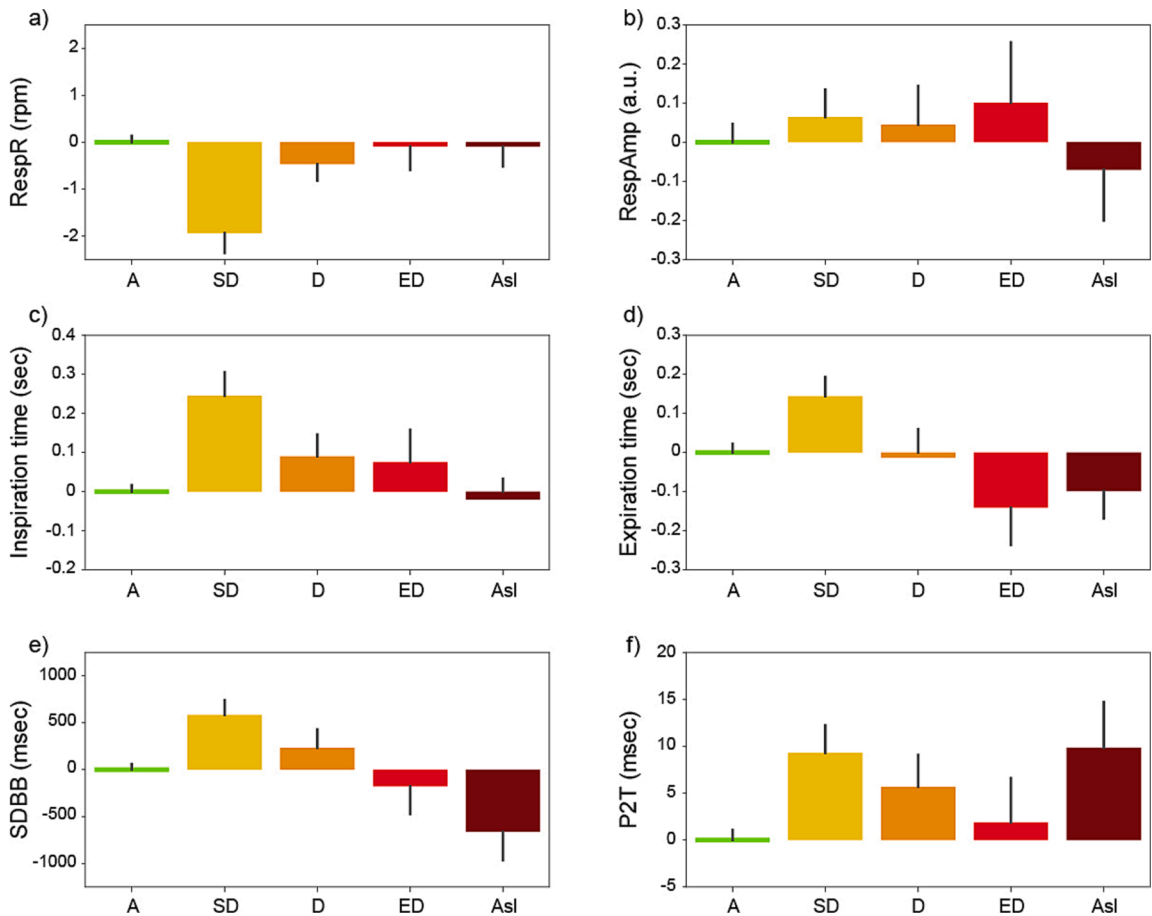


Fig. 6. Bar plots representing respiratory features and RSA (mean \pm SEM, $n = 22$) for each state of drowsiness: RespR (a), RespAmp (b), inspiration (c) and expiration (d) time, SDBB (e) and P2T (f).

NDRTs (Schömig et al., 2015; Vogelpohl et al., 2019) or in monotonous environments, due to the absence of external stimuli. The literature reports that signs of drowsiness can be detected in some drivers as early as fifteen minutes into autonomous driving (Feldhütter et al., 2019; Vogelpohl et al., 2019). In our study, drowsiness reaches its peak after 25 to 45 min, which is consistent with previously cited studies. After this period, the occurrence of deeper states of drowsiness (i.e., ED and Asl) naturally decreases without modification of the environment.

To the best of our knowledge, this study is the first to use both physiological and postural indicators to characterize the full spectrum of drowsiness at the wheel (from fully alert to asleep) during partially automated driving. The states of drowsiness experienced by the drivers were here associated with different physiological and postural features. This suggests that including these new features could improve the performance of the DMS in detecting drowsiness at the wheel.

4.1. Combining postural and physiological assessment of drivers in partially automated vehicles

The results from the oculomotor indicators are consistent with studies reporting an increase in blink duration and frequency with increasing drowsiness. In contrast, the Asl state is associated with a lower blink frequency and a longer blink duration, indicating that the eye was closed for a long time and the drivers can be considered as asleep. These results can confirm those obtained using the PERCLOS70, considered as a reference measurement for the classification of drowsiness state. Thus, due to the desire to focus on the contribution of physiological and postural measures, these results are not discussed further in the article.

Many studies have used physiological indicators to characterize drowsiness at the wheel during manual driving (e.g., Buendia et al., 2019; Kiashari et al., 2018; Persson et al., 2021). However, the use of postural indicators is less common (e.g., Gwak et al., 2020; Murata et al., 2018; Sunagawa et al., 2020). These previous studies tend to show a linear trend between the spectrum of subjective drowsiness (obtained by KSS scores or Observer Rating of Drowsiness: ORD) and variation in physiological and postural indicators. In contrast, most of the present results were distributed along U-shape or inverted U-shape curves, with the SD state as a tipping point. These differences could be explained either by the scale used to classify the different states (i.e., subjective vs. objective) or by the driving paradigm (i.e., manual vs partially automated). The use of partially automated driving, where the driving task is performed by

Table 5

Values of postural features (mean \pm SEM, $n = 22$) for each state of drowsiness. Values in bold show a significant difference compared to Alert. Significant differences are represented by * ($p < 0.05$), ** ($p < 0.01$), and *** ($p < 0.001$) and Effect Size (ES) was indicated by the Cohen's d coefficient.

| | A | SD | D | ED | Asl |
|---------------------------|------------------|--|---|--|--|
| y-COP _{seat} | 0.00 \pm 0.49 | 4.48 \pm 0.99*** (ES = 0.4) | 7.98 \pm 1.61*** (ES = 0.7) | 8.85 \pm 1.69*** (ES = 0.8) | 9.30 \pm 1.99*** (ES = 0.8) |
| CS _{postero} | 0.00 \pm 1.26 | -4.69 \pm 2.37 | -11.91 \pm 4.78* (ES = 0.4) | -11.07 \pm 5.27 | -11.87 \pm 5.32 |
| CS _{antero} | 0.00 \pm 3.08 | 11.59 \pm 7.39 | 32.91 \pm 11.35*** (ES = 0.4) | 47.0 \pm 10.17*** (ES = 0.7) | 54.54 \pm 14.75*** (ES = 0.8) |
| CP _{postero} | 0.00 \pm 48.80 | -583.61 \pm 93.92*** (ES = 0.5) | -772.2 \pm 162.46*** (ES = 0.7) | -908.74 \pm 203.18*** (ES = 0.8) | -1109.67 \pm 225.72*** (ES = 1.0) |
| CP _{antero} | 0.00 \pm 79.91 | 150.66 \pm 162.77 | 1214.55 \pm 284.47*** (ES = 0.6) | 1267.61 \pm 264.85*** (ES = 0.7) | 1379.74 \pm 345.16*** (ES = 0.7) |
| y-COP _{backrest} | 0.00 \pm 1.36 | 3.08 \pm 2.16 | 8.10 \pm 3.73 | 27.19 \pm 4.93*** (ES = 0.8) | 39.59 \pm 5.29*** (ES = 1.3) |
| CS _{up} | 0.00 \pm 4.00 | -1.82 \pm 7.08 | 8.61 \pm 13.36 | 43.15 \pm 15.84 | 73.76 \pm 18.27 |
| CS _{down} | 0.00 \pm 3.57 | -27.71 \pm 5.03** (ES = 0.4) | -36.47 \pm 8.55** (ES = 0.5) | -72.41 \pm 11.48*** (ES = 0.9) | -89.96 \pm 14.81*** (ES = 1.1) |
| CP _{up} | 0.00 \pm 53.66 | -113.12 \pm 98.12 | 113.65 \pm 176.22 | 637.77 \pm 208.2** (ES = 0.5) | 1131.92 \pm 217.66*** (ES = 0.9) |
| CP _{down} | 0.00 \pm 52.44 | -494.64 \pm 79.23*** (ES = 0.4) | -785.76 \pm 165.35*** (ES = 0.6) | -1306.53 \pm 211.03*** (ES = 1.0) | -1409.98 \pm 215.81*** (ES = 1.2) |
| CS _{head} | 0.00 \pm 0.14 | 0.57 \pm 0.25 | 1.29 \pm 0.40* (ES = 0.4) | 2.67 \pm 0.62*** (ES = 0.8) | 4.51 \pm 0.60*** (ES = 1.4) |
| CP _{head} | 0.00 \pm 2.28 | 6.18 \pm 3.51 | 18.55 \pm 6.36 | 33.63 \pm 9.44*** (ES = 0.6) | 58.52 \pm 10.56*** (ES = 1.1) |
| pHead | 0.00 \pm 0.01 | 0.03 \pm 0.02 | 0.07 \pm 0.03 | 0.18 \pm 0.04*** (ES = 0.8) | 0.31 \pm 0.05*** (ES = 1.5) |
| MOV _{seat} | 0.00 \pm 0.13 | 2.07 \pm 0.25*** (ES = 0.7) | 2.32 \pm 0.51*** (ES = 0.7) | 0.42 \pm 0.39 | -1.00 \pm 0.51 |
| MOV _{backrest} | 0.00 \pm 0.17 | 3.51 \pm 0.37*** (ES = 0.9) | 2.97 \pm 0.60*** (ES = 0.7) | 0.39 \pm 0.53 | -2.99 \pm 0.52*** (ES = 0.8) |

Table X: Values of postural features (mean \pm SEM, $n = 22$) for each different states of drowsiness. Values in bold show a significant difference compared to the alert condition. Significant differences are represented by * ($p < 0.05$), ** ($p < 0.01$), and *** ($p < 0.001$).

the car, requires better driver resistance to drowsiness and boredom than in manual mode, and might lead to these differences in the early stages of drowsiness. Moreover, during partially automated driving, the driver can reach higher levels of drowsiness (or even sleep) without immediately causing accidents than during manual driving. To further explore the difference between behaviors in manual and partially automated driving, the following section will look at two of the states from our classification: slightly drowsy and asleep.

4.2 Struggling to stay awake: a stressful situation?

The instructions given to the drivers required them to monitor the environment and stay alert in all circumstances. Thus, they had to fight against boredom and try not to fall asleep. Being involved in sustained attention and vigilance tasks while exposed to boredom and monotony can be considered stressful (Scerbo, 1998; Warm et al., 1996, 2008). Although stress during monotonous driving has not been widely assessed (see Antoun et al., 2017, for a review), some authors showed that manual monotonous driving is associated with markers of stress such as increased blood pressure (Yamakoshi et al., 2009). In their model, Vicente et al., (2016) suggested that stressful situations are characterized by high LF and low HF values. In line with this hypothesis, our results indicate that SD is associated with higher HR and LFN, as well as lower HFN (see Fig. 5). These findings suggest that the SD state is associated with deactivation of the PNS in favor of activation of the SNS, leading to an increase in HR. Consequently, these results support the idea that resistance to drowsiness may constitute a stressful situation, even during partially automated driving.

Respiratory features also differed between A and SD states, with for instance a decrease in respiratory rate and an increase in respiratory rate variability (SDBB) as well as in inspiration and expiration times. Breathing appeared to be slower without any modification of its amplitude. These results are consistent with previous studies indicating that the early stages of drowsiness at the wheel are associated with a decrease in respiratory rate (Igasaki et al., 2016; Kiashari et al., 2018, 2020) and an increase in respiratory rate variability (Kiashari et al., 2018; Sunagawa et al., 2020). However, stressful situations are mainly associated with an increase in minute ventilation (Grossman, 1983; Tipton et al., 2017), which can be induced either by an increase in respiratory rate or by an increase in amplitude (Tipton et al., 2017), contrary to our findings here. One explanation could be potential misdetection of respiratory amplitude by the chest belt. Respiration is driven by both thoracic and abdominal respiration, and our device fixed to the chest alone may fail to detect respiratory movements from the abdominal area. Furthermore, while abdominal respiration, considered to require less effort than thoracic, is predominant in relaxed situations, this tends to be reversed with sleep onset (Timmons et al., 1972). However, there is insufficient knowledge about the respiratory system's reaction to boredom and a monotonous environment, and

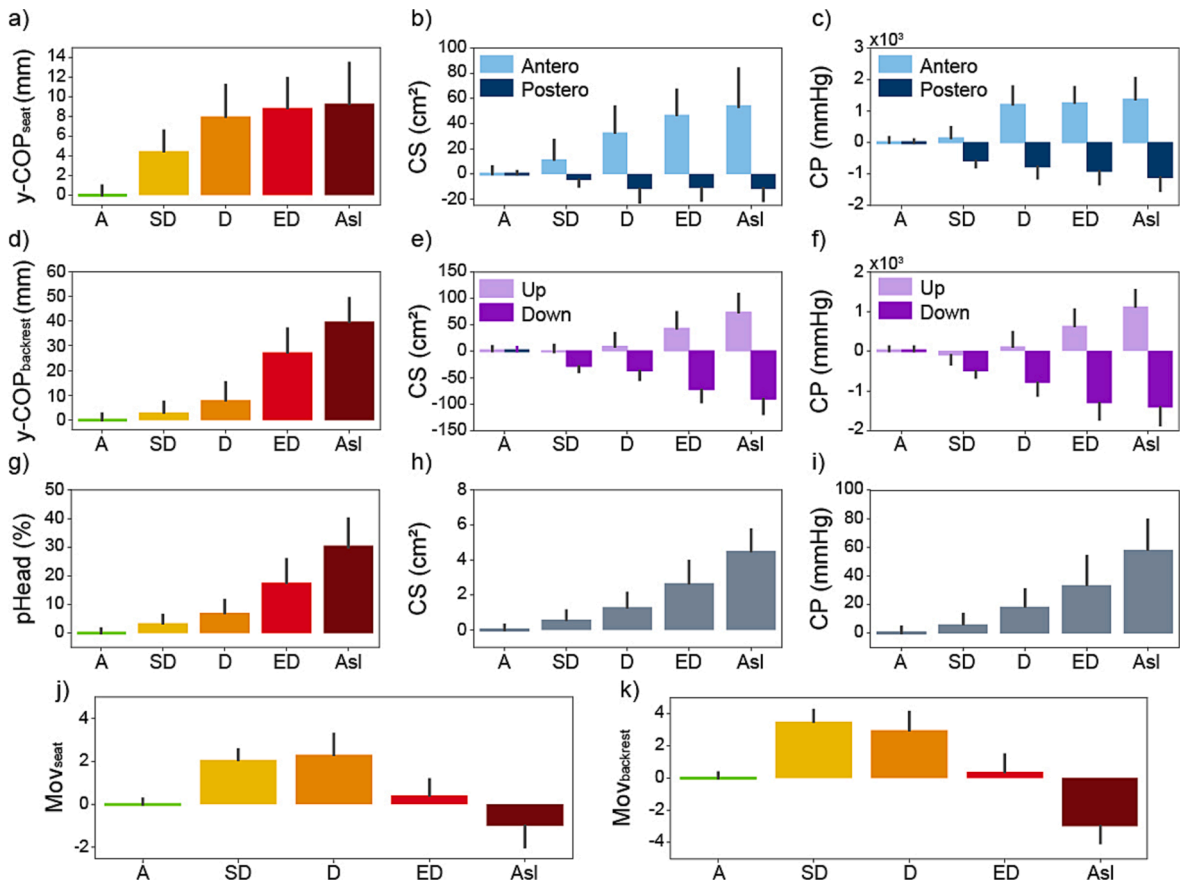


Fig. 7. Bar plots representing postural features (mean ± SEM, n = 22) for each state of drowsiness: y-coordinate of the COP for the seat (a) and the backrest (d). Percentage of headrest use is represented in (g). CS and CP over the zones are represented in (b) and (c) for the seat zones; in (e) and (f) for the backrest; and in (h) and (i) for the headrest. Movements on the seat and the backrest are represented in (j) and (k) respectively.

further investigations will be necessary.

The approach taken here used both heart rate and respiratory measurements, exploring not only each of these parameters, but also the interaction between them, usually referred to as cardiorespiratory mechanisms. The complex cardiorespiratory system interactions are illustrated by respiratory sinus arrhythmia (RSA), linked to the tonic and phasic activities of the vagus nerve (Grossman & Taylor, 2007). RSA can be explored using indicators such as HF band or peak to trough (P2T) (Grossman et al., 1990; Lewis et al., 2012). P2T represents the difference between the HRmax and the Hrmin for each respiratory cycle. A longer inspiration increases the time of inhibition of the vagus nerve, which leads to higher instantaneous HR, and vice versa for the expiration phase. Decreased RespR would lead to greater fluctuation between the HRmax and the Hrmin for each respiratory cycle, without affecting the average HR value. The two indicators are generally correlated (Grossman et al., 1990; Lewis et al., 2012), but surprisingly, our results show some divergence between them, with HFn decreasing while P2T increases (see Fig. 6). This result is consistent with the fact that P2T is more sensitive to the respiratory rate and negatively correlated to it than HF (Lewis et al., 2012). Thus, it can be assumed here that vagal tone is lower but the modulation driven by the respiratory system is greater (represented by an increase in P2T value). Both these cardiorespiratory indicators seem to be particularly relevant for the identification of slightly drowsy states. The modulation of the heart rate is known to depend on many factors (blood pressure, concentration of gas in the blood, breathing, etc.). A better understanding of the interaction of these systems during such tasks could lead to optimizing the use of these indicators to detect early states of drowsiness.

Finally, in these slightly drowsy states, drivers also move around more on the seat and the backrest. First of all, under partial automation, the driver is freer to move on the seat without impacting the driving task. Moreover, body movements are considered an early sign of drowsiness and fatigue (Anund et al., 2008; Rogé et al., 2001), being used by some drivers to counter drowsiness at the wheel (Anund et al., 2008; Rogé et al., 2001; Watling et al., 2015) in manual driving. The same strategy could apply here, with drivers moving on the seat to reactivate and remobilize themselves. Since the posture on the seat remains very similar to A state, these movements could be considered as repositioning movements (RM). Previous studies indicated that a static seat position for a prolonged period is generally associated with discomfort and neuromuscular fatigue (Lantoiné et al., 2022; Lecocq et al., 2020, 2022). Consequently, RMs could be a way to dynamically reduce the discomfort associated with the static position. This increased activity on the seat may also contribute to the increase in HR.

Overall, it can be hypothesized that during driving under level-2 automation, the need to monitor the environment without the possibility of engaging in other NDRTs or even of relaxing induces stress for drivers (see Scerbo, 1998 for a review). Further investigation will be required before comparing this situation to more classical stressful situations.

4.3 Asleep at the wheel: a new paradigm

Using level-2 automation enabled us to consider deeper sleep as well as the early stages of sleep. In fact, if participants spent half of the analysis time window with their eyes closed, they were assumed to be asleep for that time. The physiological results for drivers in *AsI* show a significantly lower value for HR and LFn and a higher value for HFn. While RespR and RespAmp did not differ from the alert state, respiratory rate variability (SDBB) was lower (see fig x). During manual driving, deeper states of drowsiness (which obviously do not correspond to our asleep state) are generally associated with a decrease not only in HR (Buendia et al., 2019; Persson et al., 2021) but also in RespR (Igasaki et al., 2016; Kiashari et al., 2018, 2020). At the same time, results obtained from HRV, particularly from frequency features, are more divergent (see Lu et al., 2022 for a review). Although our physiological results are not entirely consistent with those obtained for the deeper states of drowsiness during manual driving, they are consistent with those reported for the first stages of sleep (i.e., N1 and N2) in a study using highly automated driving (Wörle et al., 2019). This supports our assumption that the drivers were asleep during this period.

Regarding postural features, *AsI* was also associated with a shift in the center of pressure in the anterior zone of the seat and in the upper zone of the backrest. Moreover, the time spent using the headrest was significantly longer than in other states. Although the inclination of the backrest was fixed in our experiment, these postural changes indicated an inclination of the back compared to more alert states. Back inclination could be used to reduce the spinal load from a more upright sitting position (Wilke et al., 1999; Wilke et al., 2001). However, during manual driving, this position requires increased neck muscle activity to keep the head upright and the hands on the steering wheel (Michida et al., 2001). In the case of automation, since the driving task is performed by the car, the driver is not constrained in her/his position and might use the headrest as a strategy to reduce this neck muscle activity. Moreover, falling asleep at the wheel is associated with involuntary head movements, so the driver could therefore be using the headrest to provide an additional point of contact with the seat and increase postural stability. While the present study did not seek to determine a causal relationship between development of drowsiness at the wheel and driver posture, spending considerable time leaning back likely promotes the onset of drowsiness.

During manual driving, falling asleep at the wheel has serious and immediate consequences that make it impossible to characterize this state. In contrast, during autonomous driving, the driver can fall asleep without physical consequences. However, falling asleep is still not allowed in levels 2 and 3, and must be detected by the DMS to wake the driver. Our results suggest that postural and physiological indicators could be used jointly for efficient detection.

4.4 Body posture: a new indicator for driver monitoring systems?

As mentioned in the introduction, vehicle-based measures are useless in automatic conditions, while facial parameters may become ineffective indicators of drowsiness since the driver may not be facing the monitoring camera. Thus, other features need to be considered. Although HRV is one of the most commonly used physiological features during manual driving, Persson et al., (2021) pointed out that it is not sufficient to accurately detect drowsiness at the wheel, especially for intermediate states. In addition, the usefulness of cardiac features is affected by interindividual variability, leading to poor classifier accuracy for new participants (Jacobé de Naurois et al., 2018; Persson et al., 2021). Intraindividual variability is also an issue, as HRV can be modulated by many situations and cognitive states. During manual driving, postural information has shown its potential to contribute to the detection of driver drowsiness (Gwak et al., 2020; Murata et al., 2018; Sunagawa et al., 2020). This also appears to apply to partially automated driving, since our results show that drowsy states were characterized by postural and physiological manifestations. However, since most of the indicators considered (postural and physiological) do not show a linear trend, it seems that these states cannot be specifically characterized based on a single parameter. Thus, combining postural and physiological features might provide better detection of driver drowsiness, even early on, without the need for ocular and vehicle data. In addition, it can be assumed that a better understanding of driver behavior and its impact on posture is required to correctly detect drowsiness at the wheel. Once again, there is a need for further research to explore this potential using AI algorithms.

The literature on autonomous driving is increasingly interested in the issue of resting and sleeping behind the wheel (Caballero-Bruno et al., 2022). While sleeping is not allowed in partially automated driving, an increase in backrest angle was reported as a preferred position for sleeping and relaxing (71 % and 29 %, respectively; Yang et al., 2019). However, a reclining position was shown to be associated with increased occurrence of drowsiness episodes (Nicholson & Stone, 1987). The driver's posture could therefore signal driver drowsiness.

Furthermore, postural information could be used to detect other degraded driving states, such as driver distraction. For example, Zhao et al., (2021) used sensor mats to detect drivers' engagement in several NDRTs. Driver posture could therefore provide information on the psychophysiological state of the driver in autonomous mode that could enhance the DMS.

4.5. Limitations of the study

A main limitation of this study lies in comparing results obtained using an objective scale with those obtained using a subjective scale. Our aim here was to explore the full spectrum of drowsiness (even being asleep), but using KSS meant that the driver had to

interact with the experimenters or with a human–machine interface to assess their level of drowsiness. This interaction could have kept drivers alert and prevented them from falling asleep at the wheel. It has been reported that subjective ratings generally increase with time-on-task in both manual and partially autonomous driving (Ahlström et al., 2021). This effect of time-on-task on subjective ratings was also observed in our study, with a higher KSS drowsiness score post-session than pre-session. However, at the end of the driving task, almost all drivers were classified as alert according to PERCLOS70, suggesting a mismatch between objective and subjective classifications. This is confirmed by the PVT-B results, which show no difference between pre- and post-session measurements. In addition, Murata et al., (2022) showed that PERCLOS70 is associated with high heterogeneity for the same KSS score. Other scales could have been used, such as the ORD proposed by Wierwille & Ellsworth (1994). However, the ORD was designed for manual driving and does not include sleeping at the wheel. Furthermore, the fact that this scale is highly correlated with PERCLOS (Wierwille & Ellsworth, 1994) suggests that results obtained using it would be consistent with those from the present study.

In addition, as our drivers were not exposed to real driving conditions, the absence of real risk could arguably have prevented them from struggling to stay awake, which would not be representative of an ecological state. However, only 36 % of them actually reached the asleep state, suggesting that our drivers were struggling against drowsiness. It can therefore be considered that the study design was able to induce and characterize the targeted states.

Finally, this study was conducted in a static simulator, resulting in low road noises and vibrations, no lateral nor longitudinal accelerations which may affect driver's behavior and particularly postural features in real driving conditions. Real road driving studies are needed to investigate further the relevance of postural features to assess the dynamics of drowsiness.

5. Conclusion

During partially autonomous driving, drivers are free to engage in NDRTs, suggesting that currently used indicators may be partially irrelevant for detecting drowsiness. This study provides a postural and physiological characterization of drivers under level-2 partially autonomous driving during a monotonous drive. Our findings suggest that postural information used in combination with other indicators (i.e., physiological or facial information if available) could help to detect drowsiness at the wheel. The use of postural indicators in machine learning algorithms should be evaluated to confirm that a combination of postural and physiological indicators indeed better reveals drowsiness than physiological indicators alone. Moreover, this study illustrates the value of applying level-2 automation to characterize the whole spectrum of drowsiness, from resisting drowsiness to sleeping at the wheel. In these automated modes, the fact that drivers can actually fall asleep at the wheel suggests that conventional drowsiness scales need to be redefined. To validate the results presented here, further studies should be conducted, especially under real road conditions.

Funding

This study was funded by a PhD grant from Stellantis group via the OpenLab “Automotive Motion Lab” agreement between Stellantis, Aix-Marseille University and CNRS.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgments

We are grateful to Stéphane Espié for providing us with the two textile pressure sensor mats from XSENSOR® Technology. We thank Marjorie Sweetko for editing and improving the English of the manuscript.

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