Transportation Research Part F: Psychology and Behaviour 120 (2026) 103661

Contents lists available at ScienceDirect

Transportation Research Part F: Psychology and Behaviour

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

Impact of highway work zones on drivers' cognitive workload, visual activity, and risky driving behaviour

Sofia Palese [a,*], Margherita Pazzini [a], Davide Chiola [b], Andrea Simone [a], Claudio Lantieri [a], Valeria Vignali [a]

[a] Department of Civil, Chemical, Environmental and Materials Engineering – University of Bologna, Viale del Risorgimento 2, 40136 Bologna, Italy
[b] R&D and Innovation, Movyon S.p.a., 50013, Firenze, Italy

A R T I C L E I N F O

Keywords:
Driver behaviour
Work zone
Eye-tracking
Visual activity
EEG
Abrupt manoeuvres

A B S T R A C T

Road infrastructure is essential for economic and social development. However, although the presence of work zones is crucial, it also increases the risk of accidents. This study aims to evaluate drivers' subjective parameters when driving through work zones compared to normal conditions and to identify factors associated with risky driving behaviour. The analysis of abrupt manoeuvres using kinematic, visual and neurological data, still limited in the literature, offers a promising approach to identifying accident precursors, enhancing road safety. A driving test was conducted on a real highway, including sections with and without work zones of varying complexity. Drivers completed the route while wearing eye-tracking, electroencephalographic and kinematic devices, which recorded their visual, neural and driving behaviour under consistent experimental conditions. Data were analysed to compare driving conditions and predict abrupt manoeuvres using LSBoost ensemble regression models, identifying key predictive parameters in Work Zone and No Work Zone sections. Sections with work zones exhibited greater variability, lower average speeds and higher number of events. Visual analysis revealed an increased cognitive load, evidenced by higher numbers and total durations of fixations, greater pupil diameter and higher numbers and total amplitudes of saccades, while saccade peak velocity decreased. Global increases in EEG theta power, particularly in parietal areas, also reflect greater cognitive demands. LSBoost model predicted abrupt manoeuvres in Work Zone sections, with an R^2 of 0.527. Curve, velocity, complexity, and EEG index were identified as the most relevant predictors. In conclusion, kinematic and neurological factors emerged as primary indicators of risky driving behaviour, with visual parameters contributing moderately but still significantly.

1. Introduction

Road infrastructure is crucial to satisfy the mobility needs of both people and goods, as it directly affects the economic and social development of populations (Wang, Xue, et al., 2018). Providing efficient and safe transport systems is essential for the competitiveness of production systems and for improving citizens' quality of life. This is further recognised within the Sustainable Development Goals. However, the development, maintenance, and effectiveness of roads are affected by several factors. Two particularly relevant factors are the increase in transport flows in recent years (Ministero Delle Infrastrutture E Dei Trasporti, 2025) and the effects of

* Corresponding author.
E-mail address: sofia.palese2@unibo.it (S. Palese).

https://doi.org/10.1016/j.trf.2026.103661
Received 17 November 2025; Received in revised form 12 May 2026; Accepted 12 May 2026
Available online 18 May 2026
1369-8478/

climate change (Qiao et al., 2015). On the one hand, these phenomena accelerate the deterioration of existing infrastructure; on the other hand, they make their construction increasingly urgent to respond to changing environmental and traffic conditions. As a consequence, work zones are becoming progressively common along major transport routes, a trend that is set to continue, especially in light of the growing demand and diffusion of smarter infrastructures (KPMG, 2025). However, work zones pose additional risks to both drivers and workers, negatively affecting their safety (Rahman et al., 2017) and contributing to the already critical global situation regarding road accidents. According to the World Health Organization, road accidents are one of the primary causes of death, representing the leading cause for children and young adults (World Health Organization, 2023). The situation in Europe and Italy is no less serious, with high rates of mortality and injuries. In 2024 in Italy, 173,364 accidents occurred, resulting in 3030 deaths and 233,853 injuries (ISTAT, 2024). In this context, the topic of near-miss accidents is attracting growing interest among researchers. The near-miss events are linked to the concept of accident precursors. According to NASA, "an accident precursor is an anomaly that signals the potential for more severe consequences that may occur in the future, due to causes that are discernible from its occurrence today" (NASA, n.d, Winkler et al., 2019). According to the literature, near-miss accidents, which could occur in settings other than traffic environments, are defined as follows: an event that can result in a crash if one or more involved in the conflict takes no action to avoid collision (Al Shaaili et al., 2023; Park et al., 2023). Various kinematic indicators have been proposed in the literature to identify such events in naturalistic driving studies, thus contributing to the objective analysis of driving behaviour (Perez et al., 2017).

The presence of work zones further increases the severity of the situation, as various studies have shown that accidents occur more frequently and are more severe in these areas (Khattak et al., 2002; La Torre et al., 2017; Zhang et al., 2022). For these reasons, scientific research, public administrations and private companies are paying increasing attention to road safety in general, as well as to the specific issues of abrupt manoeuvrers and the management of potential critical locations, such as roadworks. This concern affects all road users and types of infrastructure, although it is particularly significant on highways, where high speeds can increase the risk and severity of accidents. Indeed, in Italy, between 2023 and 2024, the number of accidents, injuries and fatalities increased on highways (+6.9%, + 7.0% and + 7.1% respectively) (ISTAT, 2024). For this reason, scientific research is increasingly focusing on studying drivers' perceptions in standard contexts as well as in more complex scenarios, such as roadworks, to develop user-oriented solutions and infrastructure. The measurement of subjective parameters, such as visual and brain activity, combined with the study of driving behaviour, is proving to be one of the most promising analytical tools for understanding how drivers react to different traffic conditions, road geometry, and signs. In this context, the objective of this paper is twofold:

- Firstly, the aim is to determine the trend in subjective parameters reported by drivers in the presence of work zones of varying complexity, and to compare these values with data collected under normal traffic conditions.
- Secondly, the aim is to identify which of the analysed parameters are most closely related to risky driving behaviour, particularly in terms of determining near-miss accidents.

To this end, the paper is structured as follows: Section 2 – Literature review and novelty: This section analyses the current state of scientific research on accidents and near-miss accidents and the study of driving behaviour and perception in work zone areas. It also emphasises the innovative approach of the current research; Section 3 – Materials and Methods: This section describes the experiment, including the work zones layout, the test procedure, the instruments used, and the type of data collected, as well as the methods of analysis; Section 4 – Results and Discussion: This section presents and discusses the results obtained in detail; Section 5 – Conclusions: This section summarises the main findings. It also covers the future prospects and limitations of the research.

2. Literature review and novelty

In light of the alarming global statistics on accidents, scientific research continues to address this topic to reduce the number of victims. The importance of resolving accident-related issues is particularly evident La Torre et al., 2019at a European level. According to Vision Zero, the EU's long-term goal is to move as close as possible to zero road transport fatalities by 2050 (European Commission - EU Road Safety: Towards "Vision Zero". Available online, n.d). Of all the types of road infrastructure, highways are relevant in terms of accidents. This context differs from urban areas in terms of geometry, traffic flows, and signage. Consequently, driving styles and user behaviour also exhibit significant differences. Indeed, the monotonous environment and high travel speeds associated with this type of infrastructure can lead to the phenomenon of highway hypnosis, which has been widely explored in the literature (Khotimah and Sjafruddin, 2024; Zhang, Ryan, & Wu, 2025). Furthermore, numerous studies have contributed to furthering research into the frequency, also developing risk models, and the severity of accidents on freeways (La Torre et al., 2019; Zeng et al., 2019; Wen et al., 2018; Cheng et al., 2023).

Specifically, the elements that may contribute to accidents in the various types of infrastructure can be classified as follows: human factors – involving features such as drivers' characteristics and experiences, fatigue, distractions and driving behaviour in general (Bucsuházy et al., 2020; Faridiaghdam et al., 2025; Ma et al., 2023;, Zhang, Chen, et al., 2025), vehicle – involving design, maintenance and physical aspects (Cicchino, 2017), traffic conditions – involving traffic speed, speed difference between vehicles, and other relevant indicators (Theofilatos & Yannis, 2014; Wali et al., 2020; Wang, Zhou, et al., 2018), infrastructure and geometric characteristics of the road – as type, number of lanes, curvature, nearby ramps/intersections (Cafiso et al., 2010; Choudhary, Garg and Jain, 2024; Dadashova et al., 2016; Dumitrascu, 2024; Jima & Sipos, 2022; Vieira Gomes, 2013), and surrounding conditions – as rain, visibility, dark/light, ice/fog/snow, etc. (Bergel-Hayat et al., 2013; Graf et al., 2025; Pavlou et al., 2023). These elements can be interpreted within the framework of the Safe Systems Approach (SSA), which aims to reduce crashes by addressing multiple interacting system factors simultaneously. Unlike the traditional approach, the SSA considers human error and vulnerability, designing systems with redundancies to protect all users. The SSA is based on five fundamental objectives: safer people, safer roads, safer vehicles, safer speeds, and post-crash care. These are shared at international (U.S. Department of Transportation (U.S. DOT), 2025) and European/Italian levels (Ministero delle Infrastrutture e della Mobilità Sostenibili MIMS, 2021). Furthermore, they have all been, and still are, extensively studied in literature, both in relation to accidents and to investigate their interrelationships. In detail, the link between road geometry and driver behaviour has been extensively studied in both real-world experiments (Brasile et al., 2025) and simulated environments (Ben-Bassat & Shinar, 2011; Bobermin et al., 2021; Farahmand & Boroujerdian, 2018), as well as on the basis of past data (Bassani et al., 2014). The human factor and the characteristics of the infrastructure are particularly relevant to the current study. Firstly, the human factor is extremely uncertain due to its unpredictability and lack of controllability. Numerous studies have attempted to determine the trends of certain physiological and kinematic parameters in different driving situations. The most common parameters are those related to drivers' visual behaviour, which are often studied using eye-tracking techniques (Topolšek et al., 2016; Vetturi et al., 2020). Another set of parameters are those related to drivers' brain activity, particularly mental workload, fatigue and alertness, determined and studied using neural helmets (Yang, He, et al., 2018; Yang, Ma, et al., 2018). The combination of these two types of parameters has been involved in several studies. Researchers most commonly associate the two instruments with metrics related to fixations and saccades, and alpha, beta and theta waves, respectively. In order to associate the driving behaviour with the infrastructure, these variables are often linked to kinematic parameters, which are determined either through the driving simulator or via GPS sensors during on-site testing. Geometry and infrastructure incorporate many factors and this study specifically focuses on road signs and the geometry of work zones. Work zones represent critical points in the infrastructure where the geometry and signage strongly differ from standard conditions, providing greater stimuli for drivers and posing a challenge to road safety. Furthermore, the presence of work zones on highways can result in drivers performing unusual or sudden manoeuvres, often in conditions of reduced visibility or space (Hou & Chen, 2020). Additional risk factors in highway work zones arise from the difficulty of re-routing users and providing efficient alternative travel plans. For this reason, it is common practice to implement temporary measures that significantly impact the driving environment, including partial or total lane closures and flexion, as well as traffic diversions (Palese et al., 2025). These diversions may affect not only the carriageway where the works are occurring, but also the carriageway in the opposite direction (La Torre et al., 2017; Shakouri et al., 2014). Findings revealed that layout configurations involving the invasion of the opposite carriageway pose the greatest safety risk (Difei et al., 2021; Lv et al., 2021; Palese et al., 2025). Indeed, these interventions can further increase the likelihood of driving human error if they are not properly planned and signalized. Therefore, it is essential to pay particular attention to the organisational and planning phases of work zones as well as studying driver perception in these areas. Several studies have used eye-tracking technology to test the effectiveness of existing and new signage systems (Vignali et al., 2019; Zhao et al., 2025) and, similarly, studying neurological activity at work zones is also widespread(Yang, Ye, et al., 2023). Various site layouts have been examined, with a particular focus on merging areas, which are critical in terms of safety due to the drastic changes in geometry they involve (Siriwardene et al., 2024; Siriwardene et al., 2025). In light of this, the study explicitly links to the following pillars of SSA: Safer Roads, Safer Vehicles, Safer Users and Appropriate Speed. These pillars provide a framework for understanding how driver perception and infrastructure interact to influence risky driving behaviour. The SSA's theoretical approach supports the analysis of targeted interventions to reduce risk and increase road safety, such as optimising the geometry of roadworks, signage and driver assistance systems inside vehicles. Given the wide range and complexity of factors contributing to road accidents and the relevance of this issue, research has moved towards proactive approaches focusing on potential risk factors, particularly from a kinematic perspective, as well as retrospective analyses. This approach is commonly used to identify near-miss events, situations in which a driver performs sudden manoeuvres that do not result in a collision, but which nonetheless reveal a potentially hazardous condition. Therefore, near misses and abrupt manoeuvrers represent a valuable opportunity for preventive analysis, as they enable risky situations to be detected before they lead to more serious consequences, and several kinematic indicators are available in the literature to identify these events in driving studies (Perez et al., 2017).

Several kinematic indicators have been identified in the literature for recognising potentially risky driving situations. These include harsh longitudinal accelerations (Sun et al., 2021) and decelerations (Wang et al., 2022), and emergency braking (Kontaxi et al., 2021), commonly associated with sudden speed changes, and lateral acceleration (Kluger et al., 2016), which reflects sudden changes in trajectory. Other indicators, such as heading variation and yaw rate (Palat et al., 2019), have also been adopted to detect sudden manoeuvres and rapid steering corrections in response to critical road conditions. The current research examines Abrupt trajectory deviations (Atd) as potential indicators of context complexity and danger. Although various studies have identified harsh manoeuvrers and risky behaviour in standard conditions, e.g., from connected vehicle black box data or data from insurance companies (Talebpour et al., 2014; Guillen et al., 2019; Li et al., 2024), there is a lack of studies in the available literature on determining near-misses and risky driving behaviour at critical points, such as work zones. Real-environment testing is especially lacking in the existing research. Moreover, limited scientific contributions examined the relationship between visual and neurological parameters, recorded through eye trackers and neural helmets respectively, and kinematic parameters such as near-miss accidents, as well as comparing results from areas with and without work zones. To this end, the present study is an innovative contribution as it initially determines the physiological and kinematic parameters in areas with and without roadworks. The results are then comprehensively analysed and compared on the basis of different geometries and with the available literature. Finally, it identifies abrupt trajectory diversions in sections with and without work zones and assesses the relationship between their occurrence and kinematic, visual, neurological and geometric complexity parameters. Specifically, performing a feature importance analysis this research enables the identification of the most significant precursors to near miss accidents.

3. Materials and methods

Fig. 1 shows the flowchart of the methodology used in the current study and provides an overview of the main stages of the analysis. The diagram summarises the experimental context and instrumentation, classification of road sections, selection of metrics and the subsequent stages of analysis, from evaluation of individual parameters to joint analysis of factors influencing risky driving behaviour.

3.1. Test field and instrumentation

The current study aims to assess the impact of work zones on drivers' perceptions and behaviour while driving. To this end, a driving test was carried out along a 30 km stretch of highway, consisting of three lanes and an emergency lane. Along the route, there were roadworks with varying levels of complexity. Under standard conditions, the speed limit on this infrastructure is 130 km/h, gradually falling to a minimum of 40 km/h at the work zone. As shown in Fig. 2, the route has been divided into 16 sections, each 1 km long. The sections contain situations without work zones, as well as situations with low- and high-impact work zones. The representations include details of the signalling system for sections with work zones. The experiment involved a sample of 12 voluntary participants with a regular driving license and not wearing glasses (Average years of driving experience 19.7; min 4 – max 37; SD 11.6). They each drove along the route, covering the sections identified before. This produced a sample of 123 observations, each corresponding to a specific user driving along a certain 1 km section. There are not 192 potential observations (12×16) since drivers had to decide whether to take a detour and drive or not into the opposite carriageway in some sections of the path, meaning that not all users travelled along all sections. Specifically, given the presence of a split in the road with two possible routes, each user could only travel along 13 of the 16 sections, resulting in a sample of 156 potential observations. Furthermore, on rare occasions, one or more of the instruments experienced recording problems, resulting in the entire observation being removed from the sample. These two main causes brought the total number of observations in the sample to 123. The 123 observations are divided as follows among the sections: ID 1 = 8, ID 2 = 10, ID 3 = 9, ID 4 = 8, ID 5 = 9, ID 6 = 11, ID 7 = 10, IDs 8/9 = 9, IDs 10/11 = 9, IDs 12/13 = 10, ID 14 = 11, ID 15 = 9, ID 16 = 10. Please note that, based on the small sample size, each section (or pair of alternative sections) can contain a maximum of 12 observations. In addition, the sample generation method, which is based on repeated observations of the same drivers on different road sections, does not guarantee full statistical independence of all the considered observations. Therefore, future research could explore this further using modelling approaches that can explicitly account for any intra-subject dependencies.

Traffic conditions can generally be considered comparable across the various observations. However, this assessment was not supported by direct measurements of vehicle flow, but rather by an indirect evaluation based on the average travel time recorded for each observation. Future research could include direct traffic counts to provide a more accurate measure of traffic conditions. Indeed, the average journey time for the 123 observations is approximately 35 s (SD 11 s). Journey times were more homogeneous on No WZ sections (av. time 31 s, SD 4 s) than on WZ sections (av time. 39 s, SD 14 s), where greater variability was observed. These differences can be attributed to more cautious driving behaviour and more complex interactions with both the WZ and other road users, as well as to the varying geometry and complexity of the WZ sections, rather than to external congestion. In addition, data collection was performed during the two autumn days (from around 9:00 am to around 5:00 pm) to avoid peak hours, which confirms the general consistency of traffic flow, and to ensure consistent lighting conditions for all participants. Participants were selected to form a homogeneous experimental group in terms of age, gender and driving experience. To avoid distorting their vision while tracking eye movements, all participants did not wear glasses. In addition, to avoid any influence or bias, participants were not informed of the purpose of the study. All drivers were subjected to the same conditions: they used the same vehicle, drove on the same route and were provided with the same equipment. They travelled the entire route while wearing an eye tracker (Tobii Pro Glasses 3) to record their visual behaviour, and an electroencephalographic (EEG) helmet (Mindthoot EEG) to monitor their neural activity. Additionally, a Video V-Box — an instrument capable of detecting the car's kinematic components — was installed on the vehicle. The test for each user lasted around 30 min, comprising the calibration and test times. This time is not fixed due to the subjective calibration time of the instruments, the speed at which the drivers travelled and the traffic conditions. To allow drivers to adapt to the equipment, they started one kilometre before the section in question. The study and its procedure were approved by the Ethics Committee of the University of Bologna. Fig. 3 shows the Video V-Box with which the vehicle was equipped and the Tobii Pro Glasses 3 and Mindhoot EEG on a model of driver's head.

3.2. Data collection and cleaning

3.2.1. Kinematic data from vehicle and geometry related data

The Video V-Box Pro is used to record data relating to vehicle's movement along the route. It comprises a Global Positioning System (GPS) and a high-quality multicamera system, consisting of two synchronised cameras. During the test, for optimal performance, Video V-Box is placed inside the vehicle near its centre of gravity, while the two cameras were installed on the dashboard and the GPS sensor was positioned on the roof of the car, in a barycentric position, for greater accuracy of measurements. The parameters provided by the GPS are measured with a sampling rate of 10 Hz. The data is then analysed using dedicated software, Circuit Tools (VBox Motorsport – Circuit Tools, n.d). This program processes the information, examines the parameters of interest and simultaneously displays the video recorded during the test. In addition, the software interface offers graphs showing the kinematic characteristics and a map of the path covered. Of the parameters provided in the output, the most relevant for the current study are time and elapsed time, position (latitude and longitude), heading, velocity and longitudinal acceleration. Specifically, time-related parameters are used to synchronise the three instruments and position parameters to identify when each user travels through one of the 16 identified sections. This enables the

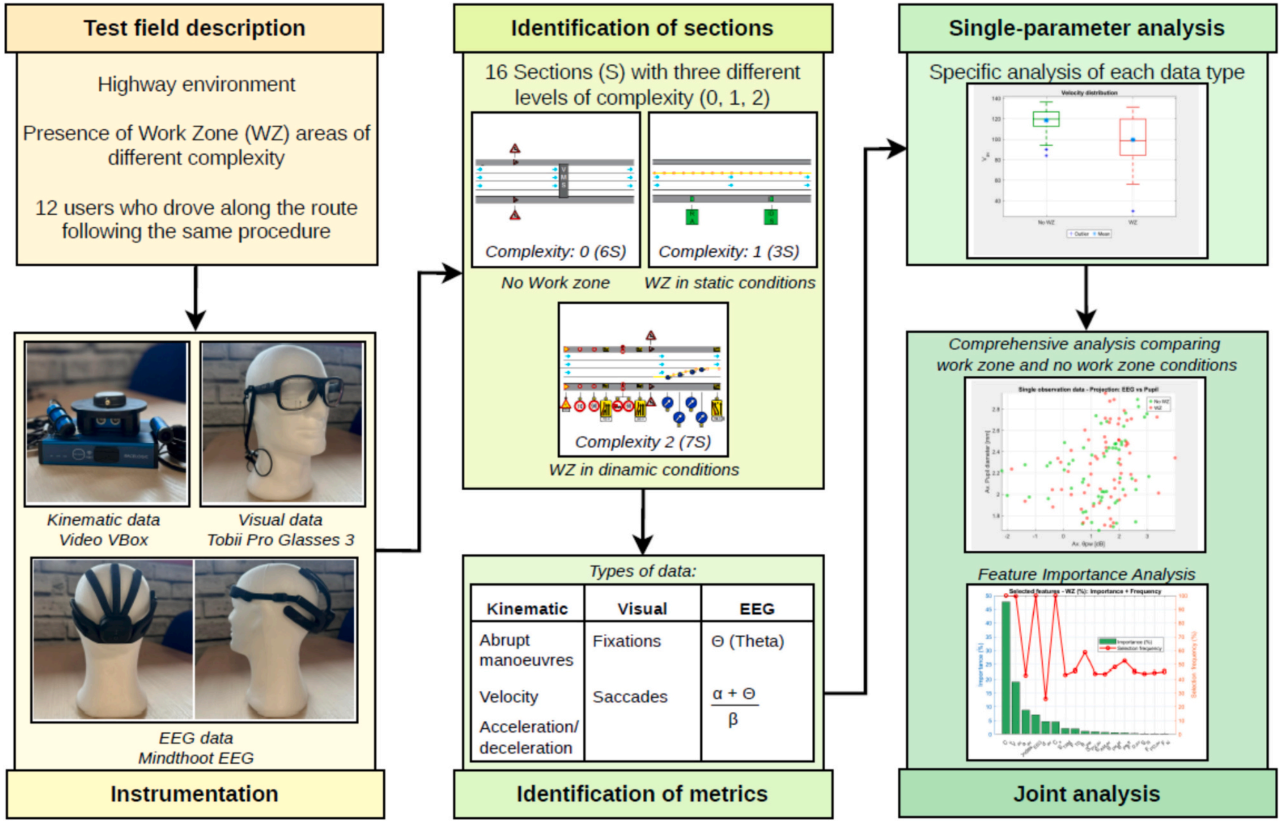

Fig. 1. Flow chart summarising the main steps of the methodology.

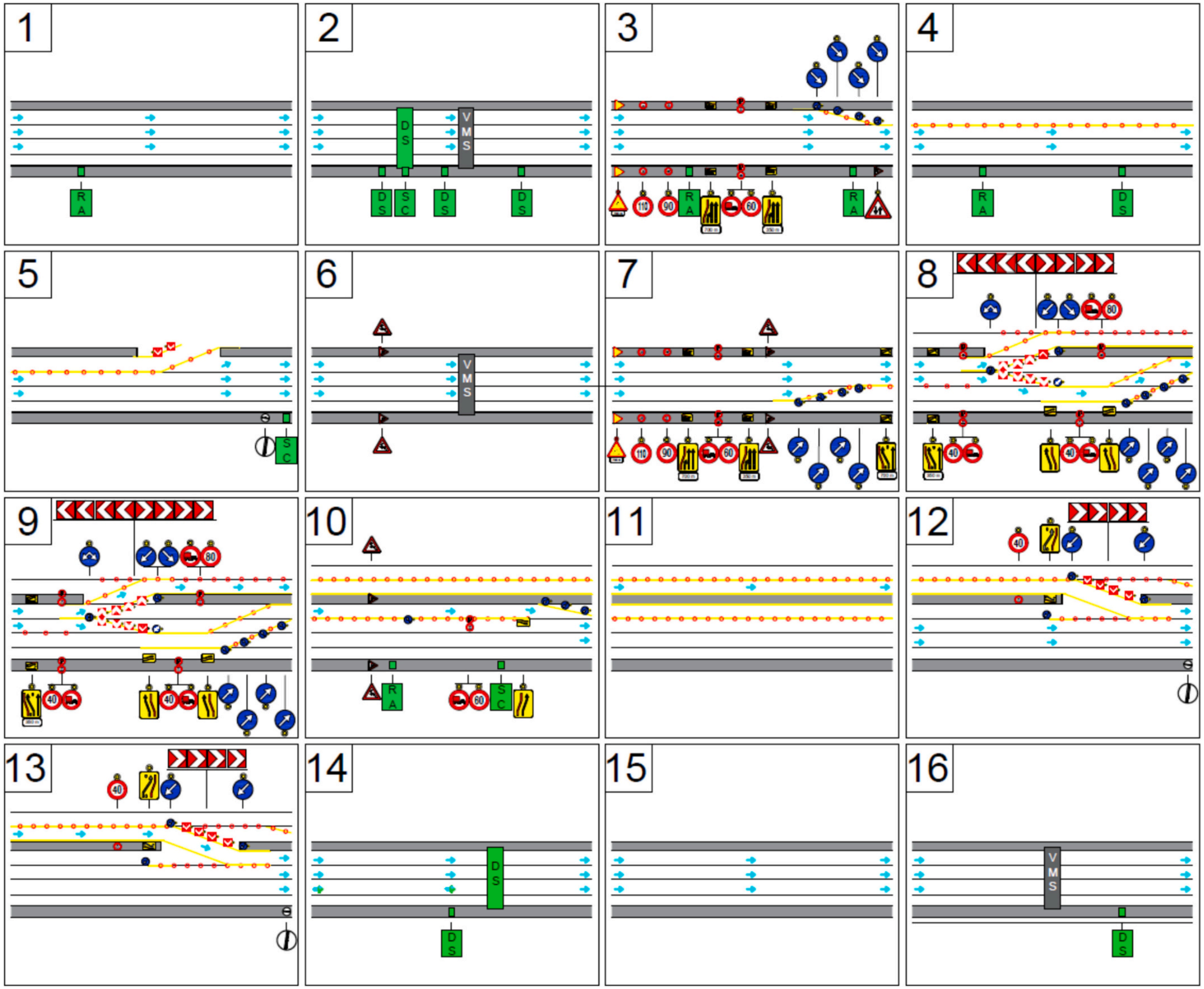

Fig. 2. Representation of the 16 sections along the route, identified by section IDs. Light blue arrows indicate the possible directions that drivers can take in each section. Ordinary signage is schematically represented in green, in accordance with standard Italian highway signage (RA: Rest Area; DS: Directional Signs; SC: Speed Control alert;
VMS: Variable Message Signs). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Fig. 3. Representation of Video V-Box and setting of Tobii Pro Glasses 3 and Mindthoot EEG on driver's head.

characteristics of the section through which they are travelling to be determined and associated with the other variables. Based on the Video VBox output data, the parameters identified and described in Table 1 were considered for each user travelling through the various sections. All of the parameters listed below refer to a single observation, which in this study is a journey performed by a specific user along a section of fixed length, which is equal to 1 km. Throughout this document, including in the table below, the term Work Zone is abbreviated to WZ.

Following the table, two clarifications are necessary. The first concerns the concept of complexity (Cx). The sections identified, and consequently all the observations, could be of three types: a – without WZ (sections 1, 2, 6, 14, 15, 16), b – with WZ that does not require users to make decisions, users travel through a section characterised by a stable situation, despite different from the standard condition (sections 4, 11, 12) and, c – with WZ that requires users to make a decision and adapt their behaviour, users travel through a section characterised by an evolving situation that differs from standard conditions (sections 3, 5, 7, 8, 9, 10, 13). These three situations were assigned increasing levels of complexity, equal to 0, 1 and 2 respectively for variable Cx. The second clarification concerns the definition of harsh manoeuvre linked to the yaw rate. This variable is of fundamental importance, as many researchers are focusing on it to investigate near miss accidents. The literature indicates that a sudden change in heading can identify a near miss accident. Previous studies have specifically determined that a change in heading greater than 4° within a 3 s window of time (yaw rate over than 4° in 3 s), according to the definition of kinematic thresholds from literature (Dingus et al., 2006; Perez et al., 2017), represent a near miss. The Atd variable measures the number of harsh manoeuvres performed during an observation period (manoeuvres with a yaw rate over the threshold). Indeed, in operating conditions in real environment, yaw rate represents a relevant indicator. In correspondence with geometric changes and work-zone layouts, road users may adapt their behaviour suddenly, not adequately responding to advance warning signs, thus performing abrupt manoeuvres in terms of trajectory and steering. Yaw rate is therefore well suited to capture these sudden lateral corrections, which are especially representative of critical driving behaviour in work zones scenarios. Nevertheless, the other kinematic indicators remain relevant and constitute an interesting direction for future investigations.

3.2.2. Visual data from drivers

After the calibration through the dedicated software Tobii Pro Glasses 3 Controller app, the Tobii Pro – Glasses 3 is the specific mobile eye tracker used to record visual behaviour during the test. This technology is designed for gaze monitoring and is suitable for application with drivers. Its lightweight and functional design ensures that drivers are not restricted in any way during the experiment. During the test, data is monitored via a software application and recorded on an SD card. The signal sampling rate is up to 50 Hz. To avoid interference with other instruments, data is transmitted wirelessly via the WiFi protocol. The output includes a pointer showing

Table 1
Definitions of the kinematic parameters.

Acronym	Parameter	Description	Type	Units or specifications
WZ	Work Zone	It identifies the presence of a WZ during observation.	Binomial	0 – if the observation doesn't involve a WZ 1 – if the observation involves a WZ
Cx	Complexity	It identifies the complexity of the observation.	Categorical	0 – if the observation doesn't involve a WZ 1 – if the observation involves a WZ considered to have a medium impact. 2 – if the observation involves a WZ considered to have a high impact.
Cu	Curve	It identifies the presence of a curve during observation.	Binomial	0 – if the observation doesn't involve a curve 1 – if the observation involves a curve
Atd	Abrupt trajectory deviations	It determines the number harsh manoeuvres over the yaw rate threshold	Discrete	Count number
V	Velocity	It involves the average velocity and the standard deviation over the entire observation period.	Continuous	Km/h
a	Acceleration	It involves the average acceleration and the standard deviation over the entire observation period.	Continuous	m/s^2
d	Deceleration	It involves the average deceleration and the standard deviation over the entire observation period.	Continuous	m/s^2

the direction in which each driver is looking. Users' visual behaviour while driving was assessed by recording eye movements. Specifically, videos recorded using Tobii Pro Glasses are analysed using Tobii Pro Lab software (Tobii – Tobii Pro Lab, 2025), which is designed to process data acquired during test sessions. Similar to the Video VBox, this tool recorded the time during the test and the start time of each trial. This enabled synchronisation between the two tools and to identify when each user travelled through one of the 16 sections, and consequently to associate the characteristics of the section with the visual variables. In each recording, a certain number of TOIs (Times of Interest) were identified within the software. In each record, each TOI corresponded to a specific section out of the 16 identified. The identification of the TOIs allows for exporting the data divided by user and section, and therefore by observation. Based on the existing literature and on data type availability, the parameters selected for the current study relate to fixations and saccades. These metrics enable obtaining measures based on eye movements. These measures are derived from pre-processed data generated by different functions of the Tobii Pro Lab gaze filter. The producer's website permits the following definition of fixations and saccades (Tobii - Understanding Tobii Pro Lab's eye tracking metrics, 2025). Fixations: the periods of time where the eyes are relatively still, holding the central foveal vision in place so that the visual system can take in detailed information about what is being looked at. In Tobii Pro Lab, fixation is a sequence of raw gaze points, where the estimated velocity is below the velocity threshold set in the I-VT gaze filter. Saccades: the type of eye movement used to move the fovea rapidly from one point to another. This movement starts with an initial fast acceleration until the eye reaches a peak velocity. After reaching the peak, it starts to decelerate until the eye reaches the target location. In Tobii Pro Lab, a saccade is a sequence of raw gaze points, where the associated velocity lies above the velocity threshold set in the I-VT gaze filter. Several parameters relating to these two types of eye movement were selected for the current study; they are all described in Table 2 and refer to a single observation.

3.2.3. EEG data from drivers

An electroencephalographic (EEG) helmet is used to record the neural activity of users while driving. The Mindtooth EEG device records the cognitive load associated with driving (Mindtooth, n.d). Through eight electrodes (AF7, AF3, AFz, AF4, AF8, P3, Pz, P4) in contact with the user's head, it measures brain activity in the form of waves. The sensors are integrated into a helmet that can be easily worn and does not obstruct driving in any way. The helmet covers the anterior frontal and parietal regions of the head. Fig. 4 shows the arrangement of the electrodes in the Mindtooth EEG system. It requires a calibration process, including both eyes open and eyes closed tasks, in order to clean the data from artefacts. The amplifier has a 24-bit resolution and a signal sampling rate of up to 125 Hz. Data is transferred wirelessly via Bluetooth. The sensors collect data, which is then transmitted to a device that processes it in real time. The Mindtooth system can collect raw data and analyse EEG signals using advanced artificial intelligence and machine learning algorithms. In the current study, raw data were collected during each driving test using this device. This data was then cleaned and processed using EEGLAB (EEGLAB – Available online, n.d). EEGLAB is an interactive MATLAB toolbox for processing EEG and other electrophysiological data. It provides an interactive graphical user interface (GUI), allowing users to process their high-density EEG and other dynamic brain data flexibly and interactively. It incorporates independent component analysis (ICA), time/frequency analysis, artefact rejection, event-related statistics, and several useful modes of visualisation of averaged and single-trial data.

Within EEGLAB, the data were analysed according to the flow chart shown in Fig. 5, showing all the steps performed. After running the procedure, the data were processed in MATLAB to determine the normalised spectral power of each frequency for each observation, using the total power in the [1–40] Hz range as reference. This was performed to reduce bias due to subjects' variability. In particular, the following frequency ranges have been adopted: Theta [4–7] Hz, Alfa [8–12] Hz, Beta [13–30] Hz. All the normalised values were then converted to decibels [dB] scale to better represent and compare all the bands. Finally, the average normalised band power was determined for each observation. Based on the existing literature, the parameters reported in Table 3 have been selected to be involved in the current analysis. Specifically, the EEG index has been included due to its adoption in previous studies conducted on work zone areas, although these were in simulated contexts (Yang, Liu, et al., 2023; Yang, Ye, et al., 2023), and due to its effectiveness in estimating driver fatigue, as highlighted in the literature (Jap et al., 2009; Zhao et al., 2012). The theta index was selected based on

Table 2
Definitions of the visual parameters.

Acronym	Parameter	Description	Type	Units
$F_{D,av}$	Average duration of whole fixations	The average duration of the fixations during an interval.	Continuous	Milliseconds
F_{TD}	Total duration of whole fixations	The total duration of the fixations during an interval	Continuous	Milliseconds
F_N	Number of whole fixations	The number of whole fixations during an interval	Discrete	Count number
$F_{PD,av}$	Average whole-fixation pupil diameter	The average pupil diameter of all whole-fixation samples in this interval. Calculated resulting pupil diameter after applying Pupil diameter filter.	Continuous	Millimetres
S_N	Number of saccades	The number of saccades occurring during an interval	Discrete	Count number
$S_{PV,av}$	Average peak velocity of saccades	The average peak velocity of all saccades in this interval	Continuous	Degrees/s
$S_{AM,av}$	Average amplitude of saccades	The average amplitude of all the saccades in this interval	Continuous	Degrees
S_{TAM}	Total amplitude of saccades	The total amplitude of all the saccades in this interval	Continuous	Degrees

Fig. 4. Electrode placement in the Mindthoot EEG device, displayed through EEGLAB, and visual representation of the electrodes from Mindthoot EEGs positioned on a model human head.

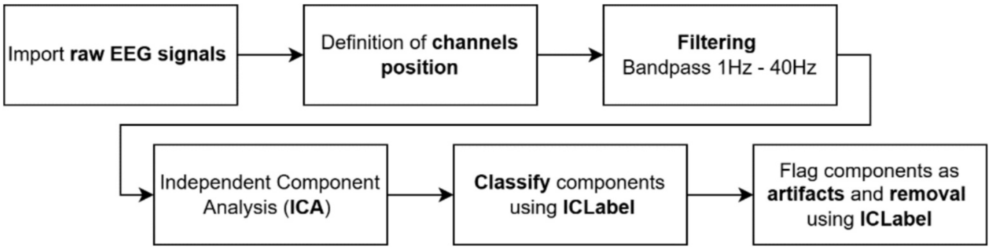

Fig. 5. Flow chart showing analysis procedure within EEGLAB.

Table 3
Definitions of the neural parameters.

Acronym	Parameter	Description	Type	Units
θ_{pw}	Global Theta Power	Theta power, normalised to total channel power and averaged across all the channels	Continuous	Decibels
$\theta_{pw,fr}$	Frontal Theta Power	Theta power, normalised to total channel power and averaged across five frontal channels (AF7, AF3, AFz, AF4, AF8)	Continuous	Decibels
$\theta_{pw,pt}$	Parietal Theta Power	Theta power, normalised to total channel power and averaged across three parietal channels (P3, Pz, P4)	Continuous	Decibels
$\frac{\alpha+\theta}{\beta}$	Index EEG based on Global parameters	Ratio of the sum of α_{pw} and θ_{pw} to β_{pw}	Continuous	Unitless

numerous studies highlighting its link with user and driver workload (Depestele et al., 2023; Diaz-Piedra et al., 2020; Puma et al., 2018), and explored in further detail, dividing it in frontal and parietal theta power. In addition to the evidence found in the literature, which allows for reliable and comparable measurements, the EEG parameters selected for this study were also chosen for methodological and theoretical reasons. Indeed, this choice is supported by the configuration of the EEG device used and the characteristics of the parameters. In detail, frontal theta is generally associated with cognitive load, parietal theta with attention and visuospatial integration, and global theta reflects an overview of brain activity. Meanwhile, the composite index effectively estimates fatigue and mental load.

3.3. Data analysis: Effects of work zones and key factors influencing near – Miss accidents

The first part of the analysis aims to highlight any differences and similarities between the parameters in two different driving situations. The data were analysed by dividing the observations into two main categories based on the presence or absence of a site

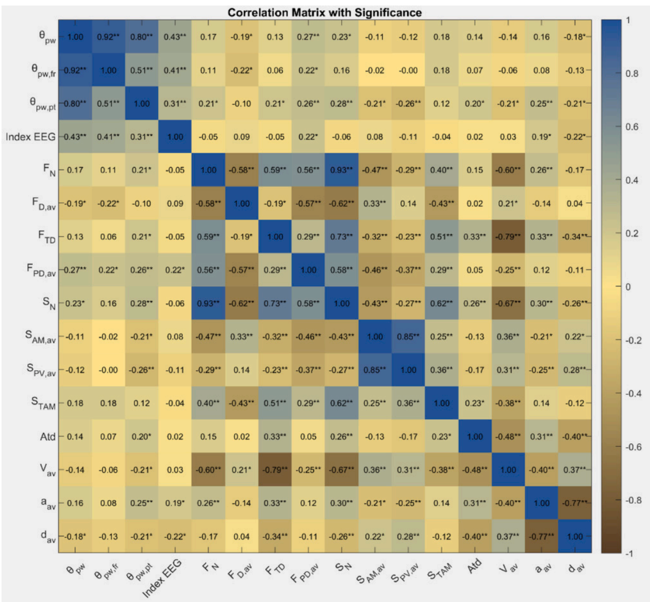

Fig. 6. Representation of the correlation matrix.

during each observation, using the binary variable WZ. The averages and standard deviations of the parameters were then calculated for each category, in order to highlight any similarities and differences between driving situations. Bar charts, box plots and scatter plots were constructed in MATLAB to facilitate visual comparison of the distributions and relationships between variables belonging to different domains (EEG, visual and kinematic). In light of the importance of research concerning accidents and near misses, the second part of the analysis further explored this issue, with a particular focus on predicting the number of abrupt manoeuvres. To predict abrupt trajectory diversions in WZ sections, an ensemble LSBoost regression model was developed on MATLAB. For each of the 500 iterations, the data were randomly divided into training (70%) and testing (30%) sets. Within the training set, Recursive Feature Elimination (RFE) with 5-fold cross-validation was used to identify the optimal number of predictive features, minimising the RMSE. At each iteration, the LSBoost model was trained on the training set with the selected features and tested on the independent test set, allowing RMSE, MAE, and R^2 to be calculated on unseen data. The final model metrics are obtained as the mean and standard deviation of the values calculated on the test set across all iterations. Simultaneously, a Feature Importance Analysis (FIA) was conducted for each resulting iteration model, enabling the normalised predictive importance of each feature and the average selection frequency to be quantified over the total number of iterations. This highlighted the most relevant variables for predicting the Atd in situations with WZs. The FIA was then repeated to evidence the most relevant variables also in No WZ sections, in order to compare the results.

4. Results and discussion

4.1. General trends and effects of work zones

As a preliminary step, an exploratory analysis of the entire dataset was conducted to identify potential trends among the investigated variables, without considering the presence of work zones. Fig. 6 displays the Pearson's correlation matrix incorporating all the parameters, without subdivision based on the presence of WZ. This matrix is created to identify the connections between the various parameters analysed in the different observations. Significative values are marked with two asterisks (**) and correspond to $p < 0.01$; values marked with a single asterisk (*) are still significative, but characterised by $p < 0.05$. Almost all the variables show a statistically significant correlation with Velocity, which is of fundamental importance in this type of study (Domenichini et al., 2017; Fondzenyuy et al., 2024). Furthermore, in line with numerous contributions to the literature, there is also a significant correlation between certain neurological and visual parameters.

Table 4 summarises the results in terms of the mean and standard deviation of the parameters determined for situations with and without WZ. Some important observations emerge when the two driving conditions are compared (No WZ and WZ). Furthermore, normality was assessed using the Shapiro–Wilk test separately for the two groups of samples. Most variables showed deviations from normality in one or both groups. Therefore, non-parametric Mann–Whitney *U* tests were applied to compare the conditions. The test reveals strong differences in the kinematic variables between the groups, all of which are statistically significant, indicating a clear effect of the presence of WZ. The visual variables related to fixations show generally low or medium differences between the groups, with F_{TD} being the only measure that both show large and significant differences, and F_N showing moderate differences with a tendency towards significance. The visual variables related to saccades show strong and significant differences between the groups. Conversely, neurological variables reveal minimal differences between groups, which are generally not statistically significant. In addition, a preliminary analysis of the effect size was conducted using Cohen's d, considering the two conditions (WZ and No WZ), in order to support the ability of the current sample to detect the meaningful effects. The results show medium-to-high effect sizes for most of the key variables, confirming both the existence of substantial differences between the conditions and the sample's ability to

Table 4
Average values (μ), standard deviations (σ), Mann–Whitney (U), and significance of kinematic, visual, and neurological parameters, divided according to the presence of WZ.

	No Work Zone (No WZ)		Work Zone (WZ)		Mann–Whitney
	μ	σ	μ	σ	U
Atd	0.101	0.357	0.859	0.794	777.500**
V	118.534	11.359	99.52	22.01	917.000**
a	0.040	0.012	0.045	0.019	1746.000
d	−0.040	0.013	−0.048	0.020	1518.000
$F_{D,av}$	556.915	372.11	540.99	268.54	1812.500*
F_{TD}	21,627.017	544.373	28,015.734	9915.502	898.500**
F_N	53.831	33.789	71.750	63.564	1549.500*
$F_{PD,av}$	2.230	0.320	2.270	0.332	1757.000
S_N	31.780	15.626	43.297	26.500	1412.000**
$S_{PV,av}$	217.370	39.634	199.790	32.520	1358.000**
$S_{AM,av}$	7.402	2.978	6.272	2.835	1425.000**
S_{TAM}	211.718	106.013	244.970	131.881	1692.000
θ_{pw}	1.255	1.178	1.429	1.026	1777.000
$\theta_{pw,fr}$	1.586	1.269	1.610	1.068	1817.000
$\theta_{pw,pt}$	0.511	1.464	0.970	1.541	1559.000*
Index EEG	13.253	3.600	13.252	3.557	1876.000

Significance of Mann Whitney: **sig. < 0.05, *sig. < 0.10

reliably detect them. In particular, the analysis ensures good statistical power for effects of at least moderate magnitude. However, small effects should be interpreted with caution. Overall, the analysis suggests that the sample size reveals adequate sensitivity for moderate effects and for the study's objective.

The kinematic results show that the average velocity in No WZ sections is significantly increased, being approximately 20 km/h higher. Conversely, there is greater speed variability in sections with WZ, where the standard deviation is approximately double that in sections without. Differences between the two conditions can also be observed in terms of acceleration and deceleration. More specifically, the results suggest that the presence of WZs is linked to increased longitudinal variation, with higher average acceleration and deceleration values in absolute terms than when there are No WZs. Furthermore, higher standard deviations suggest greater variability in driving behaviour. In detail, WZ sections are also characterised by higher deceleration than acceleration, providing a key insight in road safety in WZ. Overall, evidences suggest that drivers adopt a more responsive, variable, and cautious driving style in the presence of roadworks, probably in response to the increased complexity of the road environment. Fig. 7 highlights the differences in kinematic parameters between situations with and without WZ. Specifically, although the average velocity is higher in observations without WZ, the average number of Atd is lower (Fig. 7.a). Indeed, the average number of harsh manoeuvres is significantly higher in sections with WZ. In addition, WZ observations highlight the presence of greater variability in speed (Fig. 7.b). This greater variability could be due both to the different users' reactions and to varying complexity levels among sections in WZ category. These considerations are coherent with expectations, as the complex road geometry and change in normal carriageway alignment may have caused drivers to rapidly perform unexpected manoeuvres to adapt to the changing situation.

According to the literature, the number and duration of fixations and saccades, as well as pupil diameter, are fundamental parameters in the study of visual behaviour (Mahanama et al., 2022) and also in the current research, they reveal interesting patterns. In fact, a number of studies have confirmed the existence of a link between visual and neurological parameters, thereby highlighting the importance of visual parameters as indicators of different levels of mental workload (Van Der Wel & Van Steenbergen, 2018; Chen et al., 2022; Bitkina et al., 2021). More eye movements, in terms of both fixations (Fig. 8) and saccades (Fig. 9), are in observations characterised by the presence of the WZ. Concerning fixations, sections with WZ show an increase in the number of fixations and the total duration of fixations (Fig. 8.b). Meanwhile, the average duration of individual fixations remains almost constant or slightly lower than in sections without WZ (Fig. 8.a). This combination suggests that drivers tend to make numerous medium-duration fixations when a WZ is present, exploring the visual environment in a fragmented manner. This behaviour is consistent with the increase in visual complexity in the WZ areas. Drivers must monitor multiple elements simultaneously, such as temporary signs, cones, obstacles, diversions, workers and other vehicles, while maintaining their focus on the road and on driving activity. Other studies have determined a greater number of fixations when comparing WZ and No WZ conditions in real environment tests (Vignali et al., 2019). Furthermore, numerous contributions have highlighted longer fixation durations during driving tests in a simulated environment (Chen et al., 2022; Konstantopoulos et al., 2010). The slight increase in average pupil diameter (Fig. 8.c) can be interpreted as an indication of greater cognitive activation and attentional load when driving through WZs. Of all the visual parameters, pupil diameter is of particular importance, since it has been the subject of extensive research and it is widely recognised as an indicator of mental workload (Van Der Wel & Van Steenbergen, 2018). Specifically, several studies have confirmed that pupil diameter increases in more complex situations (Čegovnik et al., 2018; Chen et al., 2022; Konstantopoulos et al., 2010; Krejtz et al., 2018). Concerning saccades, the number of saccades increases in sections with WZ, while the average peak velocity (Fig. 9.b) and amplitude (Fig. 9.c) of saccades both decrease. This pattern suggests that drivers perform more eye movements, but these are shorter and less rapid, focusing their attention on areas of interest that are closer together. However, the total amplitude of saccades (Fig. 9.a) is greater in observations involving WZ, suggesting that visual exploration covers a larger portion of the scene overall. In summary, the presence of WZ increases visual activity and results in a more detailed and fragmented visual strategy, which is typical of situations that require careful and continuous visual control or complex tasks. However, the data show high standard deviations, particularly for sections with WZs, indicating considerable

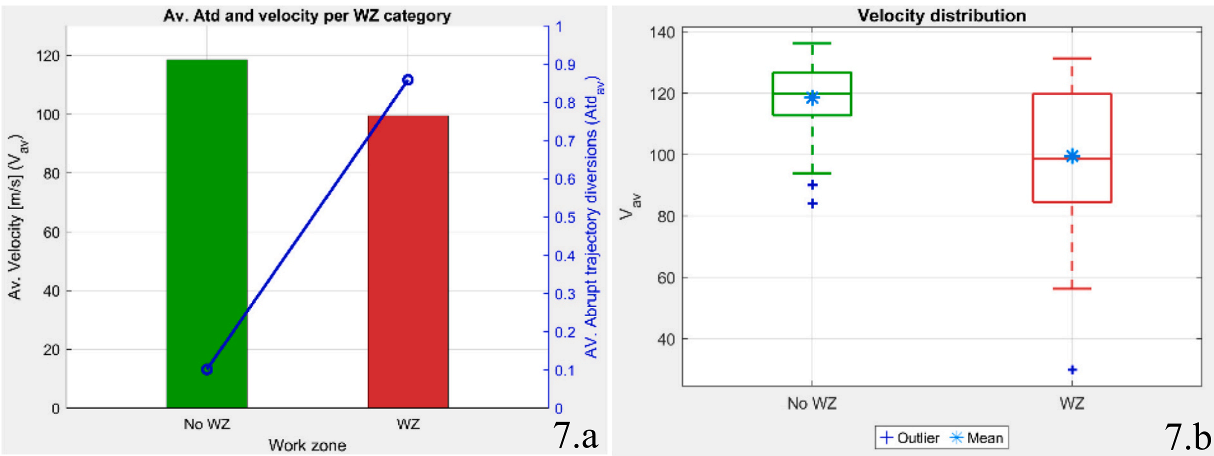

Fig. 7. Representation of kinematic data according to the presence of Work Zones.

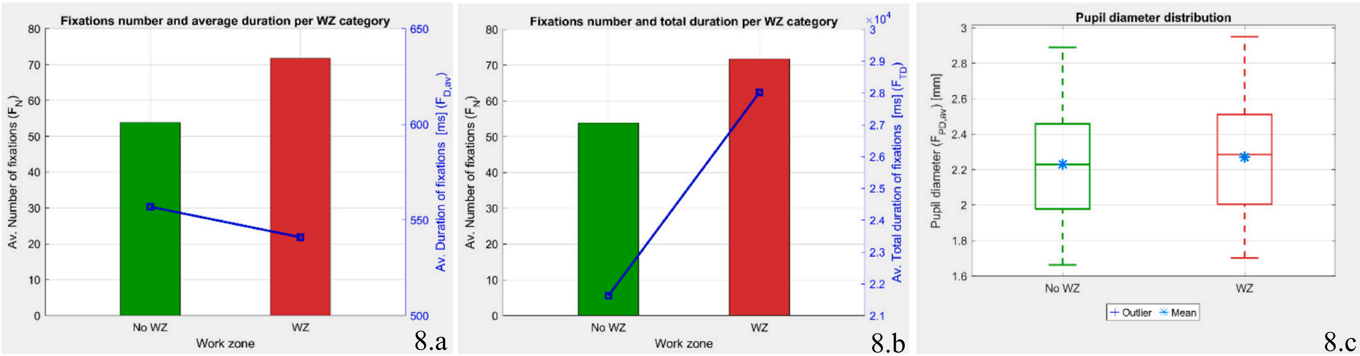

Fig. 8. Representation of fixations data according to the presence of Work Zones.

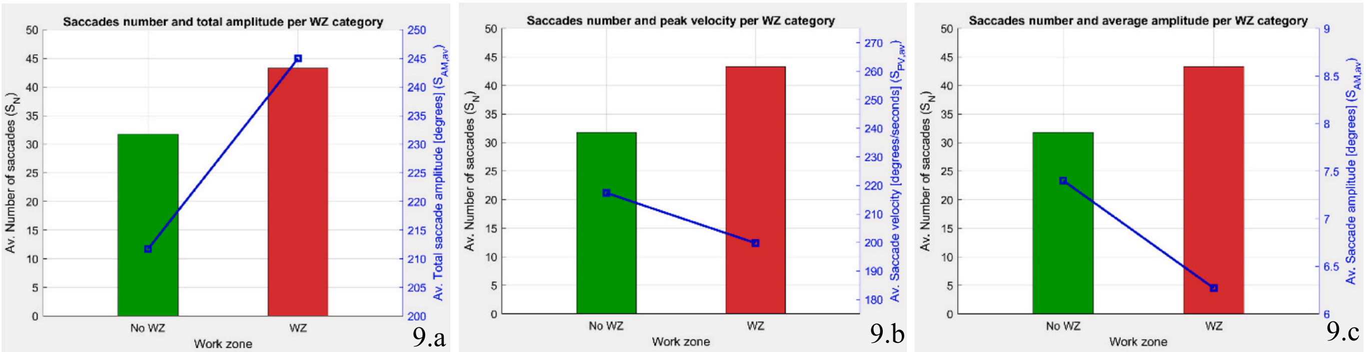

Fig. 9. Representation of saccades' data according to the presence of Work Zones.

variability in participants' visual behaviour.

With regard to the EEG data, they are expressed in decibels [dB] according to the standard logarithmic transformation used to normalise differences between subjects and channels. On this scale, small numerical variations may correspond to significant increases in linear power and hence could be physiologically relevant. Therefore, in the following discussion the variations are expressed as a percentage increase or decrease between the condition without and with WZ. Globally, there is an increase in theta power of approximately +4% (Fig. 10.a). A more detailed analysis is performed at a localized level. In the frontal areas reveals that theta power increased by approximately +0.6%, (Fig. 10.b) and in the parietal areas the variation is more pronounced since theta increases by 11.1% (Fig. 10.c). These values are consistent with greater visual-spatial processing in the WZ areas. The global EEG index changes only marginally, confirming that brain activation remains balanced and functional. Although the standard deviations are quite high, they could be still considered physiologically plausible. This is particularly true when considering subject variability and real environmental conditions, such as different road sections, different users, WZ of various complexities.

Overall, the average values are consistent with what is expected in real-life driving conditions: all the theta parameters increase in sections with WZs, indicating greater cognitive load. Indeed, the EEG data are consistent with the behavioural patterns identified within other research contributions, indicating that variations in neural activity reflect the demands placed on attention and perception when driving in complex environments. Previous contributions to the literature have highlighted the general recognition of an increase in theta values in response to high mental workload and fatigue, particularly among aircraft pilots and car drivers (Borghini et al., 2014). Indeed, EEG studies are particularly widespread in the analysis of mental workload in pilots. Previous research has shown that an increase in theta band power reflects an increase in cognitive resource involvement in a multitasking environment (Puma et al., 2018), and that higher EEG frontal and central theta power is found while pilots are performing in-flight emergencies (medium and high flight complexity) compared to recognition flights (low flight complexity) (Diaz-Piedra et al., 2019). Further research into the driving environment yielded similar results based on tests performed using driving simulators. In the first case, an increase in theta was recorded during driving scenarios involving unexpected events (Lin et al., 2008). In the second case, a higher theta EEG power spectrum was determined in the frontal, temporal and occipital areas during the most complex scenarios involving army combat drivers in simulation (Diaz-Piedra et al., 2020). Similar results are obtained outside of the driving and flight environments, too. Indeed, an increase in theta activity has been detected when comparing simple and complex tasks in other disciplines, such as in the medical field during different types of surgical procedure (Morales et al., 2019).

4.2. Factors influencing abrupt trajectory diversions

Before analysing the factors that influence the occurrence of Atd, the scope and validity of the metric should be reiterated. Atd does not directly represent near-miss events; rather, it reflects potential risky situations as sudden changes in trajectory resulting from drivers' behavioural responses to the complexity of the driving environment, including, but not limited to, mandatory diversions. A preliminary analysis shows that, while the number of Atd varies between observations within the same sections, the indicator captures individual behavioural differences. In addition, the Atd rate per observation varies considerably across different types of WZ sections. This variability highlights that Atd does not solely capture the effect of road geometry; it also reflects how different drivers respond to the same constraints and road conditions, distinguishing between smooth and abrupt manoeuvres. Therefore, though the potential impact of mandatory lane changes on Atd can't be entirely excluded, Atd remains a consistent and informative indicator for identifying abrupt driving behaviour and investigating the factors that influence its occurrence, in line with the study's objective. Fig. 11 provides a preliminary investigation into how the main EEG and visual parameters vary in accordance with the number of Atd. Specifically, it involves three 2D scatter plots, considering three main variables in the axis (Atd, θ_{pw}, $F_{PD,av}$). Therefore, it includes one variable for each type of parameters (kinematic, neurological, and visual). The selection of neurological and visual parameters was based on their established use in road safety research, covering standard and work zone contexts in both real and simulated environments. Theta power was chosen as a reliable indicator of cognitive workload, and pupil diameter was selected due to its proven association with cognitive load. Together, these parameters enable the joint analysis of cognitive and visual indicators in relation to driver performance. Observations characterised by the presence of WZ are represented by red dots, and those without are represented by green dots These graphs exhibit different patterns among the parameters. Overall, the presence of WZ results in a greater dispersion of points, which suggests greater variability in the neural and visual responses of users. This wider variation in WZ may indicate an increase in cognitive load and visual reactivity, consistent with a more complex and challenging driving scenario. No clear separation patterns emerge between the two conditions (with and without WZ) in the first plot. However, while WZ observations are more concentrated around θpw values of 1–3 dB, no WZ observations are located around lower θpw values (0–2 dB), and the pupil diameter is generally no greater than 2.5 mm. In the second and third plots, high Atd values are almost exclusively associated with WZ observations. Indeed, conditions with no WZ remain close to low Atd values (around zero, or occasionally one), suggesting greater stability in directional control in standard situations. Specifically, although no evident linear pattern can be observed between θpw and Atd in the second plot, higher Atd values coincide with increasing θpw, consistent with conditions requiring greater environmental monitoring and attention. Similar trend is observed in the last plot for pupil diameter: No WZ observations show Atd values close to zero and lower average pupil diameters, which is consistent with stable driving and lower visual-cognitive effort. Observations with Atd greater than zero, almost exclusively in the WZ condition, are characterised by a large variability in terms of pupil diameter.

Overall, the LS Boost machine learning model, applied to WZ observations, exhibits good predictive power, considering the type of behavioural study and real-world setting, with an R^2 of approximately 0.5 (0.527). More accurate models can be obtained by including factors that are not currently considered. Indeed, accidents are random events resulting from the complex and subjective behaviour and choices of drivers, which are not entirely predictable. In the current analysis, four dominant variables are consistently selected

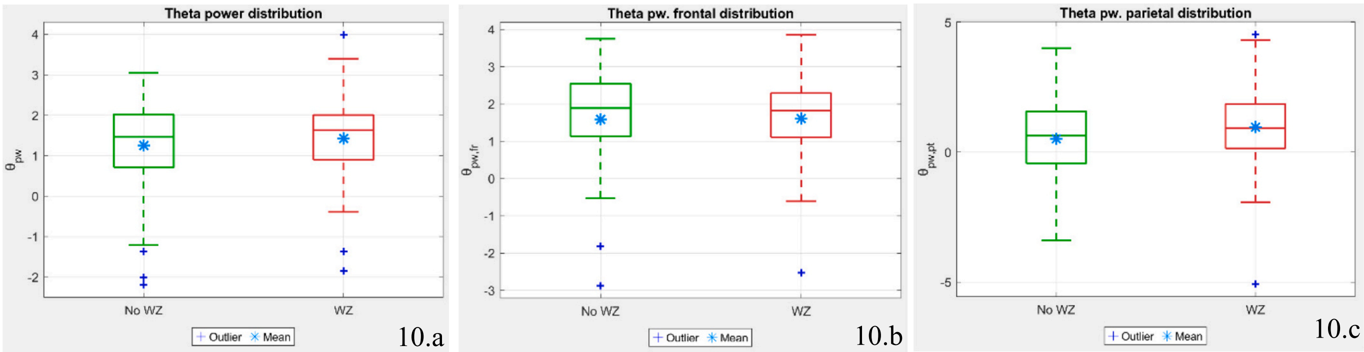

Fig. 10. Representation of EEG data according to the presence of Work Zones.

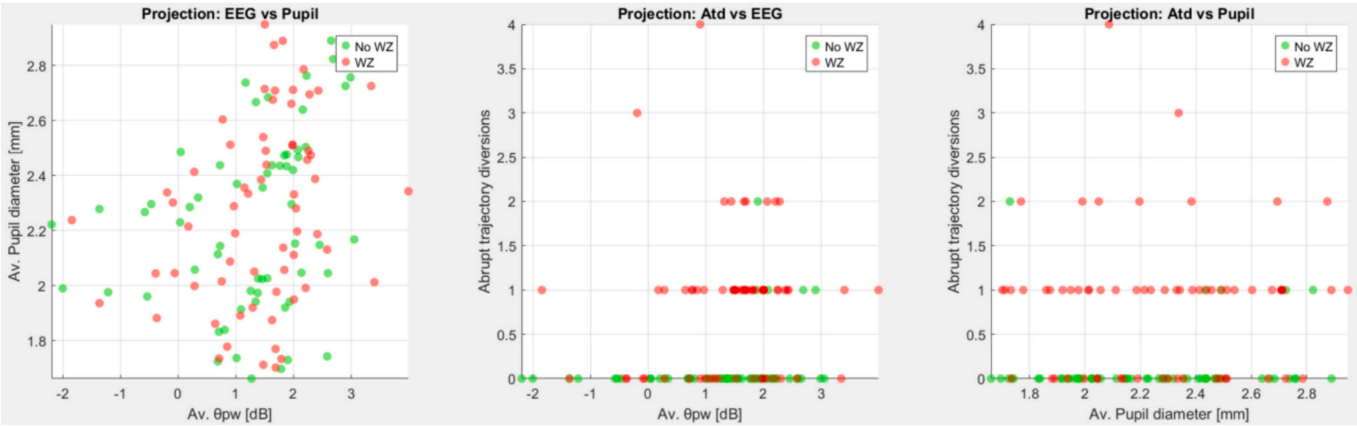

Fig. 11. 2-D Scatter plots involving all observations, divided according to the presence of WZ.

across iterations and the model exhibits structural efficiency. Furthermore, the distribution of importance is consistent and appears to reflect the hierarchy between the kinematic, neurological, and visual variables. The model was trained and validated over 500 iterations in order to estimate the number of abrupt manoeuvres related to heading, taking into account kinematic, neurological and visual features. Additionally, the most important features for determining the occurrence of abrupt manoeuvres have been identified. Cross-validation and a 70/30 train/test separation allowed for an assessment of the model's stability and the predictive relevance of the variables. Table 5 shows all the model results in detail. These results were obtained by averaging the results of the individual iterations. The RMSE and MAE values are consistent and relatively low compared to the scale of the target variable. Converted into percentage values relative to the variability of the sample, the values are 7.5% for MAE and 12.7% for RMSE, which can be considered acceptable in this context. Finally, despite the wide range of variables available, the model naturally focuses on a small, informative subset, thus reducing the risk of overfitting while maintaining good generalisation. On average, 9.82 features are selected per iteration and the sample/feature ratio is 6.52.

Further deepening the feature importance analysis, two key parameters have been considered in 500 iterations. Selection frequency (%) represents how often the feature was selected in the iterations of the model, in percentage, while Predictive importance (%) reflects the average weight of the feature in predicting Atd, normalised with respect to the total contribution of all the other factors in each iteration, and then expressed as average percentage of all iterations. The results are shown in Table 6 and Fig. 12.a. The Curve, Velocity, Complexity and EEG Index features are predominant, with selection frequencies higher than 99% and cumulative importance around 80%. These variables, which are mainly kinematic and neurological, appear to be most closely related to variations in risky driving behaviour (number of abrupt manoeuvres). Specifically, the consistent selection of the Curve variable across all iterations could be related to the sensitivity of the heading-based kinematic threshold in curved road geometries. Although highway curves typically have large turning radii, the combination of curvature and high speed may still induce measurable and harsh variations in driver behaviour. Similarly, the presence of the Complexity variable is in line with expectations, as in the event of a sudden change in geometry, users may be inclined to make decisions while driving at high speed and therefore often perform harsh manoeuvres. Interestingly, the EEG Index also appears among the most frequently selected variables, despite in the previous analysis had not shown a significant variation between the average value in cases with and without WZ. This may suggest that machine learning approaches can capture slight patterns in neurological activity that are not evident through conventional statistical comparisons. In particular, global theta activity shows a moderate but non-negligible contribution (selection frequency of 58.8% and importance of 1.1%), supporting the role of cognitive processes in driving behaviour. Good importance is also linked to other kinematic variables, such as acceleration and deceleration, further emphasizing the importance of kinematic parameters. Indeed, acceleration and deceleration are characterised by selection frequencies around 43% and 26% and importance around 9% and 5% respectively. Within the same category the Total duration of whole fixations and Total amplitude of saccades present an importance around 2% and a frequency of choice of 45.8% and 43% respectively, suggesting a secondary but still meaningful contribution. Finally, features with lower importance (<1%) and lower selection frequency (<45%), could be considered marginal for predicting Atd and may be candidates for future model reduction. These mainly include variables associated with specific visual behaviours and localized theta activity. However, within the category of visual variables, those relating to fixations are selected more frequently. Overall, the feature importance analysis revealed that kinematic and neurological factors are the primary predictors of risky driving behaviour related to heading, while visual factors provide a less significant, but still notable, contribution. Table 6 and Fig. 12.b also report the results relating to the repetition of a second FIA, this time relating only to the No WZ observations. Significant differences emerge compared to the results relating to the WZ sections, suggesting different behavioural pattern in the two contexts. In detail, in the WZ context, kinematic and geometric variables are predominant: curvature (Cu) is the most influential factor, followed by average speed (V_{av}) and complexity (Cx), indicating that driver behaviour is strongly influenced by geometric constraints and the configuration of the road-works. Conversely, under No WZ conditions, the importance of geometric variables is reduced and the contribution of EEG variables is increased, suggesting that cognitive and attentional factors play a greater role in the absence of significant structural constraints. The visual variables demonstrate a limited contribution in both contexts, though this is slightly more significant in No WZ conditions. These results suggest that the factors influencing sudden manoeuvres vary between the two scenarios, thus supporting the adoption of a separated modelling approach.

5. Conclusions

Driving through work zones is a complex and dynamic task that presents challenges to drivers' perception since temporary modifications to the road geometry could lead to risky driving behaviour and unsafe manoeuvres and the complete understanding of how drivers adapt their behaviour in these conditions is crucial for improving road safety. To achieve this goal, the research adopted an integrated approach, combining kinematic, visual and mental indicators to examine driver responses in real-world environments. For this reason, the results offer a detailed overview of the interaction between behavioural, visual and cognitive responses when drivers

Table 5
Results from the LS Boost model, related to test sets in WZ observations.

	RMSE		MAE		R^2	
	Average	St. deviation	Average	St. deviation	Average	St. deviation
WZ	0.508	0.148	0.301	0.081	0.527	0.267

Table 6
Feature importance analysis data results.

Data type	Features	Work Zone (WZ) Average Importance (%)	Work Zone (WZ) Average Selection Frequency (%)	No Work Zone (No WZ) Average Importance (%)	No Work Zone (No WZ) Average Selection Frequency (%)
Kinematic and geometry related data	**Cx**	4.56	100	/	/
	Cu	47.68	100	1.54	79.80
	$\mathbf{V_{av}}$	19.00	99.60	8.61	69.20
	$\mathbf{a_{av}}$	8.73	42.60	0.58	4.40
	$\mathbf{d_{av}}$	4.60	25.60	0.15	2.20
Visual data	$\mathbf{F_{D,av}}$	0.2	45.20	2.43	26.60
	$\mathbf{F_{TD}}$	1.94	45.80	2.85	33.00
	$\mathbf{F_{N}}$	0.12	45.20	0.63	21.40
	$\mathbf{F_{PD,av}}$	0.14	44.40	1.37	18.00
	$\mathbf{S_{N}}$	0.18	43.80	0.21	14.40
	$\mathbf{S_{PV,av}}$	0.87	43.80	0.13	10.20
	$\mathbf{S_{AM,av}}$	0.64	43.60	0.36	8.60
	$\mathbf{S_{TAM}}$	2.09	43.00	0.26	6.00
EEG data	$\boldsymbol{\theta_{pw}}$	1.11	58.80	9.04	61.8
	$\boldsymbol{\theta_{pw,fr}}$	0.43	52.60	5.34	53.4
	$\boldsymbol{\theta_{pw,pt}}$	0.53	48.00	33.00	49.4
	Index EEG	7.10	100	33.49	100

are faced with complex road scenarios as work zone areas, revealing a coherent relationship between all these factors. From a kinematic perspective, work zones are associated with a higher number of abrupt trajectory diversions, grater velocity variability and lower average velocity levels, confirming the relationship between risky driving behaviours and complex environments. Visual data reinforce this interpretation. Indeed, drivers exhibited a higher number of fixations and saccades in work zones, reflecting a fragmented and explorative visual activity. Additionally, the increase in number of fixations and total duration could indicate that visual attention is focused on multiple stimuli. The increase in pupil diameter indicates an elevation in mental workload. Saccade metrics revealed slower eye movements with greater total amplitude, indicating more extensive visual exploration. EEG analyses revealed higher theta power values, indicating enhanced brain activity. Correspondence between elevated theta activity, Atd and visual variability is also investigated and confirmed the link between these variables. Finally, the machine learning model in WZ observations identified Curve, Velocity, Complexity, and EEG Index as dominant predictors of abrupt events, highlighting the combined effect of kinematic and neural and visual factors on the prediction of risky driving behaviour in work zone areas. Comparing the results of the Feature Importance Analysis in the WZ and No-WZ environments also highlights the significant differences in the factors influencing driving behaviour between the two scenarios. This confirms the highly context-dependent nature of the processes behind abrupt manoeuvres. The current research contributes to a comprehensive understanding of driver behaviour in work zones. In detail, the analysis of the connection between the occurrence of harsh manoeuvres and visual and brain activity enables the detection of early indicators of risky driving behaviour. Investigating abrupt manoeuvres in work zones by integrating kinematic and physiological parameters offers an opportunity to apply the concept of the Human Performance Envelope (HPE) to driving. In this context, the vehicle becomes an extension of the human system and the work zone conditions represent an example of operational stress. Understanding the relationship between speed, acceleration and trajectories, as well as physiological indicators such as visual attention and brain activity, enables us to identify situations in which drivers are operating close to their performance limits. This approach has immediate, practical implications, providing an early warning of potential risks, thereby helping to prevent accidents. The data can inform the design of safer work zones by optimising geometry, signage and detours to reduce driver mental overload. Specifically, the investigation of physiological parameters may support the development of intelligent transport systems that monitor cognitive load in real time and provide adaptive driver assistance. On-board devices can detect the driver's condition, such as visual attention and workload, to identify when the drivers are approaching the limits of their HPE. In such cases, the system can activate personalised alerts (sounds, lights or vibrations) and provide driving instructions, for example by suggesting or intervening on speed, integrating information on the driver's condition and the kinematic conditions of the work zone. Furthermore, the results of the feature importance analysis can be used to inform concrete design or policy recommendations, such as the strategic placement of traffic lights or modular barriers, the definition of specific speed limits for construction sites, and targeted training programmes for drivers.

However, this study presents some limitations. First, the environmental factors, such as traffic conditions, could not be controlled in the on-site experiment. In fact, although average travel times offer some insight into traffic stability, future research could include traffic records, providing a more accurate overview of traffic conditions. Second, the sample size may impact the general applicability of the current results as well as the users' awareness of participating in an experiment and being recorded, even though they had only been informed of the general purpose — studying road safety — and not of the presence of the work zone. The sample size was particularly influenced by technical constraints related to the EEG helmet, such as limited battery life and long charging times. This meant that neurological signals could only be acquired for a subset of actual participants. Furthermore, collecting physiological data in a real environment raised additional critical issues relating to natural head movements and the characteristics of individual users (e.g. long hair). In some cases, this compromised the quality of the EEG signal. Although the number of drivers involved in the trial was

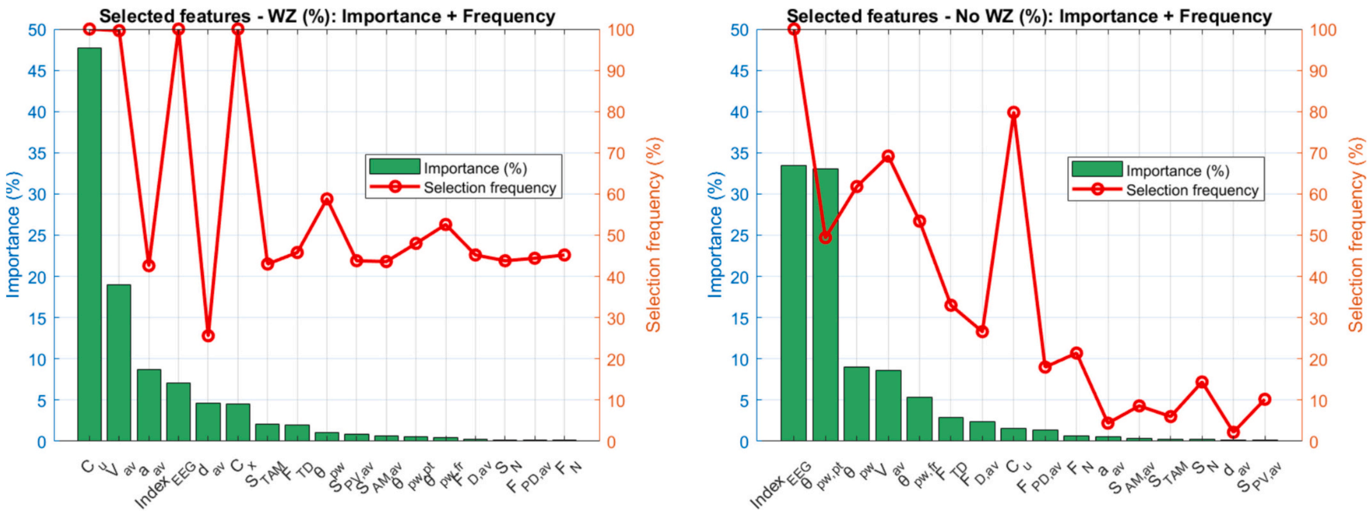

Fig. 12. Feature Importance Analysis, graphical results of WZ sections (12.a) and No WZ sections (12.b).

limited, the unit of analysis was not the individual driver but the driving section. The twelve participants travelled across thirteen of sixteen distinct road sections, resulting in a total of 156 potential observations. The reduction in the final number of observations (123) was primarily due to the requirement to include in the analysis only those traits for which all three measurement systems (kinematic, eye-tracking and EEG) provided comprehensive and reliable data. While this represents a methodological limitation, it also highlights the intrinsic complexity of collecting multimodal data in real-world contexts. Nevertheless, although the adopted methodology and aggregation of results at section level help mitigate the effect of inter-driver variability, it is not possible to completely exclude a certain degree of interdependence between observations, given that each driver contributed to multiple sections of the track. This represents a limitation of the study and suggests that, in future, methodological approaches capable of explicitly modelling intra-subject dependence should be adopted in order to ensure more reliable generalizability of results. Third, the adopted yaw rate threshold, although derived from the literature, identifies abrupt trajectory deviations rather than actual near-miss events. This suggests that the chosen criterion is more effective in representing the complexity of the driving context and the behavioural adaptations of the users than in directly identifying near-miss events. In addition, although the machine learning model proved effective, it was trained on a specific dataset and therefore requires validation on larger and more heterogeneous samples before being applied to different contexts. Finally, future studies should delve deeper into the topic of harsh manoeuvres and variations in subjective parameters in different highway work zone layouts, as well as in non-highway work zone areas (e.g. urban and extra-urban), in order to compare results and provide a comprehensive analysis of all work zone conditions. Despite these limitations, real-world testing is a strength of the study, filling a gap in the literature, which is still predominantly based on simulated contexts, and providing empirical evidence integrated into complex scenarios such as highway work zones. For these reasons, future research should focus on extending the dataset to include a wider range of drivers and road environments, integrating additional physiological indicators such as heart rate variability and skin conductance, and applying more advanced machine learning techniques to further enhance the dynamic monitoring of risky driving behaviours.

CRediT authorship contribution statement

Sofia Palese: Writing – original draft, Methodology, Investigation, Data curation, Conceptualization. **Margherita Pazzini:** Writing – review & editing, Methodology, Data curation. **Davide Chiola:** Validation, Conceptualization. **Andrea Simone:** Validation, Conceptualization. **Claudio Lantieri:** Supervision, Methodology, Investigation, Data curation. **Valeria Vignali:** Writing – review & editing, Supervision, Methodology.

Declaration of competing interest

Author Davide Chiola was employed by R&D and Innovation, Movyon S.p.A. The remaining 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.

Acknowledgements

This study is supported from the European Union Next-Generation EU (PIANO NAZIONALE DI RIPRESA E RESILIENZA-PNRR), Missione 4, Componente 1, Investimento 4.1 (D.M. 118/2023, CUP J33C23001380002). In addition, this study was also carried out whitin the Spoke 7 of the MOST-Sustainable Mobility National Research Center and also received funding from the European Union Next-Generation EU (PIANO NAZIONALE DI RIPRESA E RESILIENZA-PNRR), Missione 4, Componente 2, Investimento 1.4 (D.D. 1033 17/06/2022, CN00000023). This manuscript reflects only the authors' views and opinions. Neither the European Union nor the European Commission can be considered responsible for them.

Data availability

The data in this study will be partially available on request.

References

Al Shaaili, M., Al Alawi, M., Ekyalimpa, R., Al Mawli, B., Al-Mamun, A., & Al Shahri, M. (2023). Near-miss accidents data analysis and knowledge dissemination in water construction projects in Oman. *Heliyon, 9*(11), Article e21607. https://doi.org/10.1016/j.heliyon.2023.e21607

Bassani, M., Dalmazzo, D., Marinelli, G., & Cirillo, C. (2014). The effects of road geometrics and traffic regulations on driver-preferred speeds in northern Italy. An exploratory analysis. *Transportation Research Part F: Traffic Psychology and Behaviour, 25*, 10–26. https://doi.org/10.1016/j.trf.2014.04.019

Ben-Bassat, T., & Shinar, D. (2011). Effect of shoulder width, guardrail and roadway geometry on driver perception and behavior. *Accident Analysis & Prevention, 43*(6), 2142–2152. https://doi.org/10.1016/j.aap.2011.06.004

Bergel-Hayat, R., Debbarh, M., Antoniou, C., & Yannis, G. (2013). Explaining the road accident risk: Weather effects. *Accident Analysis & Prevention, 60*, 456–465. https://doi.org/10.1016/j.aap.2013.03.006

Bitkina, O. V., Park, J., & Kim, H. K. (2021). The ability of eye-tracking metrics to classify and predict the perceived driving workload. *International Journal of Industrial Ergonomics, 86*, Article 103193. https://doi.org/10.1016/j.ergon.2021.103193

Bobermin, M. P., Silva, M. M., & Ferreira, S. (2021). Driving simulators to evaluate road geometric design effects on driver behaviour: A systematic review. *Accident Analysis & Prevention, 150*, Article 105923. https://doi.org/10.1016/j.aap.2020.105923

Borghini, G., Astolfi, L., Vecchiato, G., Mattia, D., & Babiloni, F. (2014). Measuring neurophysiological signals in aircraft pilots and car drivers for the assessment of mental workload, fatigue and drowsiness. *Neuroscience & Biobehavioral Reviews, 44*, 58–75. https://doi.org/10.1016/j.neubiorev.2012.10.003

Brasile, C., Palese, S., Pazzini, M., Lantieri, C., & Vignali, V. (2025). Freeways' road safety analysis through accident database and human behavior. *IEEE Access, 13*, 87122–87135. https://doi.org/10.1109/ACCESS.2025.3570070

Bucsuházy, K., Matuchová, E., Zůvala, R., Moravcová, P., Kostíková, M., & Mikulec, R. (2020). Human factors contributing to the road traffic accident occurrence. *Transportation Research Procedia, 45*, 555–561. https://doi.org/10.1016/j.trpro.2020.03.057

Cafiso, S., Di Graziano, A., Di Silvestro, G., La Cava, G., & Persaud, B. (2010). Development of comprehensive accident models for two-lane rural highways using exposure, geometry, consistency and context variables. *Accident Analysis & Prevention, 42*(4), 1072–1079. https://doi.org/10.1016/j.aap.2009.12.015

Čegovnik, T., Stojmenova, K., Jakus, G., & Sodnik, J. (2018). An analysis of the suitability of a low-cost eye tracker for assessing the cognitive load of drivers. *Applied Ergonomics, 68*, 1–11. https://doi.org/10.1016/j.apergo.2017.10.011

Chen, W., Sawaragi, T., & Hiraoka, T. (2022). Comparing eye-tracking metrics of mental workload caused by NDRTs in semi-autonomous driving. *Transportation Research Part F: Traffic Psychology and Behaviour, 89*, 109–128. https://doi.org/10.1016/j.trf.2022.05.004

Cheng, W., Ye, F., Wang, C., & Bai, J. (2023). Identifying the factors contributing to freeway crash severity based on discrete choice models. *Sustainability, 15*(3), 1805. https://doi.org/10.3390/su15031805

Choudhary, A., Garg, R. D., & Jain, S. S. (2024). Safety impact of highway geometrics and pavement parameters on crashes along mountainous roads. *Transportation Engineering, 15*, Article 100224. https://doi.org/10.1016/j.treng.2023.100224

Cicchino, J. B. (2017). Effectiveness of forward collision warning and autonomous emergency braking systems in reducing front-to-rear crash rates. *Accident Analysis & Prevention, 99*, 142–152. https://doi.org/10.1016/j.aap.2016.11.009

Dadashova, B., Ramírez, B. A., McWilliams, J. M., & Izquierdo, F. A. (2016). The identification of patterns of interurban road accident frequency and severity using road geometry and traffic indicators. *Transportation Research Procedia, 14*, 4122–4129. https://doi.org/10.1016/j.trpro.2016.05.383

Depestele, S., Van Dun, K., Verstraelen, S., Ross, V., Van Hoornweder, S., Brijs, K., Brijs, T., & Meesen, R. (2023). The effect of dual-task modality on midfrontal theta power and driving performance across the adult lifespan. *Transportation Research Part F: Traffic Psychology and Behaviour, 95*, 188–201. https://doi.org/10.1016/j.trf.2023.04.007

Diaz-Piedra, C., Rieiro, H., Cherino, A., Fuentes, L. J., Catena, A., & Di Stasi, L. L. (2019). The effects of flight complexity on gaze entropy: An experimental study with fighter pilots. *Applied Ergonomics, 77*, 92–99. https://doi.org/10.1016/j.apergo.2019.01.012

Diaz-Piedra, C., Sebastián, M. V., & Di Stasi, L. L. (2020). EEG Theta power activity reflects workload among Army combat drivers: An experimental study. *Brain Sciences, 10*(4), 199. https://doi.org/10.3390/brainsci10040199

Difei, J., Cancan, S., Zhongyin, G., & Ran, L. (2021). Influence of the median opening length on driving behaviors in the crossover work zone—A driving simulation study. *Transportation Research Part F: Traffic Psychology and Behaviour, 82*, 333–347. https://doi.org/10.1016/j.trf.2021.09.001

Dingus, T. A., Klauer, S. G., Neale, V. L., Petersen, A., Lee, S. E., Sudweeks, J. D., Perez, M. A., Hankey, J., Ramsey, D. J., Gupta, S., Bucher, C., Doerzaph, Z. R., Jermeland, J., & Knipling, R. R. (2006). *The 100-Car naturalistic driving study, phase II - results of the 100-Car field experiment*. Alexandria, VA: US Department of Transportation; National Highway Traffic Safety Administration. https://rosap.ntl.bts.gov/view/dot/37370.

Domenichini, L., La Torre, F., Branzi, V., & Nocentini, A. (2017). Speed behaviour in work zone crossovers. A driving simulator study. *Accident Analysis & Prevention, 98*, 10–24. https://doi.org/10.1016/j.aap.2016.09.018

Dumitrascu, D.-I. (2024). Influence of road infrastructure design over the traffic accidents: A simulated case study. *Infrastructures, 9*(9), 154. https://doi.org/10.3390/infrastructures9090154

EEGLAB – Available online. *https://sccn.ucsd.edu/eeglab/* accessed on October 2025.

European Commission - EU Road Safety: Towards "Vision Zero". Available online. *https://cinea.ec.europa.eu/publications/digital-publications/eu-road-safety-towards-vision-zero_en accessed on October 2025*.

Farahmand, B., & Boroujerdian, A. M. (2018). Effect of road geometry on driver fatigue in monotonous environments: A simulator study. *Transportation Research Part F: Traffic Psychology and Behaviour, 58*, 640–651. https://doi.org/10.1016/j.trf.2018.06.021

Faridiaghdam, A., Mirzahossein, H., Rassafi, A. A., & Khanpour, A. (2025). Exploring the cognitive and behavioral factors impacting novice young drivers: Structural equation modeling of situational awareness, driving skills, reported crash history, and violations, using a driving simulator. *Transportation Research Part F: Traffic Psychology and Behaviour, 111*, 130–144. https://doi.org/10.1016/j.trf.2025.02.028

Fondzenyuy, S. K., Turner, B. M., Burlacu, A. F., & Jurewicz, C. (2024). The contribution of excessive or inappropriate speeds to road traffic crashes and fatalities: A review of literature. *Transportation Engineering, 17*, Article 100259. https://doi.org/10.1016/j.treng.2024.100259

Graf, M., Steinhauser, D., Vaculín, O., & Brandmeier, T. (2025). Impact of adverse weather on road safety: A survey of test methods for enhancing safety of automated vehicles and sensor robustness in challenging environmental conditions. *IEEE Access, 13*, 179817–179838. https://doi.org/10.1109/ACCESS.2025.3622501

Guillen, M., Nielsen, J. P., Pérez-Marín, A. M., & Elpidorou, V. (2019). Can automobile insurance telematics predict the risk of near-miss events? *North American Actuarial Journal, 24*(1), 141–152. https://doi.org/10.1080/10920277.2019.1627221

Hou, G., & Chen, S. (2020). Study of work zone traffic safety under adverse driving conditions with a microscopic traffic simulation approach. *Accident Analysis & Prevention, 145*, Article 105698. https://doi.org/10.1016/j.aap.2020.105698

ISTAT – Incidenti Stradali, Anno 2024. Available online: https://www.istat.it/wp-content/uploads/2025/07/REPORT_INCIDENTI_STRADALI_2024.pdf accessed on October 2025.

Jap, B. T., Lal, S., Fischer, P., & Bekiaris, E. (2009). Using EEG spectral components to assess algorithms for detecting fatigue. *Expert Systems with Applications, 36*(2), 2352–2359. https://doi.org/10.1016/j.eswa.2007.12.043

Jima, D., & Sipos, T. (2022). The impact of road geometric formation on traffic crash and its severity level. *Sustainability, 14*(14), 8475. https://doi.org/10.3390/su14148475

Khattak, A. J., Khattak, A. J., & Council, F. M. (2002). Effects of work zone presence on injury and non-injury crashes. *Accident Analysis & Prevention, 34*(1), 19–29. https://doi.org/10.1016/S0001-4575(00)00099-3

Khotimah, K., & Sjafruddin, A. (2024). Analysis of driver fatigue caused by highway hypnosis in monotonous geometrics of road: state of the arth review. In *The 9th International Conference on Civil, Structural and Transportation Engineering*. https://doi.org/10.11159/iccste24.175

Kluger, R., Smith, B. L., Park, H., & Dailey, D. J. (2016). Identification of safety-critical events using kinematic vehicle data and the discrete fourier transform. *Accident Analysis & Prevention, 96*, 162–168. https://doi.org/10.1016/j.aap.2016.08.006

Konstantopoulos, P., Chapman, P., & Crundall, D. (2010). Driver's visual attention as a function of driving experience and visibility. Using a driving simulator to explore drivers' eye movements in day, night and rain driving. *Accident Analysis & Prevention, 42*(3), 827–834. https://doi.org/10.1016/j.aap.2009.09.022

Kontaxi, A., Ziakopoulos, A., & Yannis, G. (2021). Trip characteristics impact on the frequency of harsh events recorded via smartphone sensors. *IATSS Research, 45*(4), 574–583. https://doi.org/10.1016/j.iatssr.2021.07.004

KPMG. (2025). Emerging trends in infrastructure and transportation—2025a Global Report. Available online: https://kpmg.com/kpmg-us/content/dam/kpmg/pdf/2025/emerging-trends-infrastructure-and-transport.pdf accessed on October 2025.

Krejtz, K., Duchowski, A. T., Niedzielska, A., Biele, C., & Krejtz, I. (2018). Eye tracking cognitive load using pupil diameter and microsaccades with fixed gaze. *PLoS One, 13*(9), Article e0203629. https://doi.org/10.1371/journal.pone.0203629

La Torre, F., Domenichini, L., & Nocentini, A. (2017). Effects of stationary work zones on motorway crashes. *Safety Science, 92*, 148–159. https://doi.org/10.1016/j.ssci.2016.10.008

La Torre, F., Meocci, M., Domenichini, L., Branzi, V., Tanzi, N., & Paliotto, A. (2019). Development of an accident prediction model for Italian freeways. *Accident Analysis & Prevention, 124*, 1–11. https://doi.org/10.1016/j.aap.2018.12.023

Li, J., Li, C., & Zhao, X. (2024). Optimizing crash risk models for freeway segments: A focus on the heterogeneous effects of road geometric design features, traffic operation status, and crash units. *Accident Analysis & Prevention, 205*, Article 107665. https://doi.org/10.1016/j.aap.2024.107665

Lin, C.-T., Lin, H.-Z., Chiu, T.-W., Chao, C.-F., Chen, Y.-C., Liang, S.-F., & Ko, L.-W. (2008). Distraction-related EEG dynamics in virtual reality driving simulation. *IEEE International Symposium on Circuits and Systems (ISCAS), 2008*, 1088–1091. https://doi.org/10.1109/ISCAS.2008.4541611

Lv, L., Sheng, Y., Song, C., Li, Y., & Guo, Z. (2021). Driving safety assurance method in work zone crossovers of highway reconstruction and expansion project. *Journal of Advanced Transportation, 2021*, 1–12. https://doi.org/10.1155/2021/5708779

Ma, Y., Xie, Z., Chen, S., Qiao, F., & Li, Z. (2023). Real-time detection of abnormal driving behavior based on long short-term memory network and regression residuals. *Transportation Research Part C: Emerging Technologies, 146*, Article 103983. https://doi.org/10.1016/j.trc.2022.103983

Mahanama, B., Jayawardana, Y., Rengarajan, S., Jayawardena, G., Chukoskie, L., Snider, J., & Jayarathna, S. (2022). Eye movement and pupil measures: A review. *Frontiers in Computer Science, 3*, Article 733531. https://doi.org/10.3389/fcomp.2021.733531

Mindtooth, E. E. G.. Available online: https://mindtooth-eeg.com/.

Ministero Delle Infrastrutture E Dei Trasporti – Osservatorio sulle tendenze della mobilità di passeggeri e merci (I trimestre 2025). Available online: https://www.mit.gov.it/node/19507 (accessed on October 2025).

Ministero delle Infrastrutture e della Mobilità Sostenibili (MIMS). (2021). *PIANO NAZIONALE SICUREZZA STRADALE 2030 - Indirizzi Generali e Linee Guida di Attuazione*. Available online: https://www.mit.gov.it/nfsmitgov/files/media/progetti/2022-08/PNSS_2030_-Linee_Guida-.pdf accessed on February 2026.

Morales, J. M., Ruiz-Rabelo, J. F., Diaz-Piedra, C., & Di Stasi, L. L. (2019). Detecting mental workload in surgical teams using a wearable Single-Channel electroencephalographic device. *Journal of Surgical Education, 76*(4), 1107–1115. https://doi.org/10.1016/j.jsurg.2019.01.005

NASA. Accident Precurson analysis handbook. Available online: https://ntrs.nasa.gov/api/citations/20120003292/downloads/20120003292.pdf accessed on October 2025.

Palat, B., Saint Pierre, G., & Delhomme, P. (2019). Evaluating individual risk proneness with vehicle dynamics and self-report data − toward the efficient detection of at-risk drivers. *Accident Analysis & Prevention, 123*, 140–149. https://doi.org/10.1016/j.aap.2018.11.016

Palese, S., Pazzini, M., Chiola, D., Lantieri, C., Simone, A., & Vignali, V. (2025). Crash risk analysis in highway work zones: A predictive model based on technical, infrastructural, and environmental factors. *Sustainability, 17*(13), Article 6112. https://doi.org/10.3390/su17136112

Park, J.-I., Kim, S., & Kim, J.-K. (2023). Exploring spatial associations between near-miss and police-reported crashes: The Heinrich's law in traffic safety. *Transportation Research Interdisciplinary Perspectives, 19*, Article 100830. https://doi.org/10.1016/j.trip.2023.100830

Pavlou, D., Christodoulou, G., & Yannis, G. (2023). The impact of weather conditions and driver characteristics on road safety on rural roads. *Transportation Research Procedia, 72*, 4081–4088. https://doi.org/10.1016/j.trpro.2023.11.369

Perez, M. A., Sudweeks, J. D., Sears, E., Antin, J., Lee, S., Hankey, J. M., & Dingus, T. A. (2017). Performance of basic kinematic thresholds in the identification of crash and near-crash events within naturalistic driving data. *Accident Analysis & Prevention, 103*, 10–19. https://doi.org/10.1016/j.aap.2017.03.005

Puma, S., Matton, N., Paubel, P.-V., Raufaste, É., & El-Yagoubi, R. (2018). Using theta and alpha band power to assess cognitive workload in multitasking environments. *International Journal of Psychophysiology, 123*, 111–120. https://doi.org/10.1016/j.ijpsycho.2017.10.004

Qiao, Y., Dawson, A. R., Parry, T., & Flintsch, G. W. (2015). Evaluating the effects of climate change on road maintenance intervention strategies and life-cycle costs. *Transportation Research Part D: Transport and Environment, 41*, 492–503. https://doi.org/10.1016/j.trd.2015.09.019

Rahman, M. M., Strawderman, L., Garrison, T., Eakin, D., & Williams, C. C. (2017). Work zone sign design for increased driver compliance and worker safety. *Accident Analysis & Prevention, 106*, 67–75. https://doi.org/10.1016/j.aap.2017.05.023

Shakouri, M., Ikuma, L. H., Aghazadeh, F., Punniaraj, K., & Ishak, S. (2014). Effects of work zone configurations and traffic density on performance variables and subjective workload. *Accident Analysis & Prevention, 71*, 166–176. https://doi.org/10.1016/j.aap.2014.05.016

Siriwardene, S., Ashraf, M., & Debnath, A. K. (2024). Driver preference regarding merging strategies at work zones. *Transportation Research Part F: Traffic Psychology and Behaviour, 104*, 217–233. https://doi.org/10.1016/j.trf.2024.05.023

Siriwardene, S., Ashraf, M., & Debnath, A. K. (2025). An observational study of understanding the factors influencing merging behaviour in work zones. *Transportation Research Part F: Traffic Psychology and Behaviour, 109*, 556–570. https://doi.org/10.1016/j.trf.2024.12.028

Sun, S., Bi, J., Guillen, M., & Pérez-Marín, A. (2021). Driving risk assessment using near-miss events based on panel Poisson regression and panel negative binomial regression. *Entropy, 23*(7), 829. https://doi.org/10.3390/e23070829

Talebpour, A., Mahmassani, H. S., Mete, F., & Hamdar, S. H. (2014). Near-crash identification in a connected vehicle environment. *Transportation Research Record: Journal of the Transportation Research Board, 2424*(1), 20–28. https://doi.org/10.3141/2424-03

Theofilatos, A., & Yannis, G. (2014). A review of the effect of traffic and weather characteristics on road safety. *Accident Analysis & Prevention, 72*, 244–256. https://doi.org/10.1016/j.aap.2014.06.017

Tobii – Tobii Pro Lab. (2025). Available online: https://www.tobii.com/products/software/behavior-research-software/tobii-pro-lab accessed on October 2025.

Tobii - Understanding Tobii Pro Lab's eye tracking metrics. (2025). Available online: https://connect.tobii.com/s/article/understanding-tobii-pro-lab-eye-tracking-metrics?language=en_US#FixationAndSaccadeMetrics accessed on October 2025.

Topolšek, D., Areh, I., & Cvahte, T. (2016). Examination of driver detection of roadside traffic signs and advertisements using eye tracking. *Transportation Research Part F: Traffic Psychology and Behaviour, 43*, 212–224. https://doi.org/10.1016/j.trf.2016.10.002

U.S. Department of Transportation (U.S. DOT). (2025). Safe system approach. Available online: https://www.transportation.gov/safe-system-approach accessed on February 2026.

Van Der Wel, P., & Van Steenbergen, H. (2018). Pupil dilation as an index of effort in cognitive control tasks: A review. *Psychonomic Bulletin & Review, 25*(6), 2005–2015. https://doi.org/10.3758/s13423-018-1432-y

VBox Motorsport – Circuit Tools. Available online: https://www.vboxmotorsport.co.uk/index.php/en/circuit-tools accessed on October 2025.

Vetturi, D., Tiboni, M., Maternini, G., & Bonera, M. (2020). Use of eye tracking device to evaluate the driver's behaviour and the infrastructures quality in relation to road safety. *Transportation Research Procedia, 45*, 587–595. https://doi.org/10.1016/j.trpro.2020.03.053

Vieira Gomes, S. (2013). The influence of the infrastructure characteristics in urban road accidents occurrence. *Accident Analysis & Prevention, 60*, 289–297. https://doi.org/10.1016/j.aap.2013.02.042

Vignali, V., Bichicchi, A., Simone, A., Lantieri, C., Dondi, G., & Costa, M. (2019). Road sign vision and driver behaviour in work zones. *Transportation Research Part F: Traffic Psychology and Behaviour, 60*, 474–484. https://doi.org/10.1016/j.trf.2018.11.005

Wali, B., Khattak, A. J., & Karnowski, T. (2020). The relationship between driving volatility in time to collision and crash-injury severity in a naturalistic driving environment. *Analytic Methods in Accident Research, 28*, Article 100136. https://doi.org/10.1016/j.amar.2020.100136

Wang, L., Xue, X., Zhao, Z., & Wang, Z. (2018). The impacts of transportation infrastructure on sustainable development: Emerging trends and challenges. *International Journal of Environmental Research and Public Health, 15*(6), 1172. https://doi.org/10.3390/ijerph15061172

Wang, X., Liu, Q., Guo, F., Fang, S., Xu, X., & Chen, X. (2022). Causation analysis of crashes and near crashes using naturalistic driving data. *Accident Analysis & Prevention, 177*, Article 106821. https://doi.org/10.1016/j.aap.2022.106821

Wang, X., Zhou, Q., Quddus, M., Fan, T., & Fang, S. (2018). Speed, speed variation and crash relationships for urban arterials. *Accident Analysis & Prevention, 113*, 236–243. https://doi.org/10.1016/j.aap.2018.01.032

Wen, H., Sun, J., Zeng, Q., Zhang, X., & Yuan, Q. (2018). The effects of traffic composition on freeway crash frequency by injury severity: A Bayesian multivariate spatial Modeling approach. *Journal of Advanced Transportation, 2018*, 1–7. https://doi.org/10.1155/2018/6964828

Winkler, M., Perlman, Y., & Westreich, S. (2019). Reporting near-miss safety events: Impacts and decision-making analysis. *Safety Science, 117*, 365–374. https://doi.org/10.1016/j.ssci.2019.04.029

World Health Organization. (2023). *Global Status Report on Road Safety 2023* (1st ed.) Available online: https://www.who.int/health-topics/road-safety#tab=tab_1 accessed on October 2025.

Yang, L., He, Z., Guan, W., & Jiang, S. (2018). Exploring the relationship between electroencephalography (EEG) and ordinary driving behavior: A simulated driving study. *Transportation Research Record: Journal of the Transportation Research Board, 2672*(37), 172–180. https://doi.org/10.1177/0361198118783165

Yang, L., Ma, R., Zhang, H. M., Guan, W., & Jiang, S. (2018). Driving behavior recognition using EEG data from a simulated car-following experiment. *Accident Analysis & Prevention, 116*, 30–40. https://doi.org/10.1016/j.aap.2017.11.010

Yang, Y., Liu, X., Easa, S. M., Feng, Y., & Zheng, X. (2023). Effect of distance information and number of warning signs on driving safety of young adults near road work zones in China. *Accident Analysis & Prevention, 192*, Article 107230. https://doi.org/10.1016/j.aap.2023.107230

Yang, Y., Ye, Z., Easa, S. M., Feng, Y., & Zheng, X. (2023). Effect of driving distractions on driver mental workload in work zone's warning area. *Transportation Research Part F: Traffic Psychology and Behaviour, 95*, 112–128. https://doi.org/10.1016/j.trf.2023.03.018

Zeng, Q., Gu, W., Zhang, X., Wen, H., Lee, J., & Hao, W. (2019). Analyzing freeway crash severity using a Bayesian spatial generalized ordered logit model with conditional autoregressive priors. *Accident Analysis & Prevention, 127*, 87–95. https://doi.org/10.1016/j.aap.2019.02.029

Zhang, H., Chen, L., Wang, B., Wang, X., Wang, J., Jiao, C., Feng, K., Shen, C., Wang, Q., Han, J., & Liu, Y. (2025). Research on the identification of road hypnosis based on the fusion calculation of dynamic human–vehicle data. *Sensors, 25*(9), Article 2846. https://doi.org/10.3390/s25092846

Zhang, X., Ryan, A., & Wu, Y.-J. (2025). Investigating nighttime driver behaviors and interactions at pedestrian hybrid beacons. *Transportation Research Part F: Traffic Psychology and Behaviour, 114*, 919–932. https://doi.org/10.1016/j.trf.2025.07.011

Zhang, Z., Akinci, B., & Qian, S. (2022). Inferring the causal effect of work zones on crashes: Methodology and a case study. *Analytic Methods in Accident Research, 33*, Article 100203. https://doi.org/10.1016/j.amar.2021.100203

Zhao, C., Zhang, S., Zhang, Z., & Lyu, Y. (2025). Deriving workload from driving behavior and psycho-physiology in work zones. *Accident Analysis & Prevention, 222*, Article 108240. https://doi.org/10.1016/j.aap.2025.108240

Zhao, C., Zhao, M., Liu, J., & Zheng, C. (2012). Electroencephalogram and electrocardiograph assessment of mental fatigue in a driving simulator. *Accident Analysis & Prevention, 45*, 83–90. https://doi.org/10.1016/j.aap.2011.11.019