Transportation Research Part F: Psychology and Behaviour 109 (2025) 458–479

Contents lists available at ScienceDirect

Transportation Research Part F: Psychology and Behaviour

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

A systematic review of studies investigating the impact of sleep deprivation on drivers' physiology and driving performance

Meenu Tomson, Tom V. Mathew, Nagendra Rao Velaga *

Transportation Systems Engineering, Department of Civil Engineering, Indian Institute of Technology (IIT) Bombay, Powai, Mumbai 400 076, India

A R T I C L E I N F O

Keywords:
Sleep deprivation
Driving performance
Neural
Ocular
Cardiac
Driver physiology

A B S T R A C T

Driving is a multifaceted and risky activity that requires activation and utilisation of both cognitive and physiological capabilities. Sleep deprivation tends to impair cognitive function, which compromises drivers' capabilities and increases the likelihood of crashes. Researchers have developed driver monitoring systems that can detect driving impairment by utilising driving performance measures and drivers' physiological measures. However, sleep deprivation could induce specific physiological variations accompanied by changes in driving performance, thereby rendering detection of driving impairment challenging. This study aims to categorise drivers' physiological and driving performance indicators associated with sleep deprivation and to evaluate existing evidence using a systematic review. Additionally, by examining the combined measures of behavioural and physiological state of vigilance, this review identifies correlations between various driving performance metrics and drivers' physiological responses that can help in detecting the state transitions of drivers. The twenty-five studies that met the review criteria were chosen in accordance with the PRISMA framework from four research databases: Scopus, Web of Science, Transportation Research International Documentation (TRID), and IEEE Xplore digital library. Findings from this systematic review provide consistent evidence that sleep deprived driving induces physiological variations and leads to driving performance deficits. Sleep deprived driving resulted in increased electroencephalographic slow activity (alpha and theta power) of the brain and correlated with driving performance deficits. Ocular markers, including saccadic velocity, mean blink duration, variations in gaze behaviour, and PERCLOS, were able to detect physiological impairments while driving in sleep-deprived conditions. Combining physiological measures, such as slow eye movements and increased power in the alpha and theta bands of the EEG, also served as a robust measure of impaired driving performance. Notably, this review acknowledges limitations due to the diversity of methodologies across the studies, which complicates direct comparisons of findings. Nonetheless, these research findings will give directions for future research in developing strategies for robust real-time warning systems incorporating hybrid measures to mitigate the consequences of sleep deprived driving.

1. Introduction

Road traffic accidents claim the lives of an estimated 1.19 million individuals annually, and human error contributes to a significant portion of crashes worldwide (WHO, 2023). Driver sleepiness can potentially increase human errors leading to crashes. The average prevalence of falling asleep at the wheel in recent years was estimated to be 17 % in a study conducted by the European Sleep Research

* Corresponding author.
E-mail addresses: 23d0307@iitb.ac.in (M. Tomson), tvm@civil.iitb.ac.in (T.V. Mathew), n.r.velaga@iitb.ac.in (N.R. Velaga).

https://doi.org/10.1016/j.trf.2024.12.001
Received 15 April 2024; Received in revised form 30 November 2024; Accepted 1 December 2024
Available online 24 December 2024

Society (Freitas et al., 2024). It is estimated by the US National Highway Traffic Safety Administration that approximately 1,00,000 road incidents occur annually worldwide due to driver sleepiness, resulting in over > 1500 fatalities and over 70,000 injuries (Saleem, 2022). However, crashes due to sleepy driving are generally underreported due to the absence of a standardised method to identify such types of crashes (Mahajan & Velaga, 2021).

According to the study by Chen et al. (2016), drivers typically exhibit unique circadian rhythms or sleep-wake patterns. Sleepiness arises from the accumulation of sleep pressure resulting from prolonged wakefulness and disruptions in circadian rhythm (Mahajan et al., 2019b). Sleep deprivation (≤5 h) increases the likelihood of sleepy driving compared to the recommended 7–8 h of sleep per night (Maia et al., 2013; Mahajan and Velaga, 2023). Sleep deprivation negatively impacts the state of sleep and physiological processes, which in turn may contribute to driving performance deficit. Successive commuter travel, specifically the trip after work, is susceptible to driving performance deficits when drivers experience sleep deprivation (Caponecchia and Williamson, 2018). Professional taxi drivers may engage in irregular sleep patterns or experience partial sleep deprivation, due to factors such as the desire to earn overtime pay, leading to prolonged working hours without adequate rest, and the time constraints associated with punctual arrivals and departures (Mahajan and Velaga, 2022). Likewise, night-shift workers with sleep deprivation report higher sleepiness and more dangerous driving incidents, including collisions, while commuting home after work (Lee et al., 2016; Yusoff et al., 2024). Similarly, long-haul truck drivers frequently experience sleepiness due to factors such as extended work hours, limited sleep, biological rhythms, irregular shifts, and sleep disorders, which contribute to impaired vigilance, inattention, delayed reactions, driving performance decrements, and an elevated risk of accident (Jackson et al., 2016; Mahajan et al., 2019a, 2019b).

Sleep deprivation induced crashes tend to be more severe or even fatal, as drivers are often unable to apply brakes or take corrective actions prior to a collision due to their reduced cognitive abilities or the occurrence of microsleeps (Wang and Xu, 2016; Smith et al., 2024). Accidents resulting from sleep related driving impairment are largely preventable by timely identification and the implementation of countermeasures (Cai et al., 2021). Effective driver monitoring techniques that precisely identify and detect episodes of driving impairment, with accurate time synchronization are essential to prevent accidents (Giot et al., 2022; Alvaro et al., 2016; Mulhall et al., 2020). In the absence of reliable objective metrics of sleep deprivation induced driving impairment, accurate quantification continues to be a challenging obstacle, hampering the progress of efficient interventions (Martensson et al., 2019; Mulhall et al., 2020; Soleimanloo et al., 2019; Wang and Xu, 2016).

Subjective assessments of sleepiness and objective tasks can be employed to assess and quantify the effects of sleep deprivation on drivers' sustained alertness. The impact of sleep deprivation on sustained alertness during the driving task can be assessed by self-reported evaluations of sleepiness (subjective measurements) which includes Karolinska Sleepiness Scale (KSS) (Howard et al., 2014; Wörle et al., 2021), Stanford Sleepiness Scale (SSS) (Gibbings et al., 2022), Sleepiness Symptoms Questionnaire (SSQ) (Howard et al., 2014), Epworth Sleepiness Scale (Mulhall et al., 2020), Karolinska Drowsiness Scale (KDS) (Hallvig et al., 2014), Falling Asleep Scale (FAS) (Cai et al., 2021). All these subjective measurements may require frequent intervention that tends to impede the driving task undertaken by the participant. Further, it is apparent that a continuous assessment under real-world driving conditions while maintaining driver safety seems challenging. However, vehicle-based performance measures can offer a more reliable assessment of driver performance, as they are less subjective than self-report methods. Nevertheless, it may not always accurately reflect a driver's mental state of alertness due to various external factors such as road conditions and traffic conditions which influence driving performance.

In contrast, physiological indicators of decreased arousal and the drivers' state can be measured continuously without frequent interventions via electroencephalography (EEG), heart signals, ocular activity, muscular activity, and skin conductance to determine the impact of sleep deprivation (Afghari et al., 2022; Gibbings et al., 2022; Shiferaw et al., 2018; Zeller et al., 2020). Electroencephalography (EEG) captures the electrical activity of the brain. Arousal-related activity can be inferred from the distinct spatial distributions of the frequency ranges associated with this activity, which are also associated with various states of brain function (Zeller et al., 2020). The electrocardiogram (ECG) records bioelectric currents that flow through the heart at various phases of blood circulation, which can be used to monitor and assess heart signals (Gupta et al., 2017). The electrooculogram (EOG) is utilised to capture eye movement by measuring the cornea-retinal standing potential between the anterior and posterior surfaces of the eye (Chen et al., 2015). By measuring driver physiological indicators via continuous monitoring technologies, one can objectively detect, and measure sleep deprivation induced driving impairment and take countermeasures in response to unsafe levels of impairment by providing warning alerts. Objective measures (e.g., EEG, heart rate, or ocular activity) provide precise and consistent data, thereby reducing the risk of false positives or missed detections that may occur with subjective self-reports or behaviour based observations. An effective and validated driver monitoring system (DMS) could potentially evaluate driver engagement and driver impairment. However, the current DMS faces challenges in accurately distinguishing between different causes of driver impairment (Rosekind et al., 2024). The presence of driver impairment like sleep deprivation could induce specific driver physiological variations accompanied by behavioural variations. By integrating both these measures, DMS can better predict the drivers' state of alertness to enable precise interventions to prevent safety critical events adapting to individual driver specific metrics.

1.1. Existing review on the effect of sleep deprivation on driving performance

The impact of sleep deprivation on driving behaviour has been examined in several literature reviews to date. A systematic review undertaken by Saleem (2022) investigated the correlation between driver sleepiness and motor vehicle collisions. Road traffic accidents were correlated with both sleepiness and sleep deprivation, and sleep deprivation was identified as the primary cause of sleepiness while driving. Knott et al. (2020) synthesised the existing body of knowledge pertaining to the impacts of sleep deprivation on the driving performance of shift workers. Employees on work shifts with sleep durations of less than 6.5 h per night were considerably more vulnerable to injuries and fatalities resulting from motor vehicle collisions. The review carried out by Soleimanloo et al. (2017) summarised the effect of sleep deprivation on young drivers' performance. In this context, the young driver population was disproportionately affected by sleep related collisions, which constitute one in every five fatal collisions in developed nations. This was due to reduced sleep opportunities, a decreased capacity to endure sleep deprivation, and the ongoing development of brain regions linked with decision making while driving.

1.2. Study motivation and research questions

A reduction in sleep-related collision rate could be achieved by a mechanism that monitors the drivers' mental state and alerts the motorist at critical arousal levels. The physiological signals of a driver could potentially predict the current state of the driver and trigger warning alerts via driver monitoring systems in response to critically unsafe arousal levels. However, there remains a significant research gap in ensuring the early detection of sleep deprivation induced impairment and reliability of these warning alerts. This can be addressed by incorporating physiological and behavioural variations in the detection models (Rosekind et al., 2024). Although the consequences of sleep deprivation are well documented, the underlying mechanisms of driving impairment and physiological variations during sleep deprived driving remain to be precisely understood. This underscores the necessity of the study. Moreover, the identification of physiological correlates of impaired driving performance indicators of sleep deprived drivers has not been addressed in previous reviews. Therefore, the present review comprehensively analyses the interrelationship between sleep deprivation, associated physiological alterations, and their impact on driving performance. By systematically examining a range of physiological parameters, the study aims to deepen the understanding of the underlying mechanisms of impaired driving performance during sleep-deprived conditions as well as highlighting the research needs of this topic.

The innovation of this study is emphasised by the following facts. The present study represents the first systematic literature review on sleep deprived driving behaviour focusing on physiological variations. Prior to this study, to the best of the authors knowledge, there were no published reviews highlighting the correlated measures of driver physiological and behavioural indicators under sleep deprivation indicating a significant gap in the literature. Therefore, this study stands as an innovative initiative to synthesise existing insights, contribute to evidence-based interventions and identify directions for further research in this underexplored area of human factors and driver safety.

By organising and reviewing the selected studies according to a systematic classification scheme (SCS), this investigation endeavours to address the five research questions: a) What are the characteristics of the sleep deprived driving studies? b) What are the physiological variations during sleep deprived driving? c) What are the performance measures employed to study the influence of sleep deprivation on drivers? d) What are the combined measures of behavioural and physiological state of vigilance? e) Which data analysis techniques were utilised to identify the effect of sleep deprivation on driver behaviour and associated physiological variations?

The rest of the paper is organised as follows. Section 2 presents the processes of paper identification and selection. Section 3 provides the results observed in the literature and is further subdivided into several subsections that provide information about the research questions addressed in the present study. Section 4 presents the discussion section, which summarises the key findings, policy implications and limitations of the review. Finally, in Section 5, we provide a conclusion and an outlook for possible future research directions.

2. Methods

2.1. Search strategy

A systematic review of literature synthesises research findings pertaining to a specific academic discipline, identifies significant frameworks, themes, and areas of insufficient investigation, and proposes possible avenues for future research (Golabchi et al., 2024). The present study has conducted a systematic literature review using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines, adopting the methodology used in previous reviews (Dhoke and Choudhary, 2023; Yadav and Velaga, 2021; Yadav and Velaga, 2022). We used the titles, keywords, and abstracts of the peer-reviewed papers to search the popular literature search databases such as Web of Science, Scopus, Transportation Research International Documentation (TRID), and the IEEE Xplore digital library. During the database search process, the following keywords were used in conjunction with the Boolean operators in order to locate pertinent literature:

((sleep OR sleepiness OR drowsy OR "sleep deprived") AND ((driver AND performance) OR (driving AND performance) OR (driver AND behaviour) OR (driving AND behaviour)) AND (physiology OR physiological)).

The search results were restricted by the authors to articles published between January 2013 and January 2024, a span of eleven years. These studies are likely to address research deficiencies identified by papers published prior to the current decade, making them the most suitable for identifying weaknesses in the current scenario. After combining the articles obtained from the databases, any duplicate articles within the search results were eliminated. The abstracts of the remaining articles within the search results were assessed after screening by title. The systematic review incorporated the articles that met the eligibility criteria after conducting a critical examination of the full texts.

2.2. Inclusion and exclusion criteria

In pursuit of answering the research questions, precise inclusion and exclusion criteria were established to include original research papers that investigated the distinct impacts of sleep deprivation on driving performance and driver physiology. The review included only peer-reviewed journal articles that were published in the English language. The conference papers, technical reports, and book chapters were excluded from the review. Further, the articles were screened by title manually and studies that are not directly related to the topic of investigation such as medical research studies on animal subjects were excluded. Studies that did not pertain to driver safety (i.e., not conducted on a driving simulator/on-road) or examine physiological measures while driving were excluded from the subsequent level of screening via abstract.

The full text article assessment further excluded studies that investigated driver physiology without considering driving performance measures and studies that did not consider the effect of sleep related fatigue in the driving context. As mentioned in Fig. 1, the studies conducted on participants with sleep disorders and without proper driving were also eliminated. The studies examining driving performance measures and driver physiological variations in the context of sleep deprived driving were finally included in the review. The geographical distribution of the selected studies using the PRISMA protocol is presented in Fig. 2. The results are presented in the form of a Venn diagram and the majority of studies are conducted in Australia (44 %), followed by Sweden (20 %), Germany (8 %), United States (8 %), China (4 %), Canada (4 %), Belgium (4 %), Netherlands (4 %) and France (4 %).

2.3. Methodological quality assessment

The methodological quality of the 25 selected studies was evaluated using the 'Strengthening the Reporting of Observational Studies in Epidemiology (STROBE)' checklist (Vandenbroucke et al., 2007). STROBE is a 13-item scale that is used to evaluate methodological quality, structured into three divisions as mentioned in Table 1 (Marasini et al., 2022; Yadav & Velaga, 2022).

Each item on the STROBE checklist was evaluated on a scale of 0 to 2, with a rating of '0' denoting a negative rating, '1' denoting a

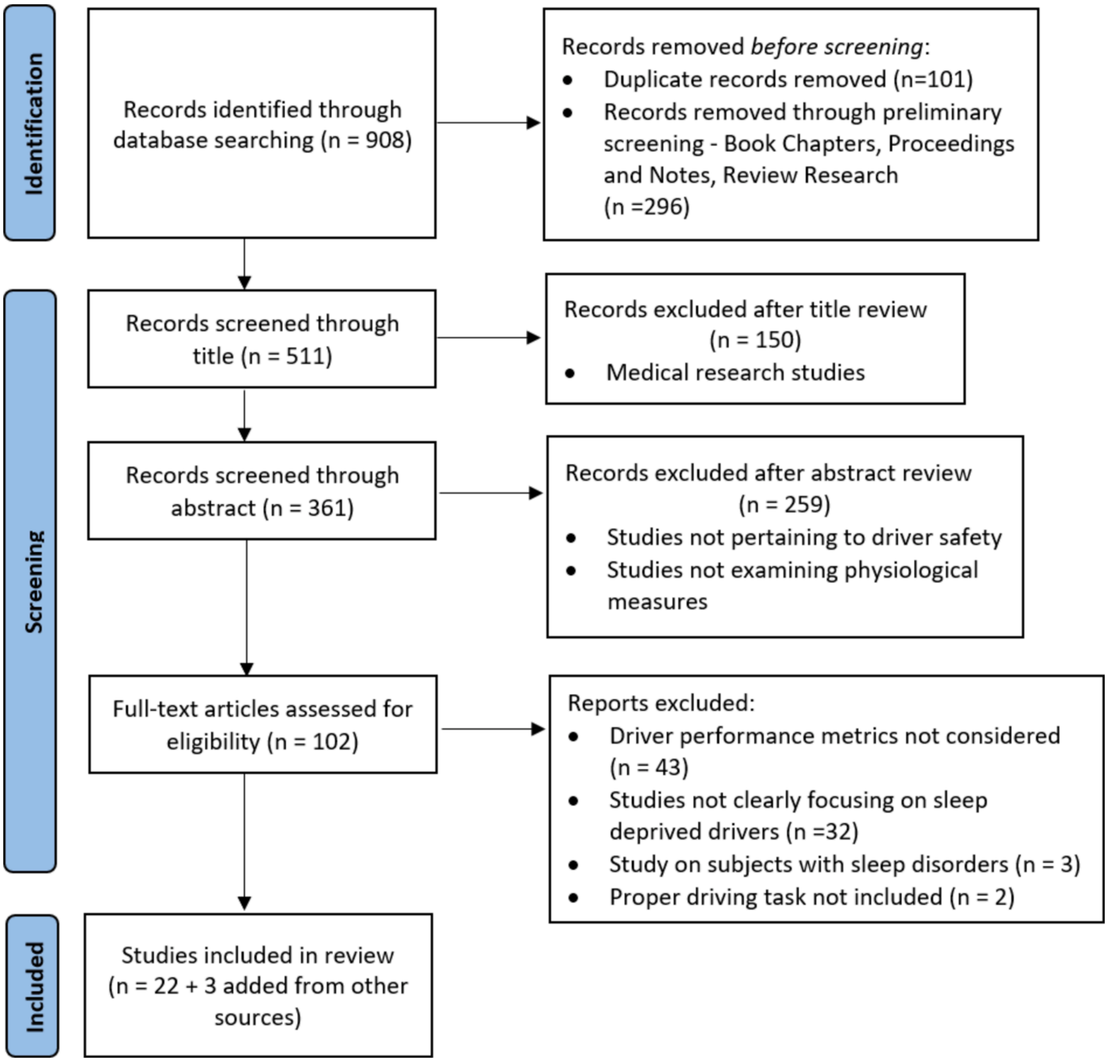

Fig. 1. Flow diagram explaining the article selection process for systematic review based on PRISMA guidelines.

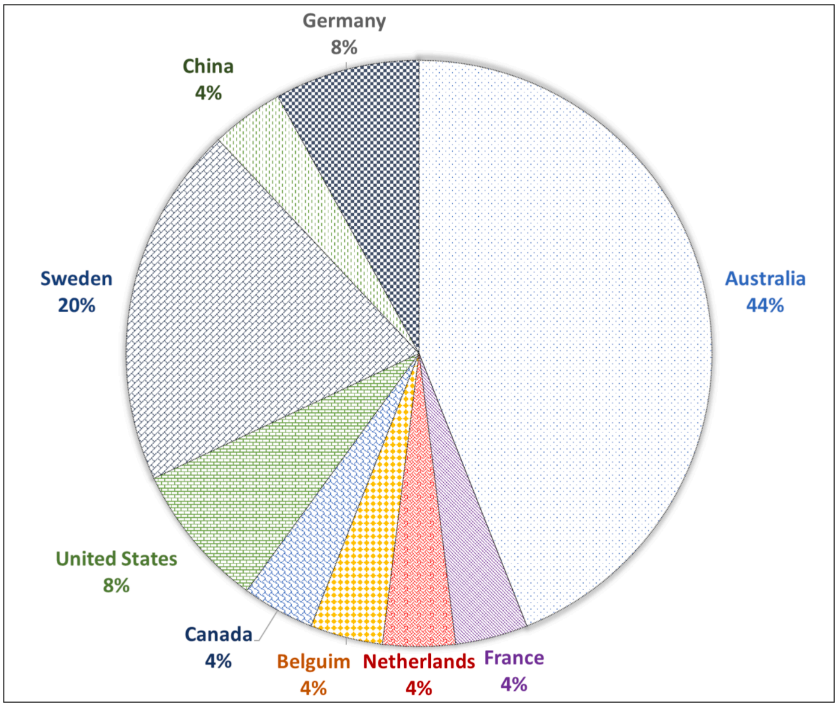

Fig. 2. Geographical distribution of the selected studies investigating the effect of sleep deprivation on driver physiology and performance.

Table 1
Methodological quality assessment.

Introduction
1. Is the scientific background clearly reported?
2. Are the objectives clearly stated?
Methods
3. Are the key elements of study design (periods of recruitment, exposure, follow-up, and data collection) clearly explained?
4. Are inclusion and exclusion criteria and selection of participants clearly explained?
5. Is the sample size considered adequate?
6. Is the method used in the assessment clearly described?
7. Is the method for assessment valid?
8. Are the statistical methods clearly described?
9. Are the statistical methods appropriate? Results/discussion
Results/Discussion
10. Are the characteristics of the subjects described?
11. Are the study outcomes clearly described?
12. Is there a cautious overall interpretation of results?
13. Are limitations of the study clearly presented?

mediocre rating, and '2′ denoting a positive rating. The total score was calculated by adding all the scores for individual studies as indicated in Table 2. The quality of the studies was categorised according to the total score values. A total score of less than 18 points was classified as poor, those between 18 and 22 were identified as medium, and those with a score of more than 22 were classified as high-quality studies (Marasini et al., 2022; Yadav & Velaga, 2022). Out of the 25 selected studies, none of the studies were of poor quality, 3 were found to be of medium quality, and the remaining 22 were of high quality.

Considering the heterogeneity of study designs in the selected papers, narrative synthesis was used to analyse the results. Narrative synthesis is useful when statistical *meta*-analysis is not feasible, as it allows for the integration of findings from multiple studies through textual descriptions (Rainieri et al., 2023).

3. Results

3.1. Characteristics of the sleep deprived driving studies reviewed

To gain an overall understanding of the current research, the key attributes of each study are tabulated in Table A1. These attributes include country of study, participant characteristics, driving characteristics, location, physiological aspect, and sleepiness scale.

Table 2
Quality assessment of selected studies using STROBE guidelines.

Authors	Introduction		Methods							Results/Discussion				Score	Quality
	1	2	3	4	5	6	7	8	9	10	11	12	13		
Shiferaw et al. (2018)	2	2	2	2	1	2	2	2	1	2	2	1	2	23	High
Giot et al. (2022)	2	2	2	2	2	2	2	1	2	2	2	2	2	25	High
Howard et al. (2014)	2	2	2	2	2	2	2	1	2	2	2	2	2	25	High
Zeller et al. (2020)	2	2	2	2	1	2	2	2	2	2	2	2	0	23	High
Perrier et al. (2016)	2	2	2	2	2	2	2	2	1	2	2	2	0	23	High
Afghari et al. (2022)	2	2	2	2	2	2	2	2	2	2	2	2	2	26	High
Gibbings et al. (2022)	2	2	2	2	2	2	2	2	2	2	2	2	0	24	High
Mulhall et al. (2020)	2	2	2	2	1	2	2	2	2	2	2	2	1	24	High
Caponecchia and Williamson (2018)	2	2	2	2	1	2	2	1	2	2	2	2	2	24	High
Soleimanloo et al. (2019)	2	2	2	2	1	2	2	2	2	2	2	2	2	25	High
Darzi et al., (2018)	2	2	2	2	1	1	2	2	2	2	1	1	2	22	Medium
Hallvig et al. (2014)	2	2	2	2	2	2	2	2	2	2	2	2	2	26	High
Jackson et al. (2016)	2	2	2	2	1	2	2	2	1	2	2	1	2	23	High
Wörle et al. (2021)	2	2	2	2	2	2	2	2	2	2	2	2	1	25	High
Wang & Xu (2016)	2	2	2	2	1	2	2	2	2	2	2	2	1	24	High
Lee et al. (2016)	2	2	2	2	1	2	2	2	2	2	2	1	1	23	High
Alvaro et al. (2016)	2	2	2	2	1	2	2	1	2	2	2	1	1	22	Medium
Liang et al. (2019)	2	2	2	2	1	2	2	2	2	1	2	2	2	24	High
Bakker et al. (2022)	2	2	2	2	1	2	2	2	2	2	2	1	2	24	High
Ahlström et al. (2018)	2	2	2	2	2	2	2	2	2	2	2	2	2	26	High
Martensson et al. (2019)	2	2	2	2	2	2	2	2	2	2	2	2	2	26	High
Filtness et al. (2014)	2	2	1	2	1	2	2	2	2	1	2	1	2	22	Medium
Hallvig et al. (2013)	2	2	2	2	1	2	2	2	2	2	2	2	2	25	High
Wörle et al. (2020)	2	2	2	2	1	2	2	2	2	2	2	2	2	25	High
Cai et al. (2021)	2	2	2	2	1	2	2	2	2	2	2	2	2	25	High

Several important observations can be made from Table A1. First, the driving duration of the studies conducted in driving simulator or on-road experiments ranges from 30 min to 2 h with an average of 80 min. Second, the sample sizes of the experiments varied between nine and eighty-six participants. The sample size was as follows: <10 subjects (1 study), 10–20 subjects (11 studies), 21–30 subjects (4 studies), 31–40 subjects (4 studies), and > 40 subjects (5 studies). Third, gender details were not available for two studies (Howard et al., 2014; Afghari et al., 2022) and no female participants were included in three studies (Alvaro et al., 2016; Bakker et al., 2022; Wang & Xu, 2016). The percentage of females in the rest of the studies ranged from 8 % to 77 % with a mean of 50 %. Fourth, the driver physiological measurements adopted in these studies include EEG, EOG, EMG, eye-tracking, GSR, respiration and ECG. Lastly, the sleepiness scale considered for the studies includes the Karolinska Sleepiness Scale (KSS), Stanford Sleepiness Scale (SSS), Sleepiness Symptoms Questionnaire (SSQ), Epworth Sleepiness Scale, Karolinska Drowsiness Scale (KDS) and Falling Asleep Scale (FAS).

Among the 25 studies, four studies specifically included professional drivers (Afghari et al., 2022; Alvaro et al., 2016; Jackson et al., 2016; Howard et al., 2014) as participants. Moreover, 3 studies included participants with night shift work schedules (Liang et al., 2019; Lee et al. 2016; Mulhall et al. 2020), which are known to influence sleep patterns uniquely. The remaining 17 studies primarily involved regular drivers possessing valid driving licenses with varying levels of driving experience, who do not drive as a primary occupation. The participants were subjected to various forms of sleep manipulation including laboratory extended wake protocols, partial sleep deprivation, shift work protocols, and total sleep deprivation. Participants' sleep and activity cycles were recorded using actigraphy and sleep logs, which also served to validate that testing methods were followed throughout the study (Gibbings et al., 2022).

3.2. Physiological indicators of driver drowsiness in sleep deprived conditions

Sleep deprivation can be assessed physiologically, as sleepiness develops gradually and is accompanied by a sequence of physiological and behavioural alterations. These physiological alterations serve as reliable indicators of impending sleepiness. The current research shows that the physiological signals deviate from their normal values during sleep deprived driving. The details of physiological and driving performance indicators explored in the selected studies are mentioned in Table A2. Efficient monitoring of the drivers' state can be accomplished through the analysis of variations in their physiological indicators. Therefore, the physiological indicators serve as objective markers for assessing sleep deprivation (Gibbings et al., 2022).

The driver physiological measures investigated in the context of sleep deprived driving studies selected using the PRISMA approach include neural measures (EEG), eye-related metrics, cardiac measures (ECG), and a combination of two or more objective metrics. The driver physiology considered in the selected 25 studies is depicted in the form of a circular dendrogram in Fig. 3. The physiological measures and the corresponding indicators explored in these studies are illustrated using a fishbone diagram (Fig. 4) and are explained in detail below.

3.2.1. Neural measures

The neural activity recorded in the cortical area of the brain reflects the potential of identifying drivers' mental states. The neural activity of the cortex can be captured through the electrophysiological monitoring method by placing electrodes along the scalp, termed as electroencephalogram (EEG). Cortical nerve cells' postsynaptic potentials represent the rhythmic activity shown in the EEG, which accumulates in the cerebral cortex and spreads to the scalp (Zeller et al., 2020). The most reliable method for early detection of hypo-vigilance is electroencephalography (EEG), which is regarded as the gold standard in vigilance monitoring due to its direct recording of neural activity and high temporal resolution, i.e. in milliseconds (Giot et al., 2022). Neural oscillations observed in the EEG are referred to as the spectral content of the EEG. The EEG spectral power shifts from the beta band (12 to 30 Hz) to the alpha band (8 to 12 Hz) and then to the theta band (4 to 8 Hz) with the onset of sleepiness (Aeschbach et al., 1997). Elevated EEG activity in the alpha and theta bands is associated with decreased vigilance and increased sleepiness (Giot et al., 2022; Perrier et al., 2016). A reduction in alpha wave activity and an increase in theta wave activity were observed as characteristic features of microsleeps, which are transient, unintentional episodes of sleep or attention loss that may occur despite seeming alert and engaged in an activity (Minhas et al., 2024). Recently, it was demonstrated that physiological arousal could be affected by partial sleep deprivation, as evidenced by increased frontal delta (0.5 to 4 Hz), increased alpha, and decreased beta activity while performing psychomotor vigilance tasks repeatedly (Gibbings et al., 2021). Nevertheless, the findings on beta activity are less consistent, as beta activity is elevated when drivers endeavour to maintain vigilance when their driving capacity decreases with time on task (Zeller et al., 2020). Therefore, it can be summarised that electroencephalographic slow wave activity increased after sleep deprivation and was linked to performance deterioration in the driving context.

3.2.2. Eye measures

Researchers have studied the effect of sleep deprivation on the ocular measures by examining the percentage of time the eyes were closed, blink duration, pupillary activity, amplitude and velocity of eyelid closure, saccadic velocity, and gaze behaviour (Alvaro et al., 2016; Mulhall et al., 2019; Lee et al., 2016; Jackson et al., 2016). Slow eyelid closure was observed as a possible precursor to sleepiness in sleep deprived individuals. This physiological response occurs due to the relaxation of the muscles involved in the thalamic motor projections to the face including the eyelids (Jackson et al., 2016). The duration of one blink is calculated as the time in milliseconds between the full eye closure to full eye opening (Cai et al., 2021). The blink duration of participants who did not experience sleep deprivation was typically between 100 and 500 ms. However, sleep deprived participants displayed blink duration that persisted longer than 500 ms (Cai et al., 2021). The average blink duration (Alvaro et al., 2016; Hallvig et al., 2014; Mulhall et al., 2019),

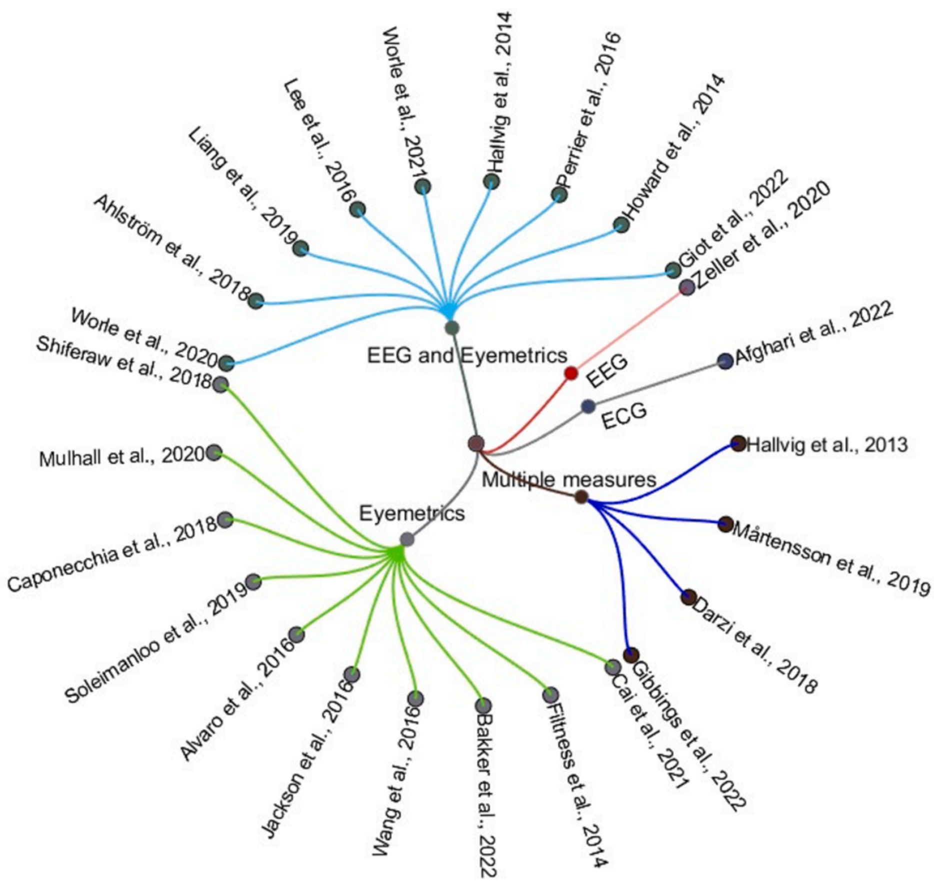

Fig. 3. A circular dendrogram representing the corresponding studies and driver physiology considered in the selected studies (N = 25).

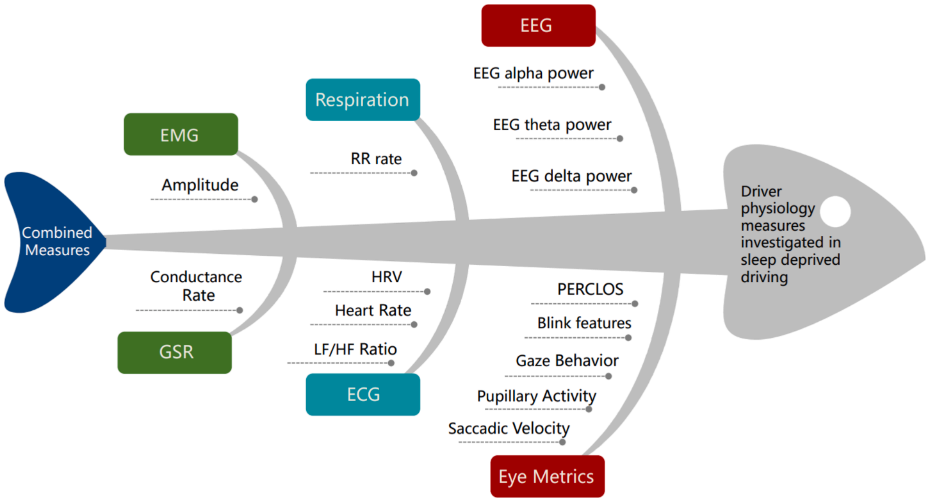

Fig. 4. Fishbone diagram showing the various driver physiology metrics investigated in sleep deprived driving studies.

amplitude and velocity of eyelid movements (Alvaro et al., 2016; Lee et al., 2016) were directly linked to reduced alertness, frequent instances of inattention, and negative driving incidents in real-world scenarios.

The percentage of eyelid closure (PERCLOS) indicates the proportion of a one-minute interval during which an eyelid covers more than 80 % of the pupil. PERCLOS is linked to sleepiness, reduced alertness, and psychomotor performance, as well as lane departures and collisions in sleep-deprived drivers during simulated driving sessions (Alvaro et al., 2016; Caponecchia and Williamson, 2018; Wörle et al., 2021; Jackson et al., 2016). Cai et al. (2021) also outlined that PERCLOS was greater in the sleep-restricted condition compared to the baseline condition without any sleep debt. However, Jackson et al. (2016) noted considerable variation among subjects in the extent of ocular closure documented after sleep deprivation, as evidenced by the considerable standard deviations. Bakker et al. (2022) also found that sleep deprivation affects eye aperture, but it is subject to interindividual variability and does not predict road departure events. Further, sleep deprivation was found to impair pupillary activity and saccadic velocity which impacts driving tasks requiring visual attention (Soleimanloo et al., 2019). Cai et al. (2021) examined how sleep deprivation interacts with driver age and its effects on ocular metrics. It was observed that younger individuals exhibited an increase in ocular indicators of sleepiness subsequent to sleep deprivation, such as blink duration, number of long eye closures, and PERCLOS in comparison with older adults.

Drivers primarily monitor their surroundings through visual perception; therefore, the capacity to selectively process visual information is crucial for safe driving operations. Decreased ability to actively scan the road and immediate surroundings correlates with an increased likelihood of road accidents and impaired perception of potential dangers (Shiferaw et al., 2018). Visual scanning, also known as gaze behaviour, pertains to the spatial distribution of overt attention to gather visual information utilising fixations that take place between saccadic eye movements. In an on-road driving task following sleep deprivation, there was an increase in the duration and rate of blinks and a decrease in fixation rates, indicating changes in gaze behaviour (Shiferaw et al., 2018). Zhang et al. (2024) observed that sleep deprived drivers monitored mainly the forward field of vision ignoring the observation of the left and right rear areas which tends to impair driving safety. Similarly, Kuo et al. (2019) observed an increased tendency of visual distraction for sleep deprived participants in naturalistic driving conditions. In conclusion, ocular markers such as mean blink duration, saccadic velocity and PERCLOS demonstrate potential in identifying physiologic impairment when driving under sleep deprived conditions in naturalistic environments.

3.2.3. Cardiac measures

Bioelectric currents traversing the heart at various phases of blood flow produce the electrical activity of the heart which is quantified by the electrocardiogram (ECG). The analysis of these bioelectric currents yields measures such as heart rate (HR), heart rate variability (HRV), time and frequency domain variables of HRV such as RMSSD (root mean square of successive differences of NN-intervals), power of lower frequencies (LF), power of higher frequencies (HF), LF/HF ratio (Afghari et al., 2022; Darzi et al., 2018; Martensson et al., 2019). These measures can be used to assess physiological changes that may impair driving performance under sleep deprivation. A reduction in sympathetic activity and an augmentation in parasympathetic activity accompany the transition from wakefulness to sleep (Tkachenko et al., 2024). Heart rate (HR) fluctuations tend to increase after sleep deprivation which occurs due to the interaction between the brain and the heart via the sympathetic and parasympathetic branches of the autonomic nervous system (Schlagintweit et al., 2023). Temporal variation between adjacent heartbeats is denoted by HRV (Razak et al., 2023). Laboratory investigations have demonstrated that heart rate variability (HRV) can serve as a robust predictor of alertness state in subjects who have experienced both total and partial sleep deprivation (Chua et al., 2012; Henelius et al., 2014; Afghari et al., 2022). The heart rate variability (HRV) time domain feature RMSSD (root mean square of successive differences of NN intervals) was used by (Martensson et al., 2019) for alertness classification in sleep deprived participants under naturalistic driving conditions. Fluctuations in the LF/HF ratio, i.e. the ratio of the powers in the low frequency (0.04 to 0.15 Hz) and high frequency (0.15 to 0.4 Hz) bands of HRV were also observed under sleep deprived conditions (Schlagintweit et al., 2023). However, inconsistency in results was reported due to variations in experimental configurations and possible constraints associated with small sample sizes (Lu et al., 2022).

3.2.4. Other measures

Sleep deprivation alters the autonomic nervous system's equilibrium and increases sympathetic activity. This physiological response can be measured using the Galvanic Skin Response (GSR) which is an indication of the electrical conductance of the skin. Since GSR is sensitive to variations in autonomic function, measurements of GSR may reveal changes in sympathetic arousal which can manifest as increased skin conductance. Meanwhile, the respiratory system displays distinct patterns when awake or asleep. Sleep deprivation is associated with heightened respiratory activity leading to an increase in respiration rate (Darzi et al., 2018). An electromyogram (EMG) uses electrodes that are placed on the skin over the muscle to record the electrical activity of the muscles (Hallvig et al., 2014). These measures can be combined with the neural, ocular, and cardiac measures to gain more understanding of the complex effects of sleep deprivation on a driver's cognitive and physiological state and earlier identification of risky driving behaviour.

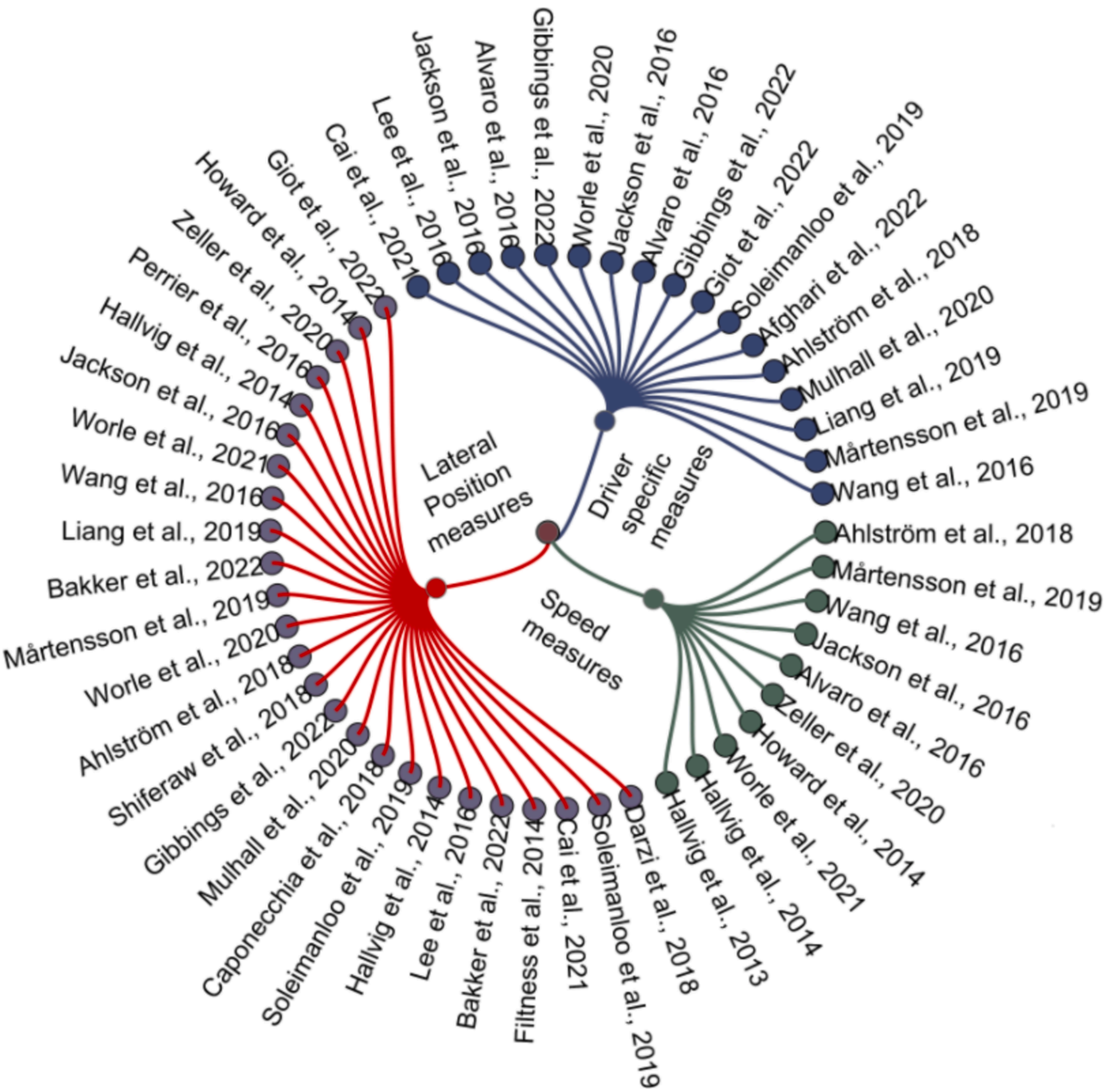

Fig. 5. A circular dendrogram representing the driving performance measures and the corresponding studies investigating the variations while sleep deprived driving.

3.2.5. Combined measures

Among the studies incorporated in the final synthesis of research, combined measures of EEG and eye metrics were used in 9 studies as indicated in Fig. 3. Slow eye movements captured using electrooculography (EOG) and increased power in the alpha and theta band of EEG was utilised as a combined measure of decreased vigilance under sleep deprived driving conditions (Giot et al., 2022; Hallvig et al., 2014; Lee et al., 2016; Howard et al., 2014; Perrier et al., 2016). Further, the duration, amplitude/velocity ratio (AVR) of the blinks from EOG and power in the alpha and theta bands of EEG were used to comprehensively assess the performance of sleep-deprived drivers (Ahlstrom et al., 2018; Lee et al., 2016; Liang et al., 2019). Elevated percentage of eyelid closure (PERCLOS) values along with EEG-defined microsleeps also served as markers of impaired performance (Wörle et al., 2021). Four studies used multiple physiological signal data by combining EEG, EMG and EOG (Gibbings et al., 2022), EEG, EOG and ECG (Martensson et al., 2019), ECG, GSR, Respiration and Skin temperature (Darzi et al., 2018) and EEG, EOG, EMG (Hallvig et al., 2014). The EOG recordings and collected EMG recordings were helpful while processing EEG data for the removal of movement artifacts (Gibbings et al., 2022; Hallvig et al., 2014). When data from different physiological sensors are fused, it tends to improve the prediction accuracy and reliability of drivers' mental state detection systems (Martensson et al., 2019). By integrating multiple physiological inputs, the detection systems can comprehensively assess the complex drivers' state mitigating the impact of noise in individual signals. Moreover, real time physiological inputs could be collected unobtrusively from sensors located in the driver seat, steering wheel or remote eye trackers (Darzi et al., 2018; Martensson et al., 2019).

3.3. Effects of sleep deprivation on driving performance

Driving performance is influenced by the driver's ability to remain vigilant for extended periods, particularly in monotonous situations. As described by Perrier et al. (2016), vigilance refers to the behavioural activity required to maintain alertness and readiness to respond in risky situations. According to the current literature, reduced vigilance as a result of mild sleep deprivation was apparent right from the start of the drive, as indicated by increased self-reported ratings of higher sleepiness and decreased alertness; however, no decline in performance was observed (Zeller et al., 2020). It appears that drivers may have attempted to compensate for their state of impairment by applying more driving effort during the beginning of the drive (Zhang et al., 2024; Zeller et al., 2020). Nevertheless, it has been noted that their performance is likely to deteriorate substantially over time, thereby increasing their vulnerability to collisions (Zeller et al., 2020). Experimental investigations are commonly conducted to investigate the impact of driver sleep restriction, often employing driving simulators (Giot et al., 2022; Howard et al., 2014; Zeller et al., 2020), standardised highway

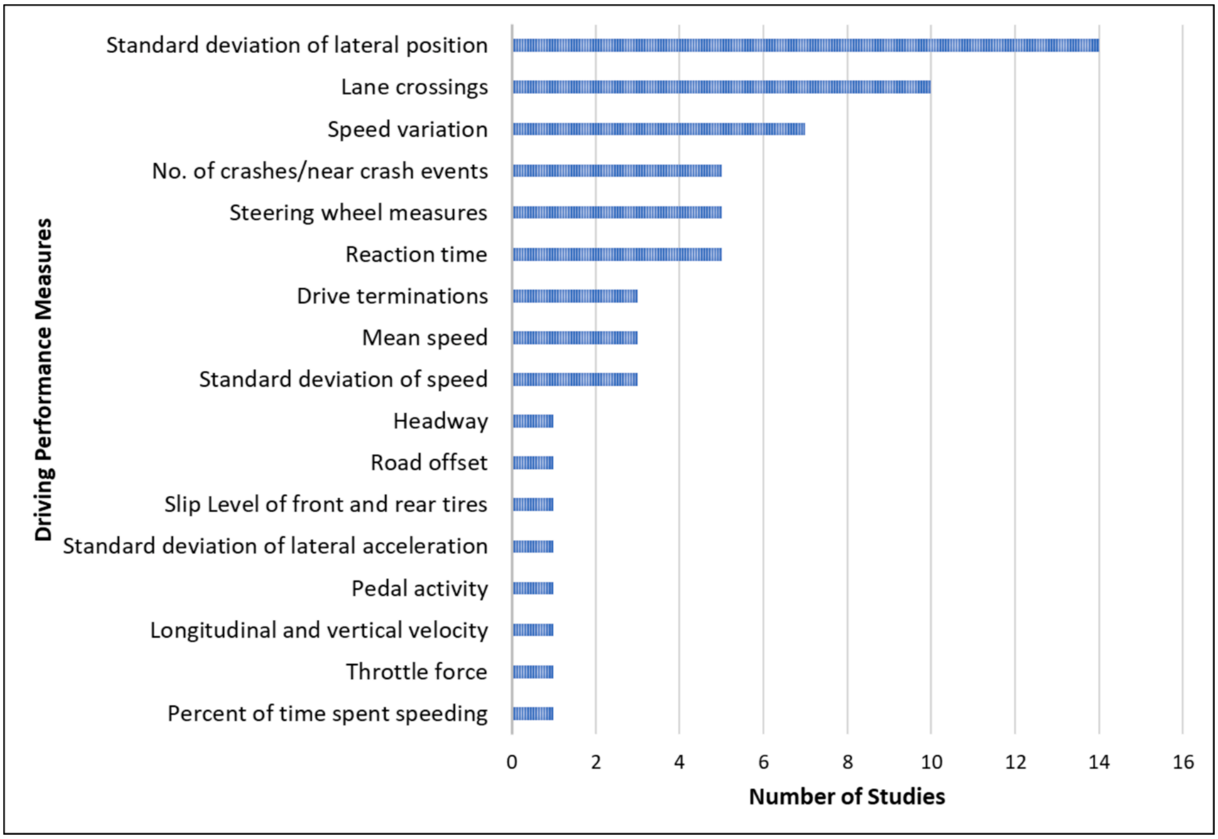

Fig. 6. Distribution of selected studies in the context of driving performance measures investigated during sleep deprived driving.

tests (Shiferaw et al., 2018) and realistic driving studies (Afghari et al., 2022). A driving simulator offers optimal control over extraneous variables, making it the most suitable method for preliminary investigations into the impact of sleepiness on driving performance. Further on-road testing conducted may validate the findings obtained from simulator studies (Caponecchia and Williamson, 2018). The literature used to describe the driving performance indicators investigated during sleep deprived driving are represented through a circular dendrogram diagram as shown in Fig. 5. On broad categorisation, the driver performance measures such as the lateral position measures, speed measures and driver specific measures tend to show significant variations from normal values during sleep deprived driving conditions.

Sleep deprivation tends to impair driving ability as evidenced by more instances of lateral deviations and dangerous manoeuvres (Bakker et al., 2022; Giot et al., 2022; Hallvig et al., 2014), slower reaction times (Alvaro et al., 2016; Gibbings et al., 2022; Giot et al., 2022; Jackson et al., 2016), improper speed management, including dozing off while driving (Caponecchia and Williamson, 2018; Williamson et al., 2011). The driving performance metrics investigated in the studies focused on sleep deprived driving are depicted in Fig. 6. The standard deviation of lateral position was observed to be the most frequently used performance measure (14 out of 25 studies), followed by lane crossings (10 studies), speed variations (7 out of 25 studies), reaction time (5 studies), steering wheel measures (5 studies), drive terminations (3 studies), mean speed (3 studies) and pedal activity (1 study) among others.

3.3.1. Lane deviations

Lane keeping performance is a critical aspect of driving performance evaluation, particularly when assessing the effects of driver impairment under sleep deprivation. According to the selected studies, there was a distinctive correlation between decreased driver vigilance and increased variability in lateral lane position under sleep deprived conditions (Alvaro et al., 2016; Bakker et al., 2022; Hallvig et al., 2014; Howard et al., 2014). For instance, the incidence of lane deviations per 15 min after total sleep deprivation was 5.5 times higher than in a normal condition without sleep deprivation (Cai et al., 2021). The standard deviation of lateral position (SDLP), which measures the ability of a driver to maintain consistent lane control, increased significantly when they were sleep deprived (Liang et al., 2019; Martensson et al., 2019; Perrier et al., 2016). The standardised highway driving study conducted by Perrier et al. (2016) required participants to drive an instrumented car at 95 km/h with a consistent lateral position inside the traffic lane. The standard deviation of the lateral position (SDLP) was calculated for each of the five-kilometre segments in the entire test, which is an indicator of the weaving error. The deterioration of driving performance as assessed by SLDP also aligns with research that documented a reduction in driving performance after sleep restriction in driving simulator settings (Giot et al., 2022; Hallvig et al., 2013; Jackson et al., 2016; Wang & Xu, 2016; Wörle et al., 2021; Zeller et al., 2020). Therefore, there exists a consistent correlation between sleep deprivation and increased lateral variability, measured by the standard deviation of the lateral position (SDLP).

Likewise, sleep deprived driving conditions are also associated with an increased frequency of lane crossings or lane departures (Ahlström et al., 2018; Bakker et al., 2022; Filtness et al., 2014; Gibbings et al., 2022; Hallvig et al., 2013; Lee et al., 2016; Mulhall et al., 2020; Shiferaw et al., 2018; Soleimanloo et al., 2019; Wang & Xu, 2016). Lane departure is said to occur when a vehicle crosses the limits of the driving lane, either entirely or partially, thus exiting the driving lane (Hallvig et al., 2013; Shiferaw et al., 2018; Soleimanloo et al., 2019). Another reliable metric for measuring lane departure events is off-road duration, which is the time in seconds a vehicle spends crossing the lanes (Giot et al., 2022). For naturalistic driving in urban areas, lane departures can be attributed to normal driving behaviour (e.g., avoiding obstacles or crossing lanes strategically), neither of which is apparent in a controlled laboratory and test track driving environments (Hallvig et al., 2014). This is consistent with the results that indicate that there was no correlation between lane departures and any of the subjective driving measures in naturalistic driving environments. This finding suggests that lane departures may not serve as the most reliable objective measure of sleep-related driving performance deficit during naturalistic driving in urban environments.

3.3.2. Steering wheel measures

Research has shown that sleep deprivation tends to alter steering wheel activity, which is investigated through steering control measures such as standard deviation of steering wheel angle, aberrant steering movements, rate of micro steering corrections, steering wheel reversals, and mean steering wheel error (Ahlström et al., 2018; Liang et al., 2019; Martensson et al., 2019; Mulhall et al., 2020; Wang & Xu, 2016). Sleep deprived drivers are more likely to make more frequent and larger steering corrections causing higher variability in steering wheel angle (Martensson et al., 2019; Mulhall et al., 2020). As sleep deprivation induces reduced motor co-ordination, the smoothness of movements is negatively affected, as indicated by the mean steering wheel error measured on the linear segments of the driving lane (Liang et al., 2019). Microsleeps or lapses in attention due to sleep deprivation can also cause aberrant steering movements and steering wheel reversals which further induce higher variability in steering wheel angle (Ahlström et al., 2018; Wang & Xu, 2016).

3.3.3. Speed

Driving performance in terms of speed management was significantly diminished during the sleepy state compared to the vigilant state under automated driving conditions (Wörle et al., 2021). Research indicates that a 5 % increase in average speed can lead to a 5 %

rise in injuries and a 20 % increase in fatal collisions (Zhang et al., 2024). It is worth mentioning that sleep deprived drivers often attempt to compensate for their diminished vigilance by reducing their speed (Hallvig et al., 2013; Martensson et al., 2019). However, the mean speed increased along with the increase in sleep debt, especially during the circadian low times when performance is at its lowest. However, some studies in the driving simulator reported insignificant variations in speed that could be due to traffic density in the simulated driving scenarios (Hallvig et al., 2014; Zeller et al., 2020). Additionally, lack of sleep slows cognitive processing, which might extend the time required to decelerate in dangerous situations where speed management is lacking. Therefore, drivers may only moderately reduce crash risk by reducing speed, while crash risk due to sleep loss is unavoidable. To obtain a speed metric that could accommodate fluctuations in the speed limit in the scenarios, the percentage of time spent speeding was incorporated by Caponecchia and Williamson (2018). During car-following events, drivers often accelerate and decelerate to maintain a safe distance from the lead vehicle, which is reflected in the speed variability. Under partially sleep deprived conditions prior to driving, drivers often exhibit significant speed variability (Alvaro et al., 2016; Jackson et al., 2016; Wang & Xu, 2016; Howard et al., 2014; Ahlström et al., 2018). As a result, the deceleration rate required to avoid collisions may be affected, thus increasing the risk of rear-end collisions under partially sleep deprived conditions (Mahajan and Velaga, 2021). Therefore, higher speeds and speed variability can result in severe braking events, intensifying the likelihood of collisions (Mahajan and Velaga, 2020, 2023).

3.3.4. Reaction time

Reaction time is the duration between the onset of a stimulus and the initial reaction of the driver, which can involve either releasing the force applied on the accelerator pedal to slow down or using the brake pedal (Mahajan and Velaga, 2020; Jackson et al., 2016). Research conducted by Mahajan and Velaga (2020) in a driving simulator environment revealed that sleep deprivation reduces their response time and hinders decision making ability. Interestingly, studies reported that participants exhibited delayed reaction time during braking events in driving simulator under sleep deprived driving conditions (Gibbings et al., 2022; Alvaro et al., 2016). In addition, reduced performance was observed in drivers following sleep deprivation while performing a psychomotor vigilance task (PVT), i.e., 10-minute PVT following the driving task. Participants were positioned in front of a visual screen that intermittently displayed a stimulus at random timings spanning from 2 to 10 s (Giot et al., 2022). Participants were required to respond by pressing a button rapidly in response to the visual stimulus. The analysis considered both the reaction time after the appearance of the stimulus and the degree of attentional lapses. Further, in automated driving conditions, Wörle et al. (2020) found that drivers had slower reactions after sleep, which might potentially result in safety critical situations, particularly in time sensitive takeover scenarios.

3.3.5. Driving terminations

Sleep deprivation resulted in a greater frequency of early drive terminations and out of lane events. According to a study by Soleimanloo et al. (2019), an increase in early drive terminations by 58 % and out-of-lane driving incidents by 3.7 times were observed as significant consequences of acute sleep deprivation lasting 32 to 34 h. The study conducted by Lee et al. (2016) on post night shift workers in an instrumented vehicle revealed that in around 37.5 % of post night shift drives, emergency braking manoeuvres were instigated by a safety observer that encountered a near crash event to avert safety critical events. According to Cai et al. (2021), although drive terminations began to occur after 30 min, driving performance deficits were evident within the first fifteen minutes of driving, indicating that even relatively brief commutes under sleep deprivation can expose drivers to safety critical incidents.

3.3.6. Headway

The driving performance metric based on headway is determined by the difference in time or distance between two consecutive vehicles as they pass a specific point. Mahajan and Velaga (2021) investigated the impact of mild sleep deprivation on driver behaviour during car following events. They hypothesised that diminished vigilance resulted in inadequate speed regulation and impaired judgement of headways, which in turn led to narrower headways. Lower headways resulting from sleep deprivation will further diminish the time accessible for reacting and applying the brakes in emergency scenarios, thereby impeding the ability to prevent a collision with the leading vehicle. Therefore, drivers who experience sleep deprivation prior to driving are more susceptible to rear end collisions. However, drivers may exercise greater caution due to risk compensating behaviour at lower headway (Oviedo-trespalacios et al., 2020). Driver situational awareness may be heightened due to the difficulty and intricacy of controlling the vehicle in narrower headways, which can lead to this behaviour (Afghari et al., 2022).

3.3.7. Other measures

Additional driving performance metrics that were examined in the selected research works include throttle force, slip level of front tyres and rear tyres, number of crashes or near crash events, standard deviation of lateral acceleration and pedal activity (Alvaro et al., 2016; Darzi et al., 2018; Martensson et al., 2019). Pedal activity was incorporated as a parameter of manoeuvring effort in a manner similar to that of steering activity. The percentage of time during which the accelerator or brake pedals were actively applied was utilised to define pedal activity (Ahlstrom et al., 2018). The correlation between sleep deprivation and driving performance is complex due to the possibility that both factors are endogenous. Sleep deprivation, although seemingly inconsequential from the drivers' perspective, can potentially interact with various dynamic elements that occur throughout the drive, such as lane changing, overtaking, braking and interaction with other road users. According to Afghari et al. (2022), when delineating the impact of sleep deprivation on driving performance, it is imperative to consider this variation, known as unobserved heterogeneity.

3.4. Combined measures of behavioural and physiological state of vigilance during sleep deprived driving

Among the twenty five studies focusing on the effects of sleep deprivation on driving performance and associated driver physiology, only eleven studies reported the combined measures of driver physiology and driving behaviour during sleep deprived driving, as summarised in Table 3. Distinct behavioural and physiological patterns can be indicative of the mechanisms underlying driving impairment (Rosekind et al., 2024). The correlation between driving tasks and EEG spectral power variations was investigated in the study by Gibbings et al. (2022). The findings revealed a significant correlation between reaction time and EEG spectral power in the sigma (12 to 16 Hz) and alpha (8 to 12 Hz) bands, with longer reaction times during braking associated with greater power in the above-mentioned frequency bands. However, there was no significant correlation between variations in EEG spectral power and the number of crashes. Higher levels of subjective drowsiness were associated with longer blink durations, an increased number of lane crossings (Ahlström et al., 2018), increased steering activity, and, to some extent, theta activity (Ahlström et al., 2018). The ocular markers, namely pre-drive mean blink duration and percentage of eyelid closure, were effectively utilised to distinguish behavioural microsleeps and detect impaired vigilance in night shift workers. Although pre-drive ocular features, specifically prolonged eye closures, could predict lane departures, their precision was lower compared to behavioural microsleeps (Mulhall et al., 2020). According to a study by Lee et al. (2016), an increase in driving duration was associated with the incidence of slow eye movements and lane departure events. PERCLOS accounted for a substantial proportion of the variability in the standard deviation of the lateral position (Jackson et al., 2016; Liang et al., 2019). Soleimanloo et al. (2019) found that a higher probability of out of lane incidents and premature drive terminations was correlated with prolonged eye closures, slowed eyelid movements, and extended blink durations.

Based on the findings of the research conducted by Shiferaw et al. (2018), it was inferred that lane departure events are more likely to be predicted by the frequency of fixations and dispersion of gaze. This is because a narrower fixation frequency and a wider dispersion of gaze would lead to diminished surveillance of the road directly in front of the vehicle. Based on EEG and EOG sleepiness indicators, the Objective Sleepiness Scale (OSS) devised by Giot et al. (2022) detects and quantifies sleepiness. OSS reflects the number of seconds between the simultaneous observation of alpha and/or theta waves in two distinct regions of the brain and the detection of slow eye movements or slow blinks on the EEG channels. The findings revealed significant correlations between the OSS score and driving performance variables such as standard deviation of lateral position, psychomotor vigilance task (PVT) reaction time, and offroad duration with good time synchronisation.

3.5. Data analysis techniques

To ascertain the significance of the impact of sleep deprivation on performance measures, numerous statistical techniques were employed in the selected studies. A considerable body of research has used analysis of variance (ANOVA) to ascertain the associations between performance variables and sleep variables (Shiferaw et al., 2018, Howard et al., 2014, Zeller et al., 2020, Perrier et al., 2016, Filtness et al., 2014, Worle 2021, Gibbings et al., 2022, Caponecchia and Williamson, 2018, Ahlström et al., 2018). These approaches

Table 3
Summary of studies that reported driving performance measures with correlated driver physiological variables.

Author, Year	Simulator/ On-road	Effect on driving performance measure	Correlated driving physiology measure
Hallvig et al., 2014	On-road	Lane departure events	Blink duration
Jackson et al., 2016	Simulator	Standard deviation of lateral position (SDLP)	PERCLOS
Alvaro et al., 2016	Simulator	SDLP, braking reaction time, crashes	Length of eyelid closure episodes
Lee et al., 2016	On-road	Lane crossing events	Frequency of slow eye movements
Shiferaw et al., 2018	On-road	Lane departure events	Dispersion of gaze and frequency of fixations
Ahlström et al., 2018	Simulator	Increased lane crossings and steering activity	Increased blink durations and theta activity
Soleimanloo et al., 2019	On-road	Lane crossing events and early drive terminations	Slowed eyelid movements, prolonged blink duration, and frequent episodes of prolonged eye closure
Liang et al., 2019	On-road	Lane crossing events	Ocular measures such as mean and SD of Amplitude/ Velocity Ratio (AVR) and PERCLOS
Mulhall et al., 2020	On-road	Lane departures	Pre-drive ocular measures (long eye closures)
Gibbings et al., 2022	Simulator	Delayed reaction time when braking	Increase in amplitude and number of alpha bursts in brain activity
Giot et al., 2022	Simulator	SDLP, offroad duration, and PVT reaction time	Objective sleepiness scale using cumulative duration of alpha and/or theta waves in two simultaneous regions of the brain

are advantageous as they require less time to analyse the effect of sleep deprivation on a variety of driving physiology and performance indicators. In contrast, for repeated measures when the data deviates from the assumptions of normality, homoscedasticity, and sphericity, multifactorial nonparametric analysis of variance is a suitable method (Giot et al., 2022). However, to quantify the impact of such significant variables on the dependent variable in a model, additional regression analysis is necessary. The presence of unobservable individual heterogeneity due to repeated measurements of the participant requires the inclusion of between-participants random effects in the regression model to yield statistically consistent results (Liu, 2015). The selected studies have employed statistical models such as Polynomial mixed models (Shiferaw et al., 2018), Poisson regression models (Shiferaw et al., 2018; Cai et al., 2021), Logistic regression models (Shiferaw et al., 2018; Soleimanloo et al., 2019), Linear mixed model (LMM) (Cai et al., 2021), Log-linked poisson model (Lee et al., 2016), Multilevel ordered logit (MOL) model (Wang & Xu, 2016), Linear regression model (Jackson et al., 2016), Bayesian multilevel model (Hallvig et al., 2014) and Poisson distribution model (Hallvig et al., 2014) to establish a relationship between driver physiological indicators, driving performance indicators, and sleep deprivation. These analytical methods facilitate distinguishing between vigilant and sleep deprivation induced driving behaviours and determining the physiological correlates and degree of impairment exhibited by the drivers.

When datasets of physiological measures were not normally distributed, nonparametric tests were performed due to their simplicity and robustness, even though larger sample size is required to draw meaningful conclusions such as McNemar exact test (Soleimanloo et al., 2019), Friedman test (Alvaro et al., 2016), Fisher's exact test (Lee et al., 2016), Mann-Whitney U tests (Filtness et al., 2014), Log-rank test (Lee et al., 2016) and Wilcoxon test (Wörle et al., 2020). Several studies employed parametric tests also due to their higher statistical power, such as the Paired *t*-test (Soleimanloo et al., 2019; Wörle et al., 2021), Student's *t*-test (Lee et al., 2016), Tukey tests (Caponecchia and Williamson, 2018; Wörle et al., 2021) for determining the physiological correlates and degree of impairment exhibited by the drivers. The correlation between driving performance and physiological indicators for both normal and deprived conditions is calculated using Spearman's rank correlation (Afghari et al., 2022; Howard et al., 2014), Pearson's correlation (Mulhall et al., 2020) and partial correlation (Filtness et al., 2014). In addition, survival analysis (Soleimanloo et al., 2019) was employed to compare probability of drive survival in sleep deprived condition and normally rested condition.

Advanced statistical methods such as support vector machines (Darzi et al., 2018; Afghari et al., 2022), decision tree analysis (Darzi et al., 2018), random forest classifiers (Martensson et al., 2019), and Artificial Neural Network (ANN) models (Wang & Xu, 2016) were also used in the selected studies to categorise alertness in sleep deprived drivers and train models for early detection of driving impairment.

4. Discussion

4.1. Key insights

The objective of this review was to systematically analyse and summarise the influence of sleep deprivation on driver physiology and driving performance. The current studies were reviewed based on the following criteria: study characteristics, physiological variations prominent during sleep deprived driving, driving performance measures used in the analysis, combined measures of behavioural and physiological state of vigilance, and data analysis methods used to quantify the effects of sleep deprivation on driver physiological and behavioural alterations. The five research questions endeavoured to address in the review can be summarised as follows:

a) What are the characteristics of the sleep deprived driving studies?

Australia has conducted a major proportion of research (44 %) on sleep deprivation induced driver impairment exploring the physiological variations. Australian researchers investigated the influence of sleep deprivation on simulated driving environments, closed loop driving tracks, and naturalistic driving environments. It was observed that the sleep deprived driving studies focusing on physiological variations was majorly conducted in developed countries except a few studies in China (4 %). Many of the studies are characterised by a critical limitation of a small sample size. A sample size of more than 40 people was used in only 24 % of the studies. This significantly affects the generalisability of the findings (Cori et al., 2021; Lu et al., 2022).

b) What are the physiological variations during sleep-deprived driving?

Sleep deprivation consistently resulted in increased electroencephalographic slow wave activity (alpha and theta power) in the frontal, central, and parieto-occipital areas of the brain and was associated with driving performance deficits (Perrier et al., 2016). However, the findings on beta activity are less consistent with drive durations (Zeller et al., 2020). Ocular markers such as mean blink duration, saccadic velocity, changes in gaze behaviour, and PERCLOS demonstrated their ability to identify physiological impairment when driving in sleep deprived conditions in naturalistic environments. Heart rate (HR) fluctuations tend to increase after sleep deprivation, and heart rate variability (HRV) can serve as a robust predictor of the state of alertness in subjects who have experienced both total and partial sleep deprivation (Chua et al., 2012; Henelius et al., 2014; Afghari et al., 2022).

c) What are the performance measures employed to study the influence of sleep deprivation on drivers?

About 56 % of the studies focussing on sleep deprivation induced physiological alterations and driving impairment employ the standard deviation of lane position (SDLP), which is a widely used driving performance measure. This result is consistent with that of Soleimanloo et al. (2017), who found that SDLP was the most sensitive driving performance indicator during sleep deprived driving. It was observed that drivers compensated for the reduced alertness by increasing their driving speed under moderate sleepiness levels. However, at higher sleepiness levels, drivers compensated for impaired performance by lowering their driving speeds (Wörle et al., 2021). According to a driving study conducted by Perrier et al. (2016) on highways, drivers compensated for sleepiness by increasing their driving efforts. This compensatory behaviour also reflected as increased beta power in the electroencephalographic frontal activity. However, it was observed that this compensatory strategy eventually led to driving performance deficits when sustained for longer driving durations.

d) What are the combined measures of behavioural and physiological state of vigilance?

Slow eye movements and increased power in the alpha and theta band of EEG serve as combined physiological measures of decreased vigilance under sleep deprived driving conditions (Giot et al., 2022; Hallvig et al., 2014; Lee et al., 2016; Howard et al., 2014; Perrier et al., 2016). Increased blink duration, frequency of slow eye movements, PERCLOS, amplitude/velocity ratio (AVR) are predictors of on-road lane departure/crossing events, providing promising evidence of using combined physiological and behavioural metrics to identify sleep deprived driving impairments (Lee et al., 2016; Liang et al., 2019; Soleimanloo et al., 2019). Increased magnitude and frequency of EEG alpha bursts were found to be correlated with diminished reaction times after a day of partial sleep deprivation and is a sensitive electrophysiological marker of driving performance impairment (Gibbings et al., 2022).

e) Which data analysis techniques were utilised to identify the effect of sleep deprivation on driver behaviour and associated physiological variations?

Majority of the studies used ANOVA to quantify the influence of sleep deprivation on driving performance measures and physiological indicators compared to the baseline condition (Ahlström et al., 2018; Shiferaw et al., 2018). Separate regression analyses were performed to determine whether physiological indicators correlated with driving performance measures and to predict driving impairment. Further, refined statistical techniques such as mixed effects models were utilised to capture heterogeneity due to repeated measurements (Cai et al., 2021; Lee et al., 2016). The application of machine learning techniques also improved the accuracy of the prediction of driving impairment under sleep deprived driving conditions when physiological alterations were used to train the models (Afghari et al., 2022; Martensson et al., 2019).

Overall, the evidence from the existing studies on sleep deprivation shows that it significantly affects the physiology and driving performance of the driver. The correlation between the driver's physiological indicators and the driving performance during sleep deprived conditions has the potential to develop sophisticated driver monitoring systems that can adapt to individual driver characteristics. However, this review found that about 96 % of the studies on sleep deprived driving focusing on the driver's physiological aspects were conducted in developed countries. This suggests that experimental research is also needed in developing countries examining the inter-country differences between the physiological indicators and driving performance measures.

4.2. Policy implications

The findings from recent studies underscore significant policy implications for addressing the effects of sleep deprivation and driving performance. The hours of service (HOS) regulations, which mandate rest periods and restrict driving hours, are designed to reduce the likelihood of accidents by ensuring that commercial drivers receive sufficient sleep. However, it is important to note that HOS regulations alone may not be sufficient to guarantee safety for all drivers. Individual variability to sleep deprivation and circadian disruption, effects of sleep apnea, shift work sleep disorder, and driving contexts may induce specific high risk patterns. For instance, sleep deprived driving is attributed to varied effects on headway on truck drivers suggesting that there may be context-specific risk patterns that hours of service regulations cannot specifically address. As a result, transport operators should identify and manage high risk patterns to guarantee safe operations (Afghari et al., 2022). Advancing the understanding of the driver physiological variations due to sleep deprivation is crucial in this context. Implementing comprehensive fitness to drive tests integrated within predictors of driving performance, such as ocular measures and EEG defined microsleeps, will better assess fitness to drive (Mulhall et al., 2020). Further, driver assistance systems with real-time interventions evaluating the current state of the driver via unobtrusive monitoring of physiological markers of sleepiness could significantly reduce safety critical events (Geissler et al., 2021). Furthermore, even modest sleep deprivation, such as a reduction of two hours, can significantly impair driving performance. This highlights the widespread nature and risks of partial sleep deprivation in the community, necessitating policies that promote awareness and preventive measures to mitigate its impact on driving and other critical activities requiring vigilance (Caponecchia & Williamson, 2018).

4.3. Limitations

This systematic review faced several limitations that must be acknowledged. Due to the extensive research on sleep deprivation, it is possible that relevant articles were missed despite a rigorous search strategy while employing the systematic review framework. Restricting the reviewed articles to English publications may have introduced language bias, potentially excluding relevant research conducted in other languages. Further, while this review offers insights into the influence of sleep deprivation on driver physiology and driving performance, the risk of bias in the results of the selected studies was not evaluated. Further, publication bias is another concern, as the review focused primarily on peer-reviewed articles, potentially overlooking significant grey literature. The heterogeneity in study designs, populations, and outcomes among the included studies also posed challenges for synthesis and interpretation.

5. Conclusions

Sleep deprivation is a growing area of concern in modern lifestyle which has a significant impact on the driving community, increasing the risk of human error related accidents. This systematic review aimed to provide a comprehensive overview of studies on driving performance and physiological variations associated with sleep deprived driving. The novelty of this review is the careful examination of the physiological parameters of a sleep deprived driver and the associated behavioural parameters. In addition, the review establishes the correlation between the physiological parameters of the sleep deprived driver and the behavioural parameters under such driving conditions.

The synthesis of previous studies highlights the methodological diversity and creates new avenues for further investigation. Additionally, the emphasis of this review on identifying correlations between behavioural and physiological state transitions of sleep deprived drivers would provide more evidence for identifying effective interventions, which have not been addressed in previous reviews. This represents a valuable step towards developing more accurate physiological-based driver warning systems applicable in the context of sleep deprived driving conditions. Moreover, by identifying specific physiological markers associated with sleep deprivation, the review can inform the development of targeted countermeasures to mitigate the risks of sleep deprived driving.

Five key review objectives addressed in this review are characteristics of the selected studies, physiological variations during sleep deprived driving, driving performance measures used in the analysis, combined measures of behavioural and physiological state of vigilance and data analysis methods used to quantify the effects of sleep deprivation on driver physiological and behavioural alterations. Sleep-deprived driving studies focussing on physiological variations were conducted primarily in developed countries, and 76 % of the studies had a sample size of less than 40 participants, indicating limitations with the generalisability of the findings. Sleep deprived driving resulted in increased electroencephalographic slow wave activity (alpha and theta power) of the brain and was significantly correlated with driving performance deficits. Ocular markers, including saccadic velocity, mean blink duration, variations in gaze behaviour, and PERCLOS, were able to detect physiological impairments while driving in sleep deprived conditions. The standard deviation of lane position (SDLP) was a sensitive driving performance parameter altered during sleep deprived driving. Combining physiological measures, such as slow eye movements and increased power in the alpha and theta bands of the EEG, also served as a robust measure of impaired driving performance. After a day of partial sleep deprivation, an increase in magnitude and frequency of EEG alpha bursts was significantly correlated with reduced reaction time of the driver. Although, ANOVA was widely used by researchers to quantify the effect of sleep deprivation on driving performance measures and physiological indicators, mixed effects models, which capture heterogeneity due to repeated measurements, yield consistent results.

5.1. Future research directions

For decades, researchers have explored strategies and technology to mitigate the adverse outcomes of sleep deprivation and disruptions in circadian rhythms in driving environments, contributing to the field of driver safety research. However, the current body of knowledge on the impact of sleep deprivation on physiology and driving performance is scarce. Furthermore, this limited literature contains methodological inconsistencies that restrict the applicability of the results (e.g., inconsistencies in study designs, subjective measurement of sleepiness, drive durations, and so forth). Due to the absence of risk perception inherent in simulated driving, drivers' behaviour may not represent their real life driving patterns and performance. To further validate the findings, additional research is necessary, including the implementation of sleep restriction protocols and the utilisation of data from a substantially larger sample size, as is the case with studies involving real world driving. Additionally, standardising the time of day for studies is also important, with considerations for lighting conditions and driving duration. Considering the complexity of sleep related driving impairment, drivers' behavioural and physiological measures are required to be investigated in detail in different traffic environments. Vehicle safety technologies such as driver monitoring, and assistance systems have been advanced to reduce sleep related safety issues and minimise the potential for human error. Despite advances in the field of driver safety systems, researchers continue to face significant methodological hurdles pertaining to sleep deprivation and its impact on driving impairment, which are highlighted as follows:

i. A frequently put forth argument is that the resolution to any human error in driving would be to automate the driving activity entirely (Fisher et al., 2016; Wörle et al., 2021; Othman, 2023). Previous studies have indicated that a period of inactivity in an automated vehicle (AV) for approximately 15 to 20 min can have an adverse impact on the degree of driver task engagement and alertness, which are necessary to regain control during takeover requests (Mahajan et al., 2021b, 2021a; Wörle et al., 2021; Wu et al., 2019). At advanced levels of automation, drivers of Level-4 automated vehicles will be granted the opportunity to even doze off for a designated portion of the drive (Wörle et al., 2021; Tomzig et al., 2024). Therefore, further research should focus on determining the optimal takeover time for future automated driving conditions, monitoring the drivers' state of alertness continuously, and examining the availability for takeovers during various phases of sleep for sleep deprived subjects.
ii. A pre-drive ocular evaluation performed before driving demonstrated the potential for effectively forecasting impairments in alertness (Mulhall et al., 2020). It could be utilised in an operational setting to identify particularly high risk work schedules or to identify high risk individuals who require further evaluation. Nevertheless, additional investigations ought to concentrate on determining the most effective duration of the test, experimenting with different durations of drive, and employing more reliable metrics of driving performance within a realistic driving environment. Further investigation is necessary to examine

how sleep deprivation intensifies distractibility in drivers, such as through modifications in gaze allocation during shorter commutes and prolonged driving duration.

iii. To estimate drivers' states, it is necessary to consider a combination of multiple measures (physiological and behavioural), to improve the accuracy of driving impairment detection. The utilisation of an objective sleepiness scale (OSS) will help in surpassing the constraints of including subjective indices and performance indicators in terms of time synchronisation, measurement, and accuracy. OSS must subsequently be evaluated in future studies using naturalistic driving data and under different traffic conditions (Giot et al., 2022).

iv. Currently, there is no comparative analysis that critically evaluates the differences in the impact of sleep deprivation on the driving behaviour of drivers in nations with different socioeconomic background. A promising area for future research could be a comparison of the physiological variations of sleep deprived drivers in developing nations and those in developed nations to gain insights into the correlated physiological and behavioural metrics.

v. Past research on sleep deprived driving behaviour has predominantly focused on car and truck drivers. The investigation could be expanded to include users of all vehicle types, as driving behaviour is likely to differ among various vehicle types (Vu et al., 2020).

vi. As a society, we lack the quantity and quality of sleep in a culture that operates round the clock, where work is prioritised, longer commutes, and exponential technological advancements (Jesmeen et al., 2023). In contrast to the well studied effects of chronic sleep loss, the impacts of mild sleep loss on physiological and cognitive behaviour have received less attention, despite the fact that the latter is far more widespread (Gibbings et al., 2022). Hence, a comprehensive understanding of the physiological implications and cognitive mechanisms linked to mild sleep loss and its correlations with driving performance measures is required.

vii. Application of machine learning and deep learning techniques in the detection of driving impairment for sleep deprived participants should be explored in detail with multiple modalities in future research works.

CRediT authorship contribution statement

Meenu Tomson: Writing – original draft, Visualization, Methodology, Data curation, Conceptualization. **Tom V. Mathew:** Writing – review & editing, Validation, Supervision, Conceptualization. **Nagendra Rao Velaga:** Writing – review & editing, Validation, Supervision, Conceptualization.

Declaration of competing interest

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

Appendix

Table A1
Details of the selected studies investigating the driver behaviour and driver physiology during sleep deprived driving (N = 25).

Author	Year	Country	Participants characteristics			Driving characteristics		Simulator/ On-road	Driver physiology considered	Sleepiness scale considered
			Sample Size	Age of Participants	% females	Roadway features	Duration of Drive			
Shiferaw et al.	2018	Australia	9	Male (33 ± 7.07), female (34 ± 10.22)	55.6	Closed track	2 hrs – 2 sessions	On-road	Eye tracking	KSS and PVT
Giot et al.	2022	France	43	(46.7 ± 17.8), 21–79 years	48.8	two-lane motorway with monotonous conditions	1.5 hrs	Simulator	EEG and EOG	OSS (Objective Sleepiness Scale)
Howard et al.	2014	Australia	40	Not mentioned	Not mentioned	Dual Lane Highway with monotonous night drive	30 min	Simulator	EEG and slow eyelid closure from video data	KSS and Sleepiness Symptoms Questionnaire (SSQ)
Zeller et al.	2020	Australia	60	(23.85 ± 3.85), 19 to 41 years	53.3	Single lane with monotonous conditions	2 hrs	Simulator	EEG	NASA-TLX
Perrier et al.	2016	Netherlands	24	(26.9 ± 3.4), 23–45 years	50	Highway drive – maintain a constant speed of 95 km/hr	1 hr	On-road	EEG and EOG	Pittsburgh Sleep Quality Index

(continued on next page)

Table A1 (*continued*)

Author	Year	Country	Participants characteristics			Driving characteristics		Simulator/ On-road	Driver physiology considered	Sleepiness scale considered
			Sample Size	Age of Participants	% females	Roadway features	Duration of Drive			
Afghari et al.	2022	Belgium	35	21–61 years	Mostly male	Rural roads with two lanes, four lanes and motorway segments	16.5 – 18 km	On-road	ECG	KSS
Gibbings et al.	2022	Canada	60	(22 ± 3), 25 to 38 years	58.33	Rural single lane highway with min features	70 min	Simulator	EOG, EMG and EEG	Stanford Sleepiness Scale
Mulhall et al.	2020	Australia	20	33.15 ± 9.04	65	Highway	≥30 min	On-road	Ocular parameters	KSS, Epworth Sleepiness Scale
Caponecchia and Williamson	2018	Australia	15	Group 1—37.00 ± 8.31, Group 2—–42.09 ± 6.26, Group 3—–38.42 ± 5.85	39.02	Arterial road and Highway	45 min	Simulator	Eye tracking	Visual analogue scale
Soleimanloo et al.	2019	Australia	12	33.7 ± 7.1 years	50	Closed-loop driving track	2 hrs	On-road	Eye tracking	KSS
Darzi et al.	2018	United States	21	25.1 ± 8.7 years	50	City and rural highway	45 min	Simulator	ECG, GSR, Respiration	NASA-TLX
Hallvig et al.	2014	Sweden	43	44 ± 8 years	48.8	two lane rural road	90 min	On-road	EEG and EOG	KSS and KDS
Jackson et al.	2016	Australia	12	45.58 ± 10.93	8.33	Highway	30 min	Simulator	Eye metrics	KSS
Worle et al.	2021	Germany	61	37.8 ± 11.9	47.5	Highway	1 hr	Simulator	EEG and Eye tracking	KSS
Wang & Xu	2016	China	16	(32.8 ± 5.0), 24–40 years	0	Rural highway	1 hr	Simulator	Ocular metrics	KSS
Lee et al.	2016	Australia	16	18—–65 years	56.3	Closed driving track	2 hrs	On-road	EEG, EOG and Infrared Reflectance Oculography	KSS and Sleepiness Symptoms Questionnaire
Alvaro et al.	2016	Australia	20	41.9 ± 8.3	0	Two lane highway	30 min	Simulator	Eye metrics from video	KSS
Liang et al.	2019	USA	16	mean age: 48.7; 19–65 years	77.8	two-lane closed-loop test track	2 hrs	On-road	EEG and EOG	John's Drowsiness Score (JDS)
Bakker et al.	2022	Sweden	20	42.6 ± 8.8 years	50	Intercity motorway	90 min	On-road	Eye metrics	KSS
Ahlström et al.	2018	Sweden	30	(23.6 ± 1.7), 18–25 years	0	Rural road and Suburban Road	90 mins	Simulator	EEG and EOG	KSS
Mårtensson et al.	2019	Sweden	86	1st exp − mean age 41 years, 2nd exp − mean age 35 years, 3rd exp − mean age 44 years	47.6	Motorway	1st exp − 90 min, 2nd exp- 135 mints, 3rd exp − 90 mints	On-road	EEG, ECG and EOG	KSS
Filtness et al.	2014	Australia	16	41.3 ± 8.7	50	Motorway	90 min	On-road and Simulator	EOG	KSS
Hallvig et al.	2013	Sweden	10	40 ± 11	50	Rural road	On-road- 45 min & simulator- 60 min	On-road & Simulator	EEG, EOG, EMG and ECG	KSS
Worle et al.	2020	Germany	25	37.8 ± 11.8	44	Three lane motorway	2 hr	Simulator	EEG and Eye tracking	EEG Scoring
Cai et al.	2021	Australia	33	'younger' adults (24.3 ± 3.1), 21–33 years and 'older' adults (57.3 ± 5.2), 50–65 years	45.5	Closed-loop track	2 hrs	On-road	Eye Tracking-Ocular metrics	KSS, Falling Asleep Scale (FAS)

Table A2
Details of the physiological and driving performance measures investigated in the selected studies during sleep deprived driving (N = 25).

Authors	Driving performance measures considered	Driver Physiology variables considered	Key Findings
Shiferaw et al. (2018)	Lane Departures	Eye fixation rate, blinking rate, blink durations, saccade amplitude and gaze entropy	Rate of fixations reduced while blink rate, blink duration and saccade amplitude increased following sleep deprivation.
Giot et al. (2022)	Standard Deviation of Lane Position (SDLP), off-road duration(sec) and PVT (reaction time and lapses)	Objective Sleepiness Scale Score (OSS considered the number of seconds during which alpha waves and/or theta waves are observed in the brain and the presence of slow eye movements on the EEG channels	OSS allows objective sleepiness scoring with a good time synchronization, OSS did not accurately predict lapses in the PVT, SDLP increased after sleep deprivation
Howard et al. (2014)	Variation in lateral lane position, Variation in speed, (EEG, slow eyelid closure) and Psychomotor Vigilance Task (PVT)	Alpha and theta activity of EEG (total seconds per hour of alpha and theta activity for each 30 min driving simulation session), slow eyelid closure	Increased alpha and theta activity and slow eyelid closure after sleep deprivation
Zeller et al. (2020)	Standard Deviation of Lane Position (SDLP), Standard Deviation of Speed	EEG Power Spectral Density (PSD) of Theta (3 – 7 Hz), Alpha (8 – 13 Hz), and Beta waves (13 – 29 Hz)	EEG alpha and beta activity increased after sleep deprivation
Perrier et al. (2016)	Standard Deviation of Lane Position (SDLP)	EEG indices (i.e., alpha and theta power spectra) and EOG recording of left eye	SDLP and EEG indices (i.e., alpha and theta power spectra) increased after sleep deprivation
Afghari et al. (2022)	Headway, speed, episodes of sleepiness while driving	Heart rate data	Quantified sleepiness using driver's heart rate in real-time
Gibbings et al. (2022)	Lane departures, number of crashes and mean reaction time.	Number and amplitude of EEG alpha bursts	Bursts of alpha activity occurred more often and intense after sleep restriction with slower reaction time
Mulhall et al. (2020)	Lane departures, steering wheel angle	Mean blink duration, duration of eye closures (blinks $<$ 400 ms) averaged over a minute; PERCLOS, average long eye closures, duration of eye closures $>$ 300 ms averaged over a minute, behavioural microsleeps (the duration of eye closures $>$ 500 ms)	Pre-drive mean blink duration and PERCLOS were the best discriminators of behavioural microsleeps, and mean blink duration was a significant predictor of lane departure
Caponecchia and Williamson (2018)	Lane deviation and percentage of time speeding	PERCLOS, blink duration	Measurements of eye closure did not reflect sleepiness despite performance impairments
Soleimanloo et al. (2019)	Lane crossings, Out-of-lane events, Drive terminations	Blink duration, amplitude/velocity ratio, long eye closures, John's drowsiness score	Increment in duration of eyelid closure, percent of time with eyes closed and maximum amplitude to velocity ratios of eyelid movements for both closing and opening phases of blink (AVR), indicating slower eyelid movement during blinks after sleep deprivation
Darzi et al., (2018)	Throttle force, Road offset, Longitudinal and vertical velocity, slip level of front and rear tires	Respiration rate (RR), GSR, ECG [mean HR, standard deviation of inter-beat intervals, power of low frequencies (LF), power of high frequencies (HF) and the power ratio of low to high frequencies (LF/HF), RR: The mean RR (number of complete breathing cycles per minute), the standard deviation of RR, and the root-mean-square of successive differences of respiration periods, GSR: mean GSR, discrete skin conductance responses	Classified hazardous driver states using different combinations of driver characteristics, vehicle kinematics, and physiology
Hallvig et al. (2013)	Mean lateral position,standard deviation of lateral position, lane departures and mean speed	KDS, blink duration	Driving simulator was associated with higher levels of subjective and physiological sleepiness than real driving
Jackson et al. (2016)	Standard deviation of lateral lane deviation, variation in speed, braking reaction time and mean number of crashes	PERCLOS (eyelid closure) and subjective drowsiness measures, driving errors, vigilance and reaction time	PERCLOS accounted for a significant amount of the variance in standard deviation of lateral position
Wörle et al. (2021)	Mean speed, Standard deviation of speed, Standard deviation of lane position	PERCLOS, EEG confirmed sleep	Lane and speed-keeping performance were impaired under the sleepy state, PERCLOS was increased under the sleepy state
Wang & Xu (2016)	Standard deviation of lateral position, Average of lateral position, Lane departure frequency, Lane departure lateral speed, Time percentage of lane crossing of the vehicle center, vehicle edge, Steering wheel reversals,Average speed, Standard	Average blink frequency per second Average blink duration (s) Percentage of eyelid closureAverage pupil diameter (mm)	Percentage of eyelid closure, average pupil diameter, standard deviation of lateral position and steering wheel reversals were the significant variables contributing to sleepiness detection accuracy

(continued on next page)

Table A2 (*continued*)

Authors	Driving performance measures considered	Driver Physiology variables considered	Key Findings
	deviation of speed, Time percentage of speed exceeding the limit speed 120 km/h.		
Lee et al. (2016)	Lane crossings, Near-crash events, and drive terminations	[EEG-Microsleep episodes, Ocular measures- Slow eye movements, Time with eyes closed, Blink time duration, AVR, JDS, Average maximum JDS	Participants had increased delta power, higher rate of lane excursions, blink duration, and number of slow eye movements during post night-shift drives compared with post sleep drives
Alvaro et al. (2016)	Lateral lane position, variation in speed, braking reaction time, and mean number of crashes	Slow eyelid closure, A scorer (MH) scrolled through the video in 0.5 s frames, recording each eyelid closure episodes (80 % closure as per PERCLOS) $\geq$ 1 s and the duration of the episode, PVT reaction time	Study identified increasing frequency and duration of prolonged eyelid closure lasting up to 18 s after 17–23 h of sleep deprivation
Liang et al. (2019)	SD of lane position, SD of steering angle, and mean of steering error	mean and SD of Amplitude/ Velocity Ratio (AVR), PERCLOS, and Johns Drowsiness Score	Driver individual differences and eyelid measures incorporated model improved in sleepiness detection accuracy
Cai et al. (2021)	Lane deviations, Near-crash events, Drive terminations	Blink duration, blink rate, long eye closures (LEC) duration and rate, PERCLOS	Ocular measures of sleepiness, including blink duration, number of long eye closures and PERCLOS increased following sleep loss
Bakker et al. (2022)	Lane positions, lane departures	Eye opening and closing information, gaze direction, head pose, facial expressiveness extracted from the face video	Developed real-time sleepiness detection model can be used in the management of sleepiness
Ahlström et al. (2018)	Lane crossing, steering wheel activity, pedal activity	Total power in the 5–9 Hz EEG theta frequency range and in the 8–14 Hz alpha frequency band EEG, blink durations from EOG	Blink durations increased at high levels of subjective sleepiness, as did the number of line crossings and steering activity, alpha content of EEG.
Martensson et al. (2019)	Speed, steering wheel angle, yaw rate, acceleration features (standard deviation of steering wheel angle, the rate of micro steering corrections, the rate of large steering corrections, standard deviation of lane position, standard deviation of lateral accelerations)	EEG absolute power in the θ and α-bands, Four HRV features: LF/HF, HF/(LF + HF), LF/(LF + HF) and the root mean square of successive differences (RMSSD), EOG: the mean and the 90th percentile of the blink duration, the blink amplitude, the eyelid closure speed and the eyelid opening speed.	Driver sleepiness detection system was trained and tested with physiological data obtained from real traffic. The results highlight the importance of personalized sleepiness detection systems
Filtness et al. (2014)	The number of line crossings per kilometre travelled was used to quantify impaired driving. Near-misses (including inappropriate lane crossings)	Mean blink duration; median blink duration; and blinks > 0.15 s longer	Eye-related symptoms, in particular, 'heavy eyelids' and 'difficulty keeping the eyes open' were associated with higher subjective sleepiness and impaired driving performance
Hallvig et al. (2014)	Lateral lane position and mean speed	EEG alpha (8–12 Hz) or theta waves (4–8 Hz), or slow rolling eye movement (KDS score)	Blink durations and lane departures increased; speed variations were not observed
Wörle et al. (2020)	Take-Over Controllability (TOC) rating	EEG defined sleep stages (according to AASM, 2017) and eye-tracking data of driver glances	Reaction times were extended by about 3 s after sleep compared to the wake condition

Data availability

No data was used for the research described in the article.

References

Aeschbach, D., Matthews, J. R., Postolache, T. T., Jackson, M. A., Giesen, H. A., & Wehr, T. A. (1997). Dynamics of the human EEG during prolonged wakefulness: Evidence for frequency-specific circadian and homeostatic influences. *Neuroscience Letters, 239*(2–3), 121–124. https://doi.org/10.1016/S0304-3940(97)00904-X

Afghari, A. P., Papadimitriou, E., Pilkington-Cheney, F., Filtness, A., Brijs, T., Brijs, K., Cuenen, A., De Vos, B., Dirix, H., Ross, V., Wets, G., Lourenço, A., & Rodrigues, L. (2022). Investigating the effects of sleepiness in truck drivers on their headway: An instrumental variable model with grouped random parameters and heterogeneity in their means. *Analytic Methods in Accident Research, 36*, Article 100241. https://doi.org/10.1016/j.amar.2022.100241

Ahlström, C., Anund, A., Fors, C., & Åkerstedt, T. (2018). Effects of the road environment on the development of driver sleepiness in young male drivers. *Accident Analysis & Prevention, 112*, 127–134. https://doi.org/10.1016/J.AAP.2018.01.012

Alvaro, P. K., Jackson, M. L., Berlowitz, D. J., Swann, P., & Howard, M. E. (2016). Prolonged eyelid closure episodes during sleep deprivation in professional drivers. *Journal of Clinical Sleep Medicine, 12*(8), 1099–1103. https://doi.org/10.5664/jcsm.6044

Bakker, B., Zablocki, B., Baker, A., Riethmeister, V., Marx, B., Iyer, G., Anund, A., & Ahlstrom, C. (2022). A Multi-Stage, Multi-Feature Machine Learning Approach to Detect Driver Sleepiness in Naturalistic Road Driving Conditions. *IEEE Transactions on Intelligent Transportation Systems, 23*(5), 4791–4800. https://doi.org/10.1109/TITS.2021.3090272

Cai, A. W. T., Manousakis, J. E., Singh, B., Kuo, J., Jeppe, K. J., Francis-Pester, E., Shiferaw, B., Beatty, C. J., Rajaratnam, S. M. W., Lenné, M. G., Howard, M. E., & Anderson, C. (2021). On-road driving impairment following sleep deprivation differs according to age. *Scientific Reports, 11*(1), 1–13. https://doi.org/10.1038/s41598-021-99133-y

Caponecchia, C., & Williamson, A. (2018). Drowsiness and driving performance on commuter trips. *Journal of Safety Research, 66*, 179–186. https://doi.org/10.1016/J.JSR.2018.07.003

Chen, G. X., Fang, Y., Guo, F., & Hanowski, R. J. (2016). The influence of daily sleep patterns of commercial truck drivers on driving performance. *Accident Analysis and Prevention, 91*, 55–63. https://doi.org/10.1016/j.aap.2016.02.027

Chen, L. L., Zhao, Y., Zhang, J., & Zou, J. Z. (2015). Automatic detection of alertness/drowsiness from physiological signals using wavelet-based nonlinear features and machine learning. *Expert Systems with Applications, 42*(21), 7344–7355. https://doi.org/10.1016/j.eswa.2015.05.028

Chua, E. C. P., Tan, W. Q., Yeo, S. C., Lau, P., Lee, I., Mien, I. H., Puvanendran, K., & Gooley, J. J. (2012). Heart rate variability can be used to estimate sleepiness-related decrements in psychomotor vigilance during total sleep deprivation. *Sleep, 35*(3), 325–334. https://doi.org/10.5665/sleep.1688

Cori, J. M., Manousakis, J. E., Koppel, S., Ferguson, S. A., Sargent, C., Howard, M. E., & Anderson, C. (2021). An evaluation and comparison of commercial driver sleepiness detection technology: A rapid review. *Physiological Measurement, 42*, Article 074007. https://doi.org/10.1088/1361-6579/abfbb8

Darzi, A., Gaweesh, S. M., Ahmed, M. M., & Novak, D. (2018). Identifying the causes of drivers' hazardous states using driver characteristics, vehicle kinematics, and physiological measurements. *Frontiers in Neuroscience, 12*, Article 392979. https://doi.org/10.3389/fnins.2018.00568

Dhoke, A., & Choudhary, P. (2023). Is there a relationship between time pressure and pedestrian non-compliance? A systematic review. *Transportation Research Part F: Traffic Psychology and Behaviour, 93*, 68–89. https://doi.org/10.1016/j.trf.2023.01.001

Filtness, A. J., Anund, A., Fors, C., Ahlström, C., Åkerstedt, T., & Kecklund, G. (2014). Sleep-related eye symptoms and their potential for identifying driver sleepiness. *Journal of Sleep Research, 23*(5), 568–575. https://doi.org/10.1111/jsr.12163

Fisher, D. L., Lohrenz, M., Moore, D., Nadler, E. D., & Pollard, J. K. (2016). Humans and intelligent vehicles: The hope, the help, and the harm. *IEEE Transactions on Intelligent Vehicles, 1*(1), 56–67. https://doi.org/10.1109/TIV.2016.2555626

Freitas, A., Almeida, R., Gonçalves, H., Conceição, G., & Freitas, A. (2024). Monitoring fatigue and drowsiness in motor vehicle occupants using electrocardiogram and heart rate − A systematic review. *Transportation Research Part F: Traffic Psychology and Behaviour, 103*(April), 586–607. https://doi.org/10.1016/j.trf.2024.05.008

Gibbings, A., Ray, L. B., Berberian, N., Nguyen, T., Shahidi Zandi, A., Owen, A. M., Comeau, F. J. E., & Fogel, S. M. (2021). EEG and behavioural correlates of mild sleep deprivation and vigilance. *Clinical Neurophysiology, 132*(1), 45–55. https://doi.org/10.1016/j.clinph.2020.10.010

Gibbings, A., Ray, L. B., Gagnon, S., Collin, C. A., Robillard, R., & Fogel, S. M. (2022). The EEG correlates and dangerous behavioral consequences of drowsy driving after a single night of mild sleep deprivation. *Physiology and Behavior, 252*, Article 113822. https://doi.org/10.1016/j.physbeh.2022.113822

Giot, C., Hay, M., Chesneau, C., Pigeon, E., Bonargent, T., Beaufils, M., Chastan, N., Perrier, J., Pasquier, F., Polvent, S., Davenne, D., Taillard, J., & Bessot, N. (2022). Towards a new approach to detect sleepiness: Validation of the objective sleepiness scale under simulated driving conditions. *Transportation Research Part F: Traffic Psychology and Behaviour, 90*, 109–119. https://doi.org/10.1016/j.trf.2022.08.007

Geissler, C. F., Schneider, J., & Frings, C. (2021). Shedding light on the prefrontal correlates of mental workload in simulated driving: A functional near-infrared spectroscopy study. *Scientific Reports, 11*(1), 1–10. https://doi.org/10.1038/s41598-020-80477-w

Golabchi, H., Abellanosa, A. D., Lefsrud, L., Pereira, E., & Mohamed, Y. (2024). A comprehensive systematic review of safety leading indicators in construction. *Safety Science, 172*, Article 106433. https://doi.org/10.1016/j.ssci.2024.106433

Gupta, N., Najeeb, D., Gabrielian, V., & Nahapetian, A. (2017). Mobile ECG-based drowsiness detection. 14th IEEE Annual Consumer Communications and Networking Conference. *CCNC, 2017*, 29–32. https://doi.org/10.1109/CCNC.2017.7983076

Hallvig, D., Anund, A., Fors, C., Kecklund, G., & Åkerstedt, T. (2014). Real driving at night - Predicting lane departures from physiological and subjective sleepiness. *Biological Psychology, 101*(1), 18–23. https://doi.org/10.1016/j.biopsycho.2014.07.001

Hallvig, D., Anund, A., Fors, C., Kecklund, G., Karlsson, J. G., Wahde, M., & Åkerstedt, T. (2013). Sleepy driving on the real road and in the simulator - A comparison. *Accident Analysis and Prevention, 50*, 44–50. https://doi.org/10.1016/j.aap.2012.09.033

Henelius, A., Sallinen, M., Huotilainen, M., Müller, K., Virkkala, J., & Puolamäki, K. (2014). Heart rate variability for evaluating vigilant attention in partial chronic sleep restriction. *Sleep, 37*(7), 1257–1267. https://doi.org/10.5665/sleep.3850

Howard, M. E., Jackson, M. L., Berlowitz, D., O'Donoghue, F., Swann, P., Westlake, J., Wilkinson, V., & Pierce, R. J. (2014). Specific sleepiness symptoms are indicators of performance impairment during sleep deprivation. *Accident Analysis and Prevention, 62*, 1–8. https://doi.org/10.1016/j.aap.2013.09.003

Jackson, M. L., Raj, S., Croft, R. J., Hayley, A. C., Downey, L. A., Kennedy, G. A., & Howard, M. E. (2016). Slow eyelid closure as a measure of driver drowsiness and its relationship to performance. *Traffic Injury Prevention, 17*(3), 251–257. https://doi.org/10.1080/15389588.2015.1055327

Jesmeen, M. Z. H., Bhuvaneswari, T., Mazbah, A. H., Chin, Y. B., Siong, L. H., & Aziz, N. H. A. (2023). SleepCon: Sleeping Posture Recognition Model using Convolutional Neural Network. *Emerging Science Journal, 7*(1), 50–59. https://doi.org/10.28991/ESJ-2023-07-01-04

Knott, M., Classen, S., Krasniuk, S., Tippett, M., & Alvarez, L. (2020). Insufficient sleep and fitness to drive in shift workers: A systematic literature review. *Accident Analysis and Prevention, 134*, Article 105234. https://doi.org/10.1016/j.aap.2019.07.010

Kuo, J., Lenné, M. G., Mulhall, M., Sletten, T., Anderson, C., Howard, M., … Collins, A. (2019). Continuous monitoring of visual distraction and drowsiness in shift-workers during naturalistic driving. *Safety Science*, (119), 112–116. https://doi.org/10.1016/j.ssci.2018.11.00

Lee, M. L., Howard, M. E., Horrey, W. J., Liang, Y., Anderson, C., Shreeve, M. S., O'Brien, C. S., & Czeisler, C. A. (2016). High risk of near-crash driving events following night-shift work. *Proceedings of the National Academy of Sciences of the United States of America, 113*(1), 176–181. https://doi.org/10.1073/pnas.1510383112

Liang, Y., Horrey, W. J., Howard, M. E., Lee, M. L., Anderson, C., Shreeve, M. S., O'Brien, C. S., & Czeisler, C. A. (2019). Prediction of drowsiness events in night shift workers during morning driving. *Accident Analysis & Prevention, 126*, 105–114. https://doi.org/10.1016/j.aap.2017.11.004

Lu, K., Sjörs Dahlman, A., Karlsson, J., & Candefjord, S. (2022). Detecting driver fatigue using heart rate variability: A systematic review. *Accident Analysis and Prevention, 178*, Article 106830. https://doi.org/10.1016/j.aap.2022.106830

Liu, X. (2015). Methods and applications of longitudinal data analysis. *In Methods and Applications of Longitudinal Data Analysis*. https://doi.org/10.1016/C2013-0-13082-6

Mahajan, K., Large, D. R., Burnett, G., & Velaga, N. R. (2021a). Exploring the benefits of conversing with a digital voice assistant during automated driving: A parametric duration model of takeover time. *Transportation Research Part F: Traffic Psychology and Behaviour, 80*, 104–126. https://doi.org/10.1016/j.trf.2021.03.012

Mahajan, K., Large, D. R., Burnett, G., & Velaga, N. R. (2021b). Exploring the effectiveness of a digital voice assistant to maintain driver alertness in partially automated vehicles. *Traffic Injury Prevention, 22*(5), 378–383. https://doi.org/10.1080/15389588.2021.1904138

Mahajan, K., & Velaga, N. R. (2020). Effects of Partial Sleep Deprivation on Braking Response of Drivers in Hazard Scenarios. *Accident Analysis and Prevention, 142*, Article 105545. https://doi.org/10.1016/j.aap.2020.105545

Mahajan, K., & Velaga, N. R. (2021). Sleep-deprived car-following: Indicators of rear-end crash potential. *Accident Analysis and Prevention, 156*, Article 106123. https://doi.org/10.1016/j.aap.2021.106123

Mahajan, K., & Velaga, N. R. (2022). Effects of partial sleep deprivation: A comparative assessment of young non-professional and professional taxi drivers. *Transportation Research Part F: Traffic Psychology and Behaviour, 85*, 209–220. https://doi.org/10.1016/j.trf.2022.01.008

Mahajan, K., & Velaga, N. R. (2023). Effects of partial sleep deprivation: Speed management ability and associated crash risk. *Transportation Letters, 15*(6), 527–536. https://doi.org/10.1080/19427867.2022.2071533

Mahajan, K., Velaga, N. R., Kumar, A., & Choudhary, P. (2019a). Effects of driver sleepiness and fatigue on violations among truck drivers in India. *International Journal of Injury Control and Safety Promotion, 26*(4), 412–422. https://doi.org/10.1080/17457300.2019.1660375

Mahajan, K., Velaga, N. R., Kumar, A., Choudhary, A., & Choudhary, P. (2019b). Effects of driver work-rest patterns, lifestyle and payment incentives on long-haul truck driver sleepiness. *Transportation Research Part F: Traffic Psychology and Behaviour, 60*, 366–382. https://doi.org/10.1016/j.trf.2018.10.028

Maia, Q., Grandner, M. A., Findley, J., & Gurubhagavatula, I. (2013). Short and long sleep duration and risk of drowsy driving and the role of subjective sleep insufficiency. *Accident Analysis and Prevention, 59*, 618–622. https://doi.org/10.1016/j.aap.2013.07.028

Marasini, G., Caleffi, F., Machado, L. M., & Pereira, B. M. (2022). Psychological consequences of motor vehicle accidents: A systematic review. *Transportation Research Part F: Traffic Psychology and Behaviour, 89*, 249–264. https://doi.org/10.1016/j.trf.2022.06.017

Martensson, H., Keelan, O., & Ahlstrom, C. (2019). Driver Sleepiness Classification Based on Physiological Data and Driving Performance from Real Road Driving. *IEEE Transactions on Intelligent Transportation Systems, 20*(2), 421–430. https://doi.org/10.1109/TITS.2018.2814207

Minhas, R., Arbatli, S., Celik, Y., Peker, Y., & Semiz, B. (2024). A Novel Approach to Quantify Microsleep in Drivers with Obstructive Sleep Apnea by Concurrent Analysis of EEG Patterns and Driving Attributes. *IEEE Journal of Biomedical and Health Informatics, 28*(3), 1341–1352. https://doi.org/10.1109/JBHI.2024.3352081

Mulhall, M. D., Cori, J., Sletten, T. L., Kuo, J., Lenné, M. G., Magee, M., Spina, M. A., Collins, A., Anderson, C., Rajaratnam, S. M. W., & Howard, M. E. (2020). A pre-drive ocular assessment predicts alertness and driving impairment: A naturalistic driving study in shift workers. *Accident Analysis & Prevention, 135*, Article 105386. https://doi.org/10.1016/J.AAP.2019.105386

Othman, K. (2023). Impact of Prior Knowledge about Autonomous Vehicles on the Public Attitude. *Civil Engineering Journal (Iran), 9*(4), 990–1006. https://doi.org/10.28991/CEJ-2023-09-04-017

Oviedo-trespalacios, O., Pooyan, A., & Haque, M. (2020). Analytic Methods in Accident Research A hierarchical Bayesian multivariate ordered model of distracted drivers ' decision to initiate risk-compensating behaviour. *Analytic Methods in Accident Research, 26*, Article 100121. https://doi.org/10.1016/j.amar.2020.100121

Perrier, J., Jongen, S., Vuurman, E., Bocca, M. L., Ramaekers, J. G., & Vermeeren, A. (2016). Driving performance and EEG fluctuations during on-the-road driving following sleep deprivation. *Biological Psychology, 121*, 1–11. https://doi.org/10.1016/j.biopsycho.2016.09.010

Rainieri, G., Buizza, C., & Ghilardi, A. (2023). The psychological, human factors and socio-technical contribution: A systematic review towards range anxiety of battery electric vehicles' drivers. *Transportation Research Part F: Traffic Psychology and Behaviour, 99*(August), 52–70. https://doi.org/10.1016/j.trf.2023.10.001

Razak, S. F. A., Sayed Ismail, S. N. M., Yogarayan, S., Abdullah, M. F. A., Kamis, N. H., & Aziz, A. A. (2023). Comparative Study of Machine Learning Algorithms in Classifying HRV for the Driver's Physiological Condition. *Civil Engineering Journal (Iran), 9*(9), 2272–2285. https://doi.org/10.28991/CEJ-2023-09-09-013

Rosekind, M. R., Michael, J. P., Dorey-Stein, Z. L., & Watson, N. F. (2024). Awake at the wheel: How auto technology innovations present ongoing sleep challenges and new safety opportunities. *Sleep, 47*(2), 1–7. https://doi.org/10.1093/sleep/zsad316

Saleem, S. (2022). Risk assessment of road traffic accidents related to sleepiness during driving: A systematic review. *Eastern Mediterranean Health Journal, 28*(9), 695–700. https://doi.org/10.26719/emhj.22.055

Schlagintweit, J., Laharnar, N., Glos, M., Zemann, M., Demin, A. V., Lederer, K., … Fietze, I. (2023). Effects of sleep fragmentation and partial sleep restriction on heart rate variability during night. *Scientific Reports, 13*(1), 1–10. https://doi.org/10.1038/s41598-023-33013-5

Shiferaw, B. A., Downey, L. A., Westlake, J., Stevens, B., Rajaratnam, S. M. W., Berlowitz, D. J., Swann, P., & Howard, M. E. (2018). Stationary gaze entropy predicts lane departure events in sleep-deprived drivers. *Scientific Reports, 8*(1), 2220. https://doi.org/10.1038/s41598-018-20588-7

Smith, S. S., Rossa, K. R., Soleimanloo, S. S., Pattinson, C. L., Mann, D. L., Edmed, S. L., Salmon, P. M., & Sullivan, K. A. (2024). Reducing crash risk for young drivers: Protocol for a pragmatic randomised controlled trial to improve young driver sleep. *Heliyon, 10*(5), Article e27066. https://doi.org/10.1016/j.heliyon.2024.e27066

Soleimanloo, S. S., White, M. J., Garcia-Hansen, V., & Smith, S. S. (2017). The effects of sleep loss on young drivers' performance: A systematic review. *PLoS ONE, 12*(8). https://doi.org/10.1371/journal.pone.0184002. e0184002.

Soleimanloo, S. S., Wilkinson, V. E., Cori, J. M., Westlake, J., Stevens, B., Downey, L. A., Shiferaw, B. A., Rajaratnam, S. M. W., & Howard, M. E. (2019). Eye-blink parameters detect on-road track-driving impairment following severe sleep deprivation. *Journal of Clinical Sleep Medicine, 15*(9), 1271–1284. https://doi.org/10.5664/jcsm.7918

Tkachenko, O. N., Dorokhov, V. B., Dementienko, V. V., Gandina, E. O., Arseniev, G. N., Taranov, A. O., Puchkova, A. N., Bakaeva, Z. V., & Sveshnikov, D. S. (2024). Assessment and prevention of inattention and sleepiness during monotonous operator activity with underlying sleep deprivation. *European Physical Journal: Special Topics, 1–12*. https://doi.org/10.1140/epjs/s11734-024-01088-4

Tomzig, M., Wörle, J., Kremer, C., & Baumann, M. (2024). Sleep in automated driving – Effects of time of day and chronotype on sleepiness and sleep inertia. *Transportation Research Part F: Traffic Psychology and Behaviour, 102*, 16–31. https://doi.org/10.1016/j.trf.2024.02.003

Vandenbroucke, J. P., Von Elm, E., Altman, D. G., Gøtzsche, P. C., Mulrow, C. D., Pocock, S. J., & Egger, M. (2007). Strengthening the reporting of observational studies in epidemiology (STROBE): Explanation and elaboration. *Epidemiology, 18*(6), 805–835. https://doi.org/10.1097/EDE.0b013e3181577511

Vu, A. T., Nguyen, M. T., Nguyen, D. V. M., & Khuat, V. H. (2020). Investigating the effect of blood alcohol concentration on motorcyclist's riding performance using an advanced motorcycle simulator. *Transportation Research Part F: Traffic Psychology and Behaviour, 73*, 1–14. https://doi.org/10.1016/j.trf.2020.06.010

Wang, X., & Xu, C. (2016). Driver drowsiness detection based on non-intrusive metrics considering individual specifics. *Accident Analysis & Prevention, 95*, 350–357. https://doi.org/10.1016/j.aap.2015.09.002

Williamson, A., Lombardi, D. A., Folkard, S., Stutts, J., Courtney, T. K., & Connor, J. L. (2011). The link between fatigue and safety. *Accident Analysis and Prevention, 43*(2), 498–515. https://doi.org/10.1016/j.aap.2009.11.011

Wörle, J., Metz, B., Othersen, I., & Baumann, M. (2020). Sleep in highly automated driving: Takeover performance after waking up. *Accident Analysis & Prevention, 144*, Article 105617. https://doi.org/10.1016/j.aap.2020.105617

Wörle, J., Metz, B., Steinborn, M. B., Huestegge, L., & Baumann, M. (2021). Differential effects of driver sleepiness and sleep inertia on driving behavior. *Transportation Research Part F: Traffic Psychology and Behaviour, 82*, 111–120. https://doi.org/10.1016/j.trf.2021.08.001

Wu, Y., Kihara, K., Takeda, Y., Sato, T., Akamatsu, M., & Kitazaki, S. (2019). Effects of scheduled manual driving on drowsiness and response to take over request: A simulator study towards understanding drivers in automated driving. *Accident Analysis and Prevention, 124*, 202–209. https://doi.org/10.1016/j.aap.2019.01.013

Yadav, A. K., & Velaga, N. R. (2021). A comprehensive systematic review of the laboratory-based research investigating the influence of alcohol on driving behaviour. *Transportation Research Part F: Traffic Psychology and Behaviour, 81*, 557–585. https://doi.org/10.1016/j.trf.2021.07.010

Yadav, A. K., & Velaga, N. R. (2022). A systematic review of observational studies investigating the influence of mobile phone distraction on road crossing behaviour of pedestrians. *Transportation Research Part F: Traffic Psychology and Behaviour, 91*, 236–259. https://doi.org/10.1016/j.trf.2022.10.008

Yusoff, H. M., Ismail, K. I., Ismail, R., Khamis, N. K., Robat, R. M., & Bryce, J. M. (2024). Development and evaluation of a scale to measure nurses' unsafe driving behaviour while commuting. *Heliyon, 10*. https://doi.org/10.1016/j.heliyon.2023.e23735. e23735.

Zeller, R., Williamson, A., & Friswell, R. (2020). The effect of sleep-need and time-on-task on driver fatigue. *Transportation Research Part F: Traffic Psychology and Behaviour, 74*, 15–29. https://doi.org/10.1016/j.trf.2020.08.001

Zhang, N., Fard, M., Xu, J., Davy, J. L., & Robinson, S. R. (2024). Road safety: The influence of vibration frequency on driver drowsiness, reaction time, and driving performance. *Applied Ergonomics, 114*, Article 104148. https://doi.org/10.1016/j.apergo.2023.104148