From Physiology to Car-Following: Analysis and Prediction Across Driver Fatigue States

YANG LIU, The Hong Kong University of Science and Technology (Guangzhou), China
FEIQI GU, The Hong Kong University of Science and Technology (Guangzhou), China
DENGBO HE*, The Hong Kong University of Science and Technology (Guangzhou), China

Although extensive research has been conducted on driver fatigue detection, few studies have explored how fatigue affects drivers' car-following behaviors and, in turn, how to detect fatigue based on car-following features. In an on-road experiment, we collected multimodal physiological data and eye-tracking data from 5 long-haul truck drivers, along with vehicle motion and surrounding traffic data. Drivers' fatigue states were labeled based on the percentage of eyelid closure over the pupil (PERCLOS). Comparative analyses of car-following behavioral parameters and physiological indicators under different fatigue states were performed. Furthermore, we explored the feasibility of estimating drivers' fatigue levels using car-following behavioral parameters and compared its performance with models based on physiological features. The results show that the models based on car-following features showed better performance than models based on physiological indicators in this preliminary endeavor. These findings provide theoretical evidence for the feasibility of detecting surrounding human-driven vehicles' fatigue states based on their driving characteristics using lightweight, interpretable, and practically deployable models.

CCS Concepts: • **Human-centered computing** → **Empirical studies in HCI**; *Field studies*; • **Applied computing** → *Transportation*; • **Computing methodologies** → *Machine learning*.

Additional Key Words and Phrases: Driver fatigue, Car-following behavior, On-road experiment, Physiological behavior, Fatigue prediction

ACM Reference Format:
Yang Liu, Feiqi Gu, and Dengbo He. 2026. From Physiology to Car-Following: Analysis and Prediction Across Driver Fatigue States. In *18th International Conference on Automotive User Interfaces and Interactive Vehicular Applications (AutomotiveUI Adjunct '26), September 20–23, 2026, Gothenburg, Sweden.* ACM, New York, NY, USA, 9 pages. https://doi.org/10.1145/3828158.3838253

1 Introduction

Driver fatigue can impair traffic safety [3], leading to slower reaction times, reduced vigilance, and an increased risk of traffic collisions [28]. This negative effect can be exacerbated in relatively monotonous scenarios [27], such as car-following. This is especially alarming given that car-following is one of the most common scenarios on the road. However, existing studies have largely treated fatigue detection and car-following behavior analysis as separate topics, with relatively limited attention to how fatigue influences car-following behavior in real-world driving scenarios. In particular, datasets containing synchronized fatigue state labels and car-following behavioral data remain scarce.

*Corresponding author.

Authors' Contact Information: Yang Liu, The Hong Kong University of Science and Technology (Guangzhou), Guangzhou, China, yliu068@connect.hkust-gz.edu.cn; Feiqi Gu, The Hong Kong University of Science and Technology (Guangzhou), Guangzhou, China, fgu519@connect.hkust-gz.edu.cn; Dengbo He, The Hong Kong University of Science and Technology (Guangzhou), Guangzhou, China, dengbohe@hkust-gz.edu.cn.



This work is licensed under a Creative Commons Attribution 4.0 International License.
© 2026 Copyright held by the owner/author(s).
Manuscript submitted to ACM

At the same time, fatigue was reported to be especially prevalent among commercial drivers [19], such as long-haul truck drivers, who needed to drive an extended period each day, often following lead vehicles on highways. However, existing studies on long-haul truck drivers' fatigue car-following behaviors are even rarer. Existing studies mostly focused on general fatigue-related crash outcomes [7] and were mostly based on simulator or field studies [28], without dedicated attention to car-following behaviors.

Constructing the linkage between fatigue and car-following behaviors has practical value. Although physiological signal-based fatigue monitoring methods have a strong theoretical foundation, they still face practical limitations in real-world applications, such as the inconvenience of wearing physiological devices and the susceptibility to data acquisition and transmission interference [23]. Thus, if a stable relationship between car-following behavioral parameters, such as mean time headway, and driver fatigue can be identified, car-following-behavior-based fatigue monitoring models can be built, offering a more non-intrusive and practical technical pathway for monitoring drivers' fatigue state.

Thus, we conducted an on-road study using an intelligent JAC K7 heavy-duty truck, enabling the acquisition of vehicle operation data and motion states of surrounding vehicles. At the same time, drivers in the study were equipped with physiological monitoring equipment throughout the experiment to continuously record their multimodal physiological signals, including electrocardiogram (ECG), electrodermal activity (EDA), and respiration (RESP). Their visual data were also collected using Smarteyes. Based on these synchronized measurements, an on-road multimodal joint dataset integrating fatigue states, physiological responses, and road-environment information was constructed.

Car-following segments were extracted from this on-road multimodal joint dataset, with percentage of eyelid closure over the pupil over time (PERCLOS) adopted as the criterion for labeling driver fatigue state [4]. The car-following samples were then categorized into two conditions: fatigued and non-fatigued. On this basis, difference analysis and significance testing were conducted on both car-following behavioral parameters and physiological parameters to systematically investigate the effects of fatigue-state changes on driving behavior regulation and physiological response characteristics. Finally, machine learning (ML) models were built on different combinations of car-following behavior and physiological features to identify drivers' fatigue states.

2 Literature Review

Fatigue driving can threaten traffic safety, and existing studies have widely investigated driver fatigue identification from the perspective of physiological signals. A substantial body of work has focused on ECG signals, where heart rate (HR) and Root Mean Square of Successive Differences (RMSSD) were commonly used to characterize changes in autonomic nervous system activity during fatigue [22, 25]. In addition, some studies have extracted EDA features, such as skin conductance level (SCL) and skin conductance response (SCR), to reflect variations in driver fatigue level [10, 21]. Note that although SCR-related indices are valuable for fatigue or arousal analysis, they generally require relatively long data windows to ensure stable event detection and statistical estimation [11]. In the car-following tasks, however, the effective continuous duration available for analysis is often insufficient for this purpose. Therefore, SCR-related parameters were not included in the subsequent analysis in this study. Finally, some studies have also investigated how RESP features, including respiration rate (RESPrate) and respiration amplitude (RESPamp) [13], are associated with fatigue.

However, to date, only a limited number of studies have examined car-following behavior characteristics under fatigue conditions. For example, Zhang et al. analyzed field-driving data to investigate the effects of fatigue on drivers' car-following behavior and reported significant differences in time headway (THW) across fatigue levels [31]. Mahajan and Velaga further explored car-following behavior with sleep deprivation in a driving simulator and showed that fatigued

driving is associated with higher rear-end crash risk [18]. Similarly, Anund et al. found in a sleep-deprivation experiment that insufficient sleep can increase driver sleepiness and impair responsiveness to traffic events [2]. Nevertheless, most existing studies remained at the level of correlation or group-difference analysis, without further evaluating whether these behavioral differences can be used for fatigue prediction. Instead, existing driver fatigue detection algorithms were mostly based on physiological signals, as summarized in Table 1, and fatigue prediction using car-following behavioral parameters remains largely unexplored.

Table 1. Typical driver fatigue prediction studies based on physiological signals.

Signal	Input parameters	Models	Classification	Performance
ECG	HR; RMSSD	SVM	Binary	56.3% [25]
		GBT	Binary	66.3% [25]
		RF	Three-class	44.5% [22]
EDA	Skin conductance	XGBoost	Binary	48%–50% [10]
	Skin temperature	AUC	Binary	50%–55% [21]
RESP	Rate; amplitude	XGBoost	Binary	64%–70% [10]
		TEDD	Binary	75% [13]

Abbreviations: SVM = Support Vector Machine; GBT = Gradient Boosting Tree; RF = Random Forest; XGBoost = eXtreme Gradient Boosting; AUC = Area Under the Receiver Operating Characteristic Curve; TEDD = Thoracic Effort Drowsiness Detection. The studies included in this table were all based on across-subjects data partition.

3 Method and Data Acquisition

3.1 Participants

Five male professional long-haul heavy-duty truck drivers (mean age = 42.6 years, SD = 3.9; range: 37–47 years) participated in this study, all of whom held valid commercial freight licenses and voluntarily completed both outbound and return experimental trips. To reduce potential confounding effects, drivers with health conditions or treatments that could substantially affect autonomic measures were excluded. The study was conducted through a university–industry partnership, with data use, analysis permissions, and privacy protection regulated by a formal agreement. All drivers were informed of the study procedures before the experiment and provided written informed consent.

3.2 Route and Driving Context

The route is illustrated in Fig. 1, The average one-way distance was approximately 830 km, with a mean driving duration of 10.7 h. The itinerary primarily consisted of expressway/motorway sections typical of long-haul freight operations. In accordance with local regulations, drivers were required to take a 15-min rest break at service areas approximately every four hours of continuous driving.

3.3 Data Acquisition

During the experiment, data on the vehicle's motion state, the surrounding traffic environment perception, and the driver's physiological signals were simultaneously collected.

3.3.1 Traffic Data. The experimental platform was a JAC K7 heavy-duty truck tractor equipped with the PlusAI pilot-assisted driving system (which provided only data collection function and the automation was not engaged) and fitted with a standard cargo container as shown in Figs. 2a and 2b. The vehicle was instrumented with an onboard perception suite, including cameras and LiDAR sensors, to capture information about the surrounding traffic environment.

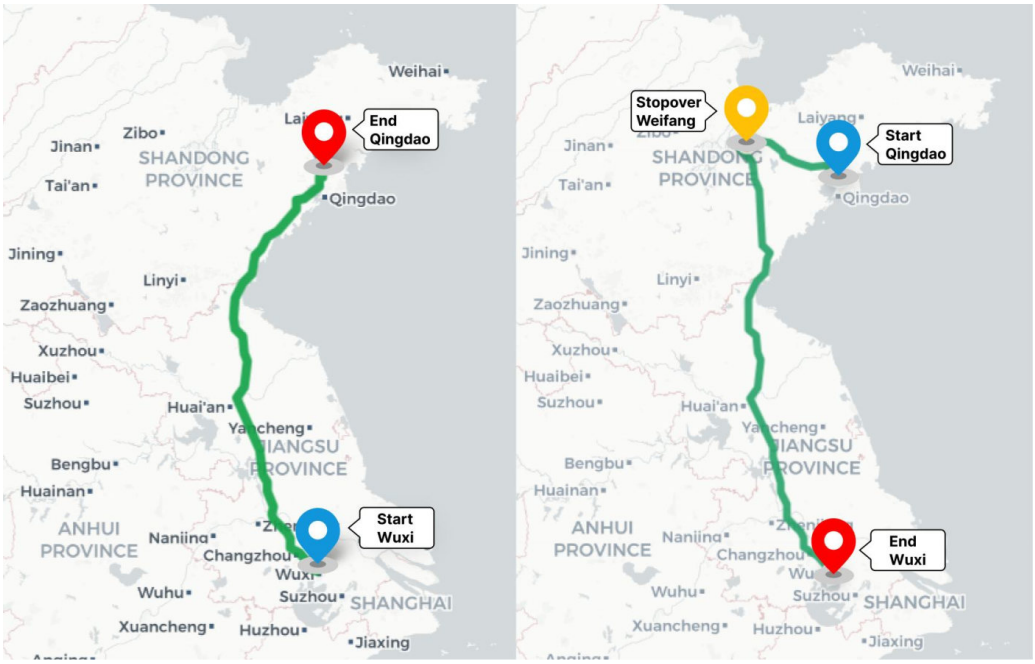
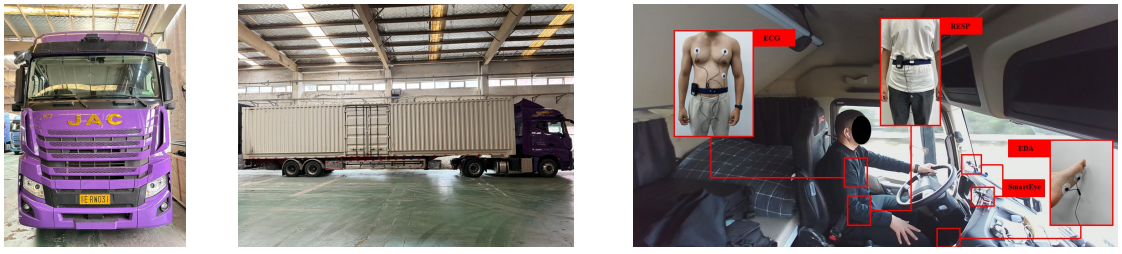


Fig. 1. Driving route overview.

3.3.2 Physiological Data. In this study, ECG, EDA, and RESP signals were acquired using a PhysioLabs physiological sensing suite in conjunction with the Human Research Tool software. Drivers' eye-movement data were captured using a SmartEye system. During each experimental session, a trained researcher remained seated in the front passenger seat to continuously monitor the acquisition process and to ensure stable signal quality under real-world on-road driving conditions. All physiological signals were sampled at 200 Hz. Fig. 2c illustrates the sensor placement configuration and the installation position of the Smart Eye system during the experiment.



(a) Front view. (b) Side view with a standard cargo container. (c) Multimodal physiological sensor setup.

Fig. 2. Experimental vehicle and physiological sensor setup.

4 Data Cleaning

4.1 Car-following Definition

Car-following segments were extracted using criteria reported in prior studies. The specific car-following segment extraction criteria are shown below:

- The lead vehicle and the ego-vehicle need to be on the same road throughout the data extraction period to ensure a continuous CF segment [30].
- The lead vehicle is within 130 m of the ego-vehicle to ensure that the behavior of the ego-vehicle can be affected by the lead vehicle [24].
- The duration of each car-following segment should be over 30 s to ensure the reliability of the car-following data and the validity of PERCLOS-based fatigue labeling[29].
- In addition, car-following segments with ego-vehicle speeds lower than 20 m/s were excluded to avoid non-highway driving conditions [26].

4.2 Eye-closure-based Fatigue Labeling

In this study, eyelid-closure data collected by the Smart Eye eye-tracking system were used to define driver fatigue states. Following previous studies, an eye-opening level below 30% was regarded as eye closure, and PERCLOS was calculated as the proportion of eye-closure time within a fixed temporal window [16]. According to Grace and Steward, PERCLOS values below 0.08 indicate a non-fatigued state, values between 0.08 and 0.14 indicate a moderately fatigued state, and values above 0.14 indicate a fatigued state [12]. Similar threshold-based strategies have also been adopted in field evaluations of driver fatigue warning systems [4].

Considering the limited number of car-following segments under moderately fatigued and fatigued conditions, a binary classification scheme was adopted in our study to reduce class imbalance and improve statistical robustness. Specifically, PERCLOS was calculated using a 30-s window, and driving states were classified as fatigued or non-fatigued. The final dataset included 5 drivers, with 175 non-fatigued car-following segments and 77 fatigued segments.

4.3 Data Filtering

Raw vehicle and physiological signals were filtered before feature extraction to reduce noise, abnormal fluctuations, and signal artifacts. The preprocessing methods are summarized in Table 2.

Table 2. Summary of data preprocessing and filtering methods.

Data type	Signals / parameters	Processing method	Key settings / refs.
Vehicle data	Ego- and lead-vehicle speeds	Vehicle-speed trend filtering	$-8 \le a(k) \le 5$ [32]
ECG	HR; RMSSD	De-meaning/detrending; zero-phase fourth-order high-pass Butterworth filter	HP = 0.5 Hz; order = 4 [6, 15]
EDA	SCL	Median filter; zero-phase fourth-order low-pass Butterworth filter	Median window = 0.25 s; LP = 5 Hz; order = 4 [20]
RESP	Respiration rate and amplitude	Hampel filter	Window = 0.30 s; threshold = 3× MAD [17]

Abbreviations: ECG = Electrocardiogram; HR = Heart Rate; RMSSD = Root Mean Square of Successive Differences; EDA = Electrodermal Activity; SCL = Skin Conductance Level; RESP = Respiration; HP = High-Pass; LP = Low-Pass; MAD = Median Absolute Deviation.

4.4 Physiological Features and Normalization

Physiological signals show substantial inter-individual variability due to differences in anatomy, health conditions, and autonomic regulation [5]. Therefore, directly using raw physiological features may introduce subject-specific bias in cross-subject analysis. To reduce this effect, baseline normalization was applied following prior studies. Specifically, a 5-minute segment recorded between 45 and 50 minutes after the start of the experiment was used as the individual baseline, when the vehicle had generally reached stable highway driving conditions. All physiological features were then normalized using ratio-based formulations to emphasize within-subject changes related to fatigue.

4.5 Machine Learning Models for Fatigue Detection

Finally, this study conducted a comparative evaluation using several commonly adopted machine learning models, including support vector machine (SVM) [8], k-nearest neighbors (KNN) [9], and long short-term memory (LSTM) [14] models, with a particular focus on the effectiveness of mean THW, RESPrate, and RESPamp for driver fatigue recognition. For model evaluation, a leave-one-driver-out (LODO) cross-validation strategy was adopted. In each round, data from one driver were used as the test set, while data from the remaining drivers were used for training, and this procedure was repeated until all drivers had been tested.

5 Results and Discussions

5.1 Statistical Analysis of Car-Following and Physiological Parameters

Table 3 reports the group-level comparison of car-following features between the fatigued and non-fatigued states using a linear mixed-effects model with a random intercept for driver, which accounts for between-driver baseline differences and repeated measurements within each driver. The pattern suggests that non-fatigued drivers may adopt a more conservative car-following strategy by maintaining longer headways.

Table 3. Comparison of car-following features between alert and non-alert states.

Feature	Alert	Non-alert	Statistics	p-value
meanEgoV	23.66 ± 1.83	23.33 ± 1.72	$F(1, 252.00) = 2.7668$	0.1
stdEgoV	0.57 ± 0.46	0.52 ± 0.51	$F(1, 252.00) = 0.9042$	0.3
stdSpacing	9.27 ± 7.49	8.98 ± 7.15	$F(1, 252.00) = 0.0558$	0.8
meanTHW	2.83 ± 1.15	3.38 ± 1.18	$F(1, 248.51) = 10.0140$	0.002^*
meanVrel	-0.44 ± 1.23	-0.42 ± 1.22	$F(1, 252.00) = 0.0052$	0.9
stdVrel	0.58 ± 0.41	0.50 ± 0.41	$F(1, 252.00) = 1.6383$	0.2

Abbreviations: meanEgoV = mean ego-vehicle speed; stdEgoV = standard deviation of ego-vehicle speed; stdSpacing = standard deviation of inter-vehicle spacing; meanTHW = mean time headway; meanVrel = mean relative speed; stdVrel = standard deviation of relative speed. $^*p < 0.05$.

The same significance-testing procedure was applied to the physiological parameters, and the results are summarized in Table 4. Among the included features, only RESPrate and RESPamp showed significant differences between fatigued and non-fatigued states. PERCLOS primarily reflects ocular manifestations of fatigue, such as eyelid closure, and is therefore an eye-behavior-based indicator of fatigue level. As a result, it may not be fully synchronized with the

autonomic nervous system changes reflected by ECG and EDA derived features [1]. In addition, HRV metrics such as RMSSD are sensitive to signal quality and window length, and their estimation stability may be limited within short time windows. For SCL, although normalization was applied in this study, it may still be affected by factors such as sensor contact, sweating conditions, and short-term environmental variations. In contrast, respiratory features can be extracted relatively stably within a 30-s window and may more directly reflect short-term reductions in fatigue levels.

Table 4. Comparison of normalized physiological features between alert and non-alert states.

Feature	Alert	Non-alert	Statistics	p-value
HR	1.07 ± 0.06	1.08 ± 0.07	$F(1, 247.70) = 2.9699$	0.08
RMSSD	1.31 ± 3.25	0.83 ± 0.93	$F(1, 249.17) = 0.4228$	0.5
SCL	2.56 ± 1.23	3.06 ± 1.35	$F(1, 211.45) = 0.7728$	0.4
RESPrate	1.20 ± 0.28	1.10 ± 0.21	$F(1, 218.37) = 8.5437$	0.004^*
RESPamp	1.18 ± 0.83	1.57 ± 1.01	$F(1, 223.00) = 12.0631$	$< 0.001^*$

Abbreviations: HR = heart rate; RMSSD = root mean square of successive differences; SCL = skin conductance level; RESPrate = respiration rate; RESPamp = respiration amplitude. $^*p < 0.05$.

5.2 Machine Learning Performance

As shown in Table 5, models built on meanTHW achieved a better performance across most evaluation metrics in our preliminary evaluation, indicating a potentially more stable and better generalizable capability for cross-driver fatigue recognition compared to models based on more intrusive physiological measures. This finding points to a new possibility: future autonomous vehicles may be able to detect the states of surrounding human-driven vehicles based on their motion features. Future research can explore fusing more car-following features to further improve model performance and explore more complex models to improve detection accuracy.

Table 5. LODO performance comparison across models using different features.

Metric	SVM				KNN				LSTM			
	meanTHW	RESPrate	RESPamp	Gap	meanTHW	RESPrate	RESPamp	Gap	meanTHW	RESPrate	RESPamp	Gap
Mean Acc	0.68	0.58	0.51	+0.10	0.65	0.55	0.52	+0.10	0.57	0.55	0.52	+0.02
Mean F1	0.54	0.49	0.42	+0.05	0.52	0.45	0.49	+0.07	0.51	0.46	0.41	+0.05
ROC-AUC	0.62	0.57	0.51	+0.05	0.54	0.58	0.57	-0.04	0.62	0.55	0.59	+0.03
PR-AUC	0.38	0.32	0.33	+0.05	0.34	0.24	0.35	-0.01	0.38	0.32	0.34	+0.04

Abbreviations: SVM = Support Vector Machine; KNN = K-Nearest Neighbors; LSTM = Long Short-Term Memory; ROC-AUC = Area Under the Receiver Operating Characteristic Curve; PR-AUC = Area Under the Precision–Recall Curve. *Gap* indicates the performance difference between the car-following feature and the best-performing physiological feature under the same model.

6 Summary

6.1 Limitations

Several limitations of this study should be noted. First, the number of drivers and car-following segments was limited. Future studies should collect data from more drivers and include more driving segments to improve the reliability

and generalizability of the findings. More potential influencing factors, such as traffic conditions, time of day, road conditions, and lead-vehicle behavior, should be considered when modeling the association between fatigue states and car-following behaviors. In addition, future studies should also consider using Electroencephalography as a more reliable ground truth of drivers' fatigue states.

6.2 Conclusions

This study conducted real-world on-road experiments with synchronous collection of vehicle driving data and driver physiological signals to examine differences in car-following behavior and physiological responses across fatigue states. Results show that fatigue significantly alters car-following regulation and yields stable differences in key behavioral and physiological measures. Based on these findings, we proposed a fatigue prediction approach using meanTHW as the input feature. Experimental results indicated that models based on car-following features outperformed physiology-based models on most evaluation metrics. Compared with physiological sensing approaches that relied on wearable devices, meanTHW is easier to obtain and more robust, providing a practical foundation for lightweight, interpretable, and readily deployable driver fatigue monitoring systems.

References

[1] Takashi Abe. 2023. PERCLOS-based technologies for detecting drowsiness: current evidence and future directions. *Sleep Advances* 4, 1 (2023), zpad006.

[2] Anna Anund, Göran Kecklund, Albert Kircher, Andreas Tapani, and Torbjörn Åkerstedt. 2009. The effects of driving situation on sleepiness indicators after sleep loss: a driving simulator study. *Industrial health* 47, 4 (2009), 393–401.

[3] Suzan Ayas, Dengbo He, and Birsen Donmez. 2025. Driver State Classification: Identifying High Cognitive Load and Drowsiness Through Driver Performance and Physiology. *IEEE Transactions on Intelligent Transportation Systems* (2025).

[4] Myra Blanco, Joseph L Bocanegra, Justin F Morgan, Gregory M Fitch, Alejandra Medina, Rebecca L Olson, Richard J Hanowski, Brian Daily, Richard P Zimmermann, Heidi D Howarth, et al. 2009. Assessment of a drowsy driver warning system for heavy-vehicle drivers. (2009).

[5] Karel A Brookhuis and Dick De Waard. 2010. Monitoring drivers' mental workload in driving simulators using physiological measures. *Accident Analysis & Prevention* 42, 3 (2010), 898–903.

[6] F Buendía-Fuentes, MA Arnau-Vives, Antonio Arnau-Vives, Yolanda Jiménez-Jiménez, J Rueda-Soriano, E Zorio-Grima, A Osa-Sáez, LV Martínez-Dolz, L Almenar-Bonet, and MA Palencia-Pérez. 2012. High-bandpass filters in electrocardiography: Source of error in the interpretation of the ST segment. *International Scholarly Research Notices* 2012, 1 (2012), 706217.

[7] Jennie Connor, Robyn Norton, Shanthi Ameratunga, Elizabeth Robinson, Ian Civil, Roger Dunn, John Bailey, and Rod Jackson. 2002. Driver sleepiness and risk of serious injury to car occupants: Population based case control study. *BMJ* 324, 7346 (2002), 1125. doi:10.1136/bmj.324.7346.1125

[8] Corinna Cortes and Vladimir Vapnik. 1995. Support-Vector Networks. *Machine Learning* 20, 3 (1995), 273–297. doi:10.1007/BF00994018

[9] Thomas Cover and Peter Hart. 1967. Nearest Neighbor Pattern Classification. *IEEE Transactions on Information Theory* 13, 1 (1967), 21–27. doi:10.1109/TIT.1967.1053964

[10] Kapotaksha Das, Salem Sharak, Kais Riani, Mohamed Abouelenien, Mihai Burzo, and Michalis Papakostas. 2021. Multimodal detection of drivers drowsiness and distraction. In *Proceedings of the 2021 international conference on multimodal interaction*. 416–424.

[11] Don C Fowles, Margaret J Christie, Robert Edelberg, William W Grings, David T Lykken, and Peter H Venables. 1981. Publication recommendations for electrodermal measurements. *Psychophysiology* 18, 3 (1981), 232–239.

[12] Richard Grace and Sonya Steward. 2001. Drowsy driver monitor and warning system. In *Driving Assessment Conference*, Vol. 1. University of Iowa.

[13] Federico Guede-Fernandez, Mireya Fernandez-Chimeno, Juan Ramos-Castro, and Miguel A Garcia-Gonzalez. 2019. Driver drowsiness detection based on respiratory signal analysis. *IEEE access* 7 (2019), 81826–81838.

[14] Sepp Hochreiter and Jürgen Schmidhuber. 1997. Long Short-Term Memory. *Neural Computation* 9, 8 (1997), 1735–1780. doi:10.1162/neco.1997.9.8.1735

[15] Paul Kligfield, Leonard S Gettes, James J Bailey, Rory Childers, Barbara J Deal, E William Hancock, Gerard Van Herpen, Jan A Kors, Peter Macfarlane, David M Mirvis, et al. 2007. Recommendations for the standardization and interpretation of the electrocardiogram: part I: the electrocardiogram and its technology: a scientific statement from the American Heart Association Electrocardiography and Arrhythmias Committee, Council on Clinical Cardiology; the American College of Cardiology Foundation; and the Heart Rhythm Society endorsed by the International Society for Computerized Electrocardiology. *Circulation* 115, 10 (2007), 1306–1324.

[16] Lucas Kratzel, Martin Glos, Christian Veauthier, Sven Rekow, Clémentine François, Ingo Fietze, and Thomas Penzel. 2021. Video-based sleep detection using ocular signals under the standard conditions of the maintenance of wakefulness test in patients with sleep disorders. *Physiological measurement* 42, 1 (2021), 014004.

[17] Christophe Leys, Christophe Ley, Olivier Klein, Philippe Bernard, and Laurent Licata. 2013. Detecting outliers: Do not use standard deviation around the mean, use absolute deviation around the median. *Journal of experimental social psychology* 49, 4 (2013), 764–766.

[18] Kirti Mahajan and Nagendra R Velaga. 2021. Sleep-deprived car-following: Indicators of rear-end crash potential. *Accident Analysis & Prevention* 156 (2021), 106123.

[19] Anne T. McCartt, John W. Rohrbaugh, Mark C. Hammer, and Sandra Z. Fuller. 2000. Factors associated with falling asleep at the wheel among long-distance truck drivers. *Accident Analysis & Prevention* 32, 4 (2000), 493–504. doi:10.1016/S0001-4575(99)00067-6

[20] NeuroKit2 Developers. 2025. *NeuroKit2 Documentation: Electrodermal Activity (EDA).* https://neuropsychology.github.io/NeuroKit/functions/eda.html Accessed: 2026-01-21.

[21] Michalis Papakostas, Kapotaksha Das, Mohamed Abouelenien, Rada Mihalcea, and Mihai Burzo. 2020. Distracted and drowsy driving modeling using deep physiological representations and multitask learning. *Applied Sciences* 11, 1 (2020), 88.

[22] Anna Persson, Hanna Jonasson, Ingemar Fredriksson, Urban Wiklund, and Christer Ahlström. 2020. Heart rate variability for classification of alert versus sleep deprived drivers in real road driving conditions. *IEEE Transactions on Intelligent Transportation Systems* 22, 6 (2020), 3316–3325.

[23] Adil Ali Saleem, Hafeez Ur Rehman Siddiqui, Muhammad Amjad Raza, Furqan Rustam, Sandra Dudley, and Imran Ashraf. 2023. A systematic review of physiological signals based driver drowsiness detection systems. *Cognitive neurodynamics* 17, 5 (2023), 1229–1259.

[24] Toru Seo, Takahiko Kusakabe, and Yasuo Asakura. 2015. Estimation of flow and density using probe vehicles with spacing measurement equipment. *Transportation Research Part C: Emerging Technologies* 53 (2015), 134–150.

[25] Cláudia Sofia Silveira, Jaime S Cardoso, André L Lourenço, and Christer Ahlström. 2019. Importance of subject-dependent classification and imbalanced distributions in driver sleepiness detection in realistic conditions. *IET Intelligent Transport Systems* 13, 2 (2019), 347–355.

[26] Standing Committee of the National People's Congress. 2011. Road Traffic Safety Law of the People's Republic of China. Online. https://peace.tsinghua.edu.cn/__local/4/03/FA/4077917867EFE21E03925182E4A_6CB4BB24_9F46E.pdf?e=.pdf Article 67; Accessed: 2026-02-18.

[27] Pierre Thiffault and Jacques Bergeron. 2003. Monotony of road environment and driver fatigue: a simulator study. *Accident Analysis & Prevention* 35, 3 (2003), 381–391.

[28] Ping-Huang Ting, Jiun-Ren Hwang, Ji-Liang Doong, and Ming-Chang Jeng. 2008. Driver fatigue and highway driving: A simulator study. *Physiology & behavior* 94, 3 (2008), 448–453.

[29] Keyin Wang, Yahui Yang, Sishan Wang, and Zhen Shi. 2022. Research on Car-Following Model considering Driving Style. *Mathematical Problems in Engineering* 2022, 1 (2022), 7215697.

[30] Xiao Wen, Zhiyong Cui, and Sisi Jian. 2022. Characterizing car-following behaviors of human drivers when following automated vehicles using the real-world dataset. *Accident Analysis & Prevention* 172 (2022), 106689.

[31] Hui Zhang, Chaozhong Wu, Xinping Yan, and Tony Z Qiu. 2016. The effect of fatigue driving on car following behavior. *Transportation research part F: traffic psychology and behaviour* 43 (2016), 80–89.

[32] Feng Zhu, Cheng Chang, Zhiheng Li, Boqi Li, and Li Li. 2024. A generic optimization-based enhancement method for trajectory data: Two plus one. *Accident Analysis & Prevention* 200 (2024), 107532.