

Monitoring Technologies for Truck Drivers: A Systematic Review of Safety and Driving Behavior

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Abstract: Truck drivers are essential to global freight operations but face disproportionate safety risks due to fatigue, distraction, and demanding working conditions, all of which significantly elevate crash likelihood. This systematic review assesses how monitoring technologies have been used to improve safety among professional truck drivers, focusing on the types of technologies deployed, the variables monitored, and reported safety outcomes. Conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines, the review includes 40 peer-reviewed articles published in English between 2009 and 2024, identified through systematic searches in PubMed, Scopus, Web of Science, and IEEE Xplore. Due to methodological heterogeneity, a formal risk of bias assessment was not conducted. Most studies examined wearable devices, in-vehicle cameras, telematics systems, and AI-driven platforms. These technologies monitored variables such as fatigue, stress, distraction, speed, and environmental conditions. While the findings demonstrate considerable potential to enhance safety outcomes, persistent challenges include implementation costs, privacy concerns, and variability in effectiveness. The evidence is also geographically concentrated in high-income regions, limiting broader applicability. This review highlights the urgent need for harmonized evaluation frameworks, robust validation protocols, and context-sensitive strategies to support the effective adoption of monitoring technologies in the trucking sector.



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1. Introduction

Road traffic accidents remain a global concern, resulting in significant human and economic impacts. Annually, over 1.19 million lives are lost, and millions more sustain long-term injuries due to road crashes [1]. These incidents impose substantial financial burdens, often exceeding 3% of a country's gross domestic product, particularly in developing economies with limited resources to address these challenges [2]. Among the most vulnerable are professional drivers, particularly truck drivers, who face heightened risks due to the demanding nature of their occupation, behavioral factors, and challenging environmental conditions. These unique vulnerabilities underscore the need for tailored safety interventions to address this issue.

Truck drivers are integral to global logistics and freight systems, yet their work environment exposes them to significant safety risks. Prolonged working hours, irregular sleep schedules, and extensive highway driving contribute to fatigue, cognitive impairments, and slower reaction times [3,4]. Delivery pressures and economic incentives further increase the

prevalence of risky behaviors such as speeding, distracted driving, and stimulant use [5,6]. Research indicates that human behavior contributes to up to 90% of road accidents, underscoring the importance of addressing these behavioral factors through effective safety measures [7,8].

Traditional safety interventions, such as driver screening, training programs, and vehicle maintenance, have had limited success in addressing the multifaceted risks associated with truck driving. Safety monitoring systems offer a technology-driven alternative by enabling continuous or event-triggered data collection of critical metrics, including speed, acceleration, braking patterns, and contextual factors surrounding unsafe events [9,10]. These systems deliver real-time feedback to drivers and support post-event analysis, facilitating risk mitigation strategies and the development of evidence-based safety protocols.

In addition to their safety benefits, safety monitoring systems provide significant operational advantages for commercial fleets. These systems document unsafe driving behaviors, enable prompt corrective actions, and deliver frequent, objective feedback to drivers. They establish benchmarks for fleet-wide safety norms, incentivize adherence to safe driving practices, and reduce the need for in-person evaluations. Moreover, safety monitoring systems enhance regulatory compliance, improve productivity, and support liability management, positioning them as essential tools for modern fleet operations [11].

Despite their potential, safety monitoring systems face barriers to widespread adoption in commercial trucking. High implementation costs, technical complexities, and concerns regarding data privacy and security remain significant challenges [12,13]. Addressing these obstacles is critical to achieving the full potential of safety monitoring systems in enhancing road safety and operational efficiency.

This systematic review examines the effectiveness, benefits, and limitations of safety monitoring systems for truck drivers. It consolidates existing evidence to evaluate their role in addressing safety challenges, encouraging safer driving behaviors, and identifying barriers to their widespread adoption. The review is structured around the following research questions (RQ):

RQ1: Which monitoring technologies are currently employed to evaluate and improve the driving behavior and safety performance of professional truck drivers?

RQ2: Which physiological, behavioral, and environmental variables are tracked by these technologies in the context of professional truck driving?

RQ3: How do monitoring technologies affect safety outcomes among professional truck drivers, including accident mitigation and behavior modification?

RQ4: What are the primary strengths and limitations of current monitoring technologies for professional truck drivers?

By addressing these questions, this review aims to provide actionable insights for researchers, policymakers, and practitioners, guiding the development and implementation of effective safety monitoring systems for truck drivers.

The remainder of this paper is organized as follows: Section 2 outlines the systematic review methodology, detailing the criteria and processes used to select and evaluate relevant studies. Section 3 presents the results, highlighting key findings and themes identified in the reviewed literature. Section 4 provides a detailed discussion of the findings, their implications, and limitations, while offering recommendations and proposing directions for future research to advance truck driver safety. Finally, Section 5 concludes by summarizing the main insights and contributions of this review.

2. Methods

This systematic review was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines [14]. The

PRISMA framework provides a rigorous and structured approach to systematic reviews, enhancing their transparency, reproducibility, and reliability. Additional details are available in the PRISMA 2020 checklist (see Supplementary Materials, Document S1). The methods employed in this review are detailed below.

2.1. Protocol

A structured protocol was developed prior to the review to define its objectives, research questions, eligibility criteria, and methodological approach. It was prospectively registered in the International Prospective Register of Systematic Reviews (PROSPERO) under the reference CRD420250644355 [15], providing a transparent framework to guide the review process, minimize potential bias, and ensure consistency across all stages.

The review process followed four main phases: identifying relevant studies through database searches, screening titles and abstracts for relevance, evaluating full-text articles to determine eligibility, and including studies that met all predefined criteria. Inclusion and exclusion criteria were applied at each stage, and decisions were documented to ensure transparency and reproducibility. This approach ensured alignment with the research objectives and adherence to the outlined methodology.

2.2. Eligibility Criteria

The review focused on professional truck drivers as the population of interest. Eligible studies evaluated monitoring technologies designed to monitor driving behavior, such as wearable devices, in-vehicle cameras, telematics systems, and artificial intelligence (AI)-based platforms. To qualify, studies had to report on safety-related outcomes, including reductions in accident rates, mitigation of driving risks, or behavioral improvements linked to the implementation of these technologies. Only original research articles published in peer-reviewed journals, written in English, and published between January 2009 and October 2024 were included to ensure the relevance and quality of the evidence.

Studies were excluded if they targeted populations other than professional truck drivers, such as passenger vehicle or bus operators. Research addressing outcomes not directly tied to road safety, such as vehicle performance or driver comfort, was also excluded. Furthermore, review articles, editorials, opinion pieces, conference abstracts, and grey literature were rejected to maintain a focus on primary, scientifically validated evidence.

2.3. Search Strategy

A systematic search was conducted in November 2024 across four major electronic databases: PubMed, Scopus, Web of Science, and IEEE Xplore. These databases were selected for their coverage of research in occupational health, transportation, and road safety. The search utilized Boolean operators with the following keyword combination: “truck driver” or “professional driver” or “commercial driver” and monitor* or detect* or track* or assess* and “technology” or “system” or “device” or “platform” and “safety” or “accident” or “risk” or “behavior”.

No supplementary techniques, such as citation tracking or snowballing, were employed. This focused approach ensured a systematic and replicable identification of eligible studies while minimizing potential biases associated with non-standardized search methods.

2.4. Data Collection and Extraction

The data collection and extraction procedures were conducted by a single reviewer, following a standardized protocol to ensure methodological consistency and minimize potential bias. After completing the database searches, all retrieved records were imported into the Rayyan platform for systematic reviews (Rayyan Systems Inc., 2025), which enabled

the automatic identification and removal of duplicate entries. Title and abstract screening was also performed in Rayyan, using predefined inclusion and exclusion criteria to assess the relevance of each record. Studies meeting the initial eligibility criteria were then subjected to full-text review to determine final inclusion. This systematic and transparent process ensured that only studies directly addressing the review's research questions were retained for synthesis.

For data extraction, a structured spreadsheet was developed in Microsoft Excel (Microsoft Corporation, Version 16.77.1, 2025) to systematically collect key information from each included study. The extraction process was supported by ChatGPT (OpenAI, GPT-4, 2025), which assisted in identifying and organizing study details such as objectives, data collection methods, analytical techniques, principal findings, types of monitoring technologies, monitored variables, monitoring frequency, and temporal coverage. All extracted information was manually reviewed and cross-verified against the original study reports by the reviewer to ensure accuracy and consistency.

2.5. Data Synthesis

Data synthesis is presented as a narrative summary of the evidence on monitoring technologies used to improve truck driver safety, organized by technology types. Due to substantial heterogeneity across the included studies, particularly in methodologies, variables assessed, and reported outcomes, a standardized risk of bias assessment was not feasible.

To offer a comprehensive overview, Table A1 in Appendix ?? provides a detailed summary of each selected study, including information on authorship, geographic context, objectives, data collection methods, analytical techniques, and key findings. Additionally, Table A2 outlines the monitoring technologies employed, the variables measured, the frequency of monitoring, and the temporal context of data collection.

This synthesis underscores the diversity of monitoring technologies and methodological advancements in driver safety research. It highlights emerging trends, practical applications, and identifies critical gaps, providing valuable insights for future studies on technology-based interventions to enhance truck driver safety.

3. Results

This systematic review synthesizes findings from multiple studies on the use of monitoring technologies to improve truck driver safety. The studies collectively highlight the global application of various technologies, diverse methodological approaches, and thematic focuses within the field of driver safety monitoring. Below, we discuss the characteristics, trends, and key findings of the included studies, focusing on technology types, monitored variables, safety outcomes, and identified challenges.

3.1. Study Selection

The study selection process, encompassing identification, screening, and inclusion of eligible studies, is presented in the PRISMA flow diagram (Figure 1). A total of 725 records were identified through systematic searches conducted across four major electronic databases: PubMed, Scopus, Web of Science, and IEEE Xplore. No additional records were retrieved from other sources or registers.

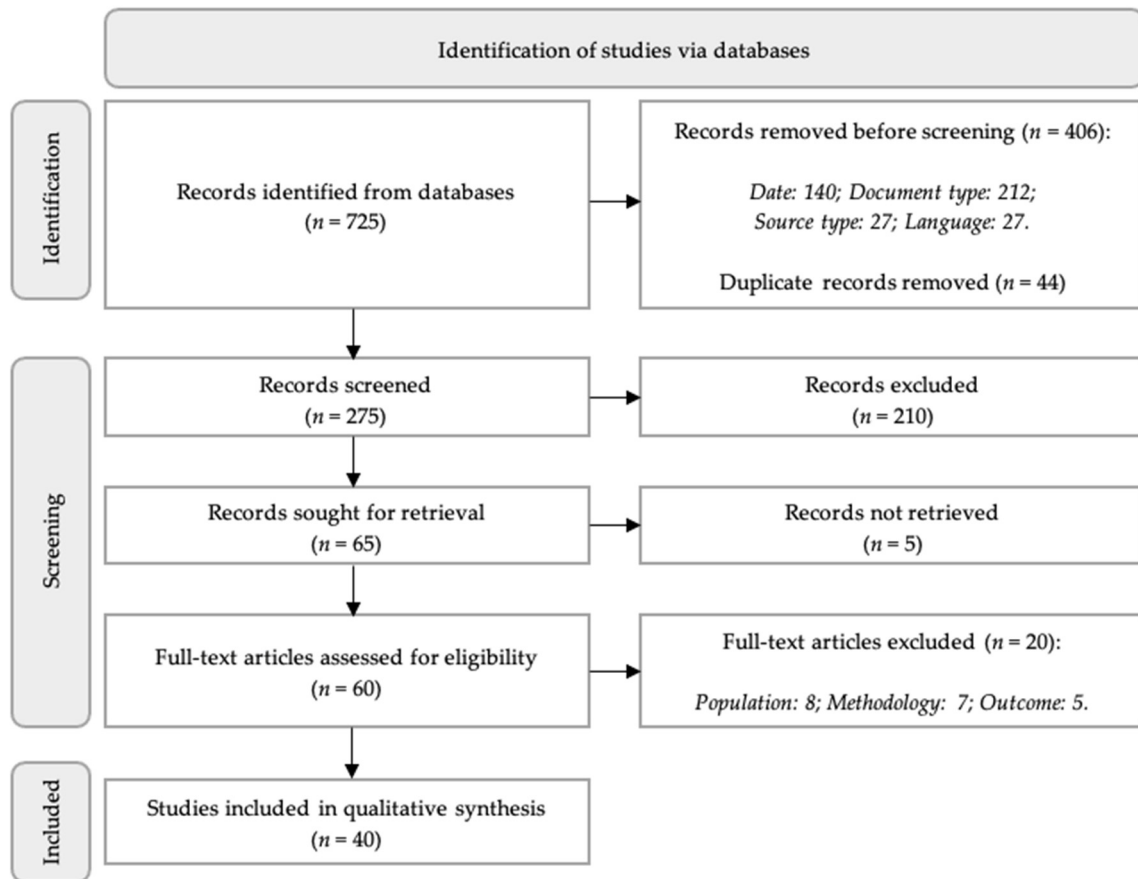


Figure 1. The identification, screening, and inclusion process of eligible studies using PRISMA 2020.

During the initial identification phase, 406 records were excluded based on predefined criteria. These exclusions included 140 records published outside the specified date range, 212 excluded due to document type, 27 based on source type, and 27 for language reasons. Additionally, 44 duplicate records were removed, resulting in 275 unique records eligible for title and abstract screening.

In the screening phase, the titles and abstracts of the remaining records were thoroughly analyzed to determine their alignment with the inclusion criteria. A total of 210 records were excluded for failing to meet criteria related to the population, methodology, or outcomes. Specifically, these records either did not focus on professional truck drivers, failed to evaluate monitoring technologies aimed at enhancing driving safety, or reported outcomes unrelated to road safety. Following this screening, 65 records were selected for full-text review.

Of the 65 records identified for full-text retrieval, 60 articles were successfully obtained. Despite efforts to access them through institutional resources, five records could not be retrieved. The 60 full-text articles underwent an eligibility assessment, resulting in the exclusion of 20 studies. Eight studies did not focus on professional truck drivers, seven failed to evaluate monitoring technologies, and five examined outcomes unrelated to road safety.

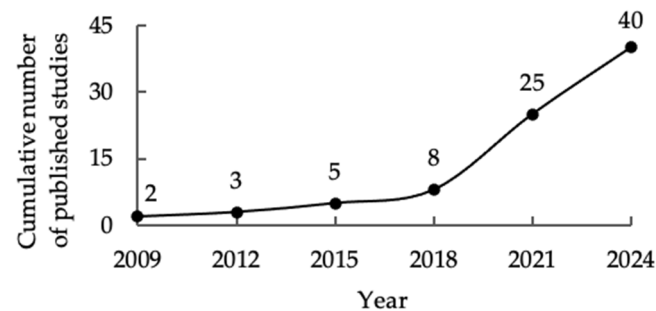
Ultimately, 40 studies met all inclusion criteria and were included in the qualitative synthesis, representing a diverse range of geographical contexts, methodologies, and study designs. The majority of studies identified in the literature search were published in high-impact journals, with 30 appearing in Q1 journals, followed by 8 in Q2, as detailed in Table 1.

Table 1. Number of selected studies per quartile.

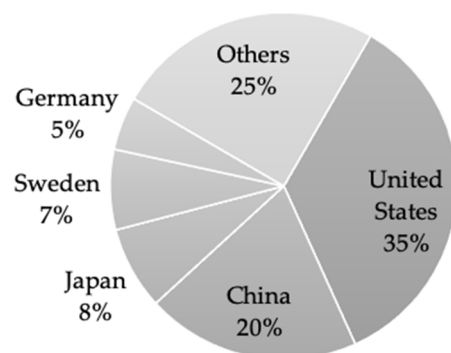
Quartile Ranking	Number of Studies
Q1	30
Q2	8
Q3	1
Q4	0
Not assigned	1

3.2. Characteristics of Studies

The temporal distribution of studies illustrates a consistent increase in research activity over the 15-year period analyzed (see Figure 2). By 2009, two studies had been published, increasing incrementally to three by 2012 and five by 2015. A notable acceleration occurred from 2018 onward, with the cumulative number of studies reaching 8 by 2018, 25 by 2021, and 40 by 2024. This upward trend underscores a growing emphasis on leveraging monitoring technologies to enhance truck driver safety.

**Figure 2.** Cumulative number of published studies on monitoring technologies for truck driver behavior assessment.

Geographically, the distribution of research remains uneven across the globe (see Figure 3). The majority of studies were conducted in the United States (35%) and China (20%), followed by Japan (8%) and Sweden (7%). Germany accounted for 5% of the studies, while 25% originated from various other countries. This pattern highlights a concentration of research in developed regions with advanced transportation systems. In contrast, regions with high accident rates, such as Sub-Saharan Africa and parts of South America [1], are underrepresented in the literature.

**Figure 3.** Country-wise distribution of selected studies.

The reviewed studies employed a variety of methodologies and technologies to address critical aspects of truck driver monitoring and safety. A significant portion of the

research focused on advanced systems such as Camera/Video Imaging Systems (C/VISs), which were designed to mitigate blind spot risks and improve driver visibility. These systems underwent real-world testing to evaluate their effectiveness in preventing safety-critical events, such as during lane changes.

Fatigue monitoring emerged as another prominent theme, with several studies exploring non-intrusive methods utilizing wearable devices, physiological data, and machine learning algorithms. These approaches aimed to detect driver fatigue in real-time without disrupting driving tasks. Multi-feature fusion techniques were frequently employed to integrate various data types, enhancing the precision and reliability of fatigue detection.

Forward collision warning (FCW) systems were extensively studied, with considerable efforts directed toward optimizing their algorithms to better align with driver response behaviors. Machine learning models were commonly used to improve warning accuracy and reduce false alarms, addressing key challenges associated with FCW system adoption and reliability.

Additionally, many studies leveraged GPS and telemetric data to analyze driver behavior. These datasets allowed researchers to identify risky driving patterns, such as erratic speed variations, and to establish risk profiles for truck drivers. Such analyses were often applied in fleet management strategies to monitor and mitigate on-road risks effectively.

The methodologies utilized in these studies were diverse, encompassing real-world field testing, simulation-based experiments, and the integration of wearable and in-vehicle technologies. Advanced systems such as telematics, connected vehicle platforms, and artificial intelligence were frequently employed to assess and enhance truck driver safety across varied operational scenarios.

This body of research represents a broad and methodical investigation into monitoring technologies within the trucking industry. The studies collectively highlight the range of innovative approaches used to address safety challenges, emphasizing the importance of advanced systems, data-driven methods, and interdisciplinary collaboration.

3.3. Monitoring Technologies

The integration of monitoring technologies into the trucking industry represents a transformative advancement in addressing safety and operational challenges. These technologies, designed to systematically monitor and assess both driver behavior and vehicle performance, have become indispensable in mitigating risks and enhancing road safety. By leveraging data-driven insights, these tools not only enable real-time interventions but also facilitate long-term strategies for accident prevention and behavioral improvement. The following sections delve into the distinct categories of monitoring technologies employed in trucking, including wearable devices, in-vehicle systems, vision-based monitoring, advanced driver assistance systems, data logging and event recording systems, and connectivity platforms.

3.3.1. Wearable Monitoring Devices

Wearable monitoring devices have shown substantial potential in monitoring physiological and behavioral parameters to enhance safety for professional truck drivers. Giorgi et al. [16] explored a multimodal approach combining electroencephalographic (EEG), electrooculographic (EOG), photoplethysmography (PPG), and electrodermal activity to monitor fatigue in professional drivers during a simulated driving task. Their findings highlighted brain activity as the most sensitive and immediate indicator of fatigue onset, followed by ocular parameters, which exhibited delayed effects. This study demonstrates the effectiveness of wearable devices in capturing critical physiological changes that sig-

nal mental fatigue, thus providing essential inputs for real-time interventions among truck drivers.

Similarly, Ito et al. [17] utilized wearable devices to analyze heart rate variability (HRV) for predicting collision risks associated with driver fatigue. Their research employed autonomic nerve function (ANF) indices derived from HRV data to develop a novel model that predicts collision risks within a 30 min window. With an accuracy of 74.9%, the system demonstrated the feasibility of leveraging physiological data from wearable devices to anticipate fatigue-induced risks, allowing for timely and targeted safety interventions. The study also highlighted the importance of integrating physiological data with external variables, such as speed and road conditions, to improve prediction accuracy.

Minusa et al. [18] further extended this line of research by examining the relationship between physiological conditions, such as stress-induced fatigue, and rear-end collision risk. Their study used autonomic nerve function indices, monitored continuously during real-world truck driving conditions, to reveal that acute stress increased rear-end collision risks by exacerbating sympathetic nerve activity and inhibiting parasympathetic responses. The findings underscore the critical role of wearable devices in capturing these physiological states, enabling the development of systems that warn drivers or automatically adjust vehicle behavior to mitigate risks.

Despite these promising findings, wearable monitoring devices face several limitations that could hinder their effectiveness. Environmental factors, such as extreme temperatures, vibrations, or poor lighting conditions, can affect the accuracy and reliability of physiological data collection. For example, photoplethysmography sensors used for HRV monitoring are sensitive to motion artifacts or improper placement, which may introduce noise into the data. Privacy concerns are another significant barrier, as continuous monitoring of physiological data may be perceived as intrusive by drivers, potentially leading to resistance or non-compliance. Additionally, drivers may find wearable devices uncomfortable or burdensome during long-haul trips, reducing consistent usage and undermining their overall effectiveness. Finally, while wearable devices can detect physiological changes indicative of fatigue or stress, their practical utility relies heavily on integration with external systems and effective calibration to provide actionable insights tailored to individual driver conditions.

3.3.2. In-Vehicle Monitoring Systems

In-vehicle monitoring systems (IVMSs) are recognized as effective tools for improving road safety among professional truck drivers. These systems incorporate technologies such as real-time feedback mechanisms, behavioral analytics, and data monitoring to address unsafe driving behaviors and enhance operational safety. Research has shown that IVMSs, combining in-cab warning lights and supervisory coaching using video footage, lead to measurable reductions in unsafe behaviors. A study involving 315 vehicles reported a significant reduction in risky behaviors when both mechanisms were employed, compared to using warning lights alone. This approach facilitates immediate feedback and supports behavioral adjustments, contributing to improved safety outcomes [19].

The integration of GPS technology with IVMSs has enabled the monitoring of driver behavior under various operational conditions. A study analyzing data from 4357 trucks identified distinct driving styles—aggressive, normal, and cautious—using clustering methods. The findings revealed that aggressive driving behaviors under heavy-load conditions were associated with elevated risks, highlighting the potential of IVMS to tailor interventions based on driving styles and load conditions [20].

IVMSs also facilitate the tracking of safety-critical events (SCEs), such as hard braking and near-collisions. A large-scale naturalistic study involving 496 drivers and 13 million

miles of driving data applied point process models to analyze these events. The results indicated that SCE frequency increased with driver fatigue and insufficient rest breaks. This suggests that IVMSs can identify periods of heightened risk and support timely interventions to mitigate potential incidents [21].

Vision-based monitoring systems extend the capabilities of IVMSs by enabling the detection of distractions and other unsafe behaviors. These systems employ algorithms to track hand and head movements, allowing for the identification of manual distractions, such as improper steering wheel grip. Real-time detection of such behaviors enhances the effectiveness of IVMSs in addressing contributing factors to accidents [22].

Incorporating psychological and physiological metrics into IVMSs further enhances its functionality. Studies have demonstrated that driver anger and fatigue are significant factors influencing driving safety. For instance, a longitudinal study using GPS data found that increased levels of anger were associated with speeding behaviors. Similarly, fatigue-related metrics, such as heart rate variability, were found to correlate with an elevated risk of rear-end collisions. Integrating these metrics into IVMSs allows for tailored recommendations, such as suggesting rest breaks or adjustments to driving behavior [23,24].

Data logging capabilities within IVMSs enable detailed post-event analyses of driving patterns. Systems that record variables such as speed, acceleration, and lane changes provide insights into recurring risky behaviors. These analyses allow fleet managers to implement targeted training programs and revise safety policies to reduce the likelihood of future incidents [25].

Evidence highlights the role of IVMSs in reducing unsafe driving behaviors, identifying context-specific risks, and enabling proactive interventions. However, challenges such as high implementation costs, privacy concerns, and resistance from drivers may limit adoption. Addressing these challenges is critical to maximizing the potential of IVMSs for improving road safety among professional truck drivers.

3.3.3. Vision-Based Monitoring Systems

Vision-based monitoring systems have emerged as a critical component in monitoring truck driver behavior and enhancing road safety. These systems employ advanced imaging technologies to observe driver activities and the surrounding environment, providing real-time feedback to mitigate risk factors such as fatigue, distraction, and blind spot-related crashes.

Camera/Video Imaging Systems (C/VISs) are among the most commonly used vision-based tools in commercial vehicles. These systems provide live video feeds of a truck's surroundings, allowing drivers to monitor blind spots and make safer lane changes or merging maneuvers. Studies have demonstrated that C/VISs can improve situational awareness, particularly in challenging conditions such as nighttime driving and during complex tasks like right lane changes [26]. However, despite their potential, field evaluations have reported no significant reduction in safety-critical events (SCEs). Additionally, user feedback highlights discomfort with glare from monitors, particularly at night, and suggests that advanced features, while effective, are underutilized without sufficient driver acceptance and training [26].

Another critical application of vision-based systems is fatigue detection. These systems typically rely on facial metrics, such as eyelid closure and eye movement patterns, to identify signs of drowsiness. While effective under controlled conditions, their performance diminishes in real-world scenarios due to challenges such as low-light environments, sensor limitations, and driver resistance to intrusive monitoring [27]. To address these issues, alternative approaches leveraging non-visual features, such as physiological and vehicular data, have shown promise. These systems utilize metrics like heart rate, skin conductance,

and vehicle operation patterns, offering a privacy-preserving and robust solution for continuous fatigue monitoring. Comparative studies suggest that non-visual methods outperform traditional vision-based systems in terms of reliability and user acceptance, particularly in environments where visual cues are compromised [28].

Driver monitoring systems (DMSs) extend the capabilities of vision-based systems by issuing real-time alerts for distraction and drowsiness. These systems typically employ auditory and visual alerts to prompt drivers to regain focus. Field studies have demonstrated an increase in driver alertness following such interventions, but their long-term effectiveness relies heavily on user engagement and trust [29,30]. High rates of false alarms, coupled with poorly designed feedback mechanisms, can lead to driver frustration and disengagement, undermining the system's intended safety benefits [30,31].

Across the various vision-based technologies, several critical observations emerge. These systems demonstrate significant potential in enhancing road safety by reducing blind-spot-related crashes and improving situational awareness. However, their widespread adoption is hindered by high costs, operational complexity, and privacy concerns. The effectiveness of these systems is highly dependent on driver engagement. Systems that generate excessive false alarms or provide unclear feedback are prone to being disregarded by drivers. Finally, the integration of vision-based tools with non-visual monitoring technologies, such as physiological data sensors, offers an opportunity to enhance reliability and address limitations in challenging conditions [27,28].

3.3.4. Advanced Driver Assistance Systems

Advanced driver assistance systems (ADASs) play a pivotal role in enhancing the safety of commercial truck drivers by integrating technologies that assist in real-time decision-making and mitigate potential risks. Studies demonstrate that these systems, which include features like FCWs, lane departure warning (LDW), headway monitoring and warning (HMWs), and speed limit indicators (SLIs), significantly influence driver behavior and safety outcomes.

The FCW system, as analyzed by Bao and Wang [32], optimizes truck safety by issuing alerts based on driver response behavior. Their study categorized driver responses into three clusters: Response Before Warning, Response After Warning, and No Response. By tailoring warning distances to these clusters using machine learning techniques, the optimized FCW system demonstrated a 97.92% accuracy and reduced false alarm rates to 1.73%, improving overall safety outcomes by up to 5%.

In a naturalistic driving study by Wu et al. [33], ADASs, particularly FCW and LDW, were evaluated for their impact on real-world truck driver behavior. The study found that the activation of these systems led to a reduction in warnings issued for speeding and lane departures, correlating with improved safety behaviors. For instance, LDWs effectively decreased lane departure warnings by 28%, while HMWs reduced insufficient headway warnings by 45%.

The haptic-based lane-keeping assistance (LKA), evaluated by Roozendaal et al. [34], further highlights the efficacy of continuous and bandwidth-based steering aids. The study found that continuous haptic assistance provided superior lane-keeping performance compared to bandwidth assistance, particularly under conditions of driver distraction. This underscores the importance of designing systems that adapt to varying levels of driver attention and workload.

Elbaum et al. [35] explored how ADASs function under supervisory monitoring in a military setting, specifically with drivers diagnosed with attention deficit hyperactivity disorder (ADHD). The results revealed that drivers with ADHD exhibited significantly higher

rates of safety events despite the implementation of ADASs, highlighting the necessity for tailored interventions and system adjustments for specific driver populations.

Similarly, Raddaoui and Ahmed [36] examined the distraction and workload implications of connected vehicle (CV) warnings in ADASs. They noted that while spot weather warnings were well-received, work zone warnings caused prolonged off-road glances, potentially compromising safety. These findings emphasize the need for refined human-machine interface (HMI) designs to reduce distraction while maintaining effectiveness.

Mehdizadeh et al. [37] addressed the predictive capabilities of ADASs using machine learning models to forecast safety-critical events (SCEs) up to 30 min in advance. By leveraging extensive kinematic data, the study achieved a predictive accuracy of 76%, offering a proactive approach to mitigate risks associated with unsafe driving behaviors.

ADAS's capacity to address interactions with vulnerable road users was demonstrated by Schindler and Bianchi Piccinini [38]. Their test-track experiment analyzed truck drivers' kinematic and visual behavior when encountering cyclists and pedestrians. The findings inform the design of ADASs for better detecting and responding to such scenarios, thereby reducing collision risks.

Collectively, these studies underscore the transformative potential of ADASs in reducing risks and enhancing safety for truck drivers. However, challenges remain, including addressing system limitations such as false alarms, driver over-reliance, and workload imbalances. Continued advancements in ADAS design, coupled with tailored training and deployment strategies, will be crucial in maximizing their effectiveness in diverse operational contexts.

3.3.5. Data Logging and Event Recording Systems

Data logging and event recording systems, such as electronic logging devices (ELDs) and event data recorders (EDRs), have been pivotal in monitoring professional truck drivers, enhancing safety, and improving compliance with regulations. These systems provide real-time data on driver behavior and vehicle performance, offering insights for both immediate interventions and long-term safety improvements.

Crizzle et al. [39] explored the impact of ELDs on Canadian long-haul truck drivers, finding that ELD use significantly reduced driver fatigue and stress by ensuring compliance with hours-of-service (HOS) regulations. Drivers using ELDs reported improved sleep quality and less difficulty unwinding after work, suggesting a positive influence on their overall well-being. However, challenges such as limited parking infrastructure and concerns about income reductions due to stricter adherence to HOS regulations were noted, highlighting operational constraints.

Hickman et al. [40] demonstrated the safety benefits of ELDs in a U.S.-based study, where trucks equipped with ELDs experienced an 11.7% reduction in total crash rates and a 53% decrease in HOS violations compared to trucks without these devices. The study attributed these improvements to the system's ability to limit falsification of driving hours, thereby reducing fatigue-related risks.

Furthermore, de Oliveira et al. [41] evaluated the integration of event data recorders (EDRs) with training and feedback programs in Brazil, finding significant reductions in unsafe driving behaviors, such as speeding, and improvements in fuel efficiency. The study highlighted that EDRs are most effective when combined with tailored feedback and continuous training, reinforcing safe driving practices. Over a 13-month period, the frequency of speeding events decreased by 94.4%, underscoring the potential of EDR systems to reshape driving habits when used in conjunction with active managerial oversight.

Scott et al. [42] examined unintended consequences of the ELD mandate in the United States. While the mandate effectively reduced HOS violations, it also led to offense displace-

ment, where drivers compensated for lost productivity by engaging in riskier behaviors, such as speeding. This phenomenon was especially pronounced among small carriers, suggesting that increased monitoring in one area may inadvertently shift unsafe practices to other dimensions.

In conclusion, data logging and event recording systems provide a robust framework for improving safety and compliance in the trucking industry. However, to maximize their impact, it is essential to address systemic challenges, ensure equitable access, and integrate these technologies with broader safety initiatives. Through a balanced approach, these systems can significantly contribute to reducing crash rates and promoting safer driving behaviors among professional truck drivers.

3.3.6. Connectivity and Communication Systems

Connectivity and communication systems, such as vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) technologies, have revolutionized the monitoring and management of truck drivers' safety by enabling real-time data exchange and communication. These systems enhance situational awareness, facilitate decision-making, and reduce the likelihood of accidents.

Ahmed et al. [43] analyzed the implementation of connected vehicle (CV) technology in Wyoming under the Wyoming Department of Transportation pilot program. The program aimed to improve safety along the Interstate 80 corridor through vehicle-to-everything (V2X) communication technologies, offering applications such as forward collision warnings, traveler information messages, and distress notifications. Results highlighted the effectiveness of CV training programs for professional truck drivers, with participants demonstrating increased understanding and usage of CV warnings. The study also underscored the role of V2X technology in mitigating risks under adverse weather conditions, such as low visibility and icy roads.

Fank et al. [44] explored the use of a human-machine interface (HMI) for cooperative truck overtaking maneuvers enabled by V2X communication. The system facilitated the negotiation of overtaking requests between drivers, improving coordination and reducing traffic conflicts. However, the study noted limitations in the success rate of automated cooperation requests, primarily due to suboptimal HMI design. Furthermore, system failures, such as communication disruptions, were not perceived as safety-critical by drivers, but effective information delivery was crucial to maintain trust and system acceptance.

Khoda, Bakhshi, and Ahmed [45] assessed the use of Basic Safety Messages (BSMs) transmitted in connected vehicle environments to detect crash-prone conditions. By leveraging trajectory-level data, the study demonstrated the potential for detecting and mitigating rear-end and run-off-road crashes. The introduction of kinematic-based surrogate measures of safety, such as steering and acceleration variability, allowed for the precise identification of crash-prone scenarios. The findings highlighted how real-time data sharing in CV environments can significantly enhance predictive safety measures.

Yang et al. [46] investigated the impact of a connected vehicle-based variable speed limit (CV-VSL) application on truck driver behavior under adverse weather conditions. Utilizing a high-fidelity driving simulator, the study found that CV-VSL systems significantly reduced speed variability and improved compliance with speed limits. This reduction in speed inconsistencies directly correlated with a decreased likelihood of crashes, especially in hazardous weather conditions. The study emphasized that such systems provide proactive warnings to drivers, enabling better decision-making and safer driving.

Despite the numerous advantages, connectivity and communication systems face challenges such as high implementation costs, infrastructure requirements, and varying driver acceptance rates. Furthermore, system failures or partial adoption in mixed-traffic

environments may undermine the full potential of these technologies. Addressing these limitations through comprehensive training programs, infrastructure investments, and system reliability improvements can ensure wider adoption and enhanced safety outcomes for truck drivers.

3.4. Monitored Variables

Identifying the variables monitored by truck driver monitoring technologies is essential for evaluating their effectiveness in improving road safety and driver performance. These technologies leverage specific physiological, behavioral, and environmental metrics, each offering unique insights into safety outcomes and operational efficiency. This section analyzes how the six primary monitoring technologies—wearable devices, in-vehicle monitoring systems, vision-based systems, ADASs, data logging and event recording systems, and connectivity and communication systems—contribute to a comprehensive framework for addressing the complex challenges of modern transportation systems.

Wearable monitoring devices specialize in capturing physiological variables such as heart rate, heart rate variability, skin temperature, electrodermal activity, and blink rates. These real-time metrics provide critical insights into fatigue, stress, and alertness levels, which are particularly vital for long-haul operations. Additionally, wearable devices monitor behavioral variables, including posture, micro-movements, and physical activity patterns, to assess driver alertness and well-being. Complementing this, these devices track environmental variables, such as ambient temperature and humidity, which directly influence comfort and fatigue. Continuous monitoring across both daytime and nighttime contexts ensures a comprehensive understanding of the driver's physiological state under varying conditions.

In-vehicle monitoring systems are designed to track behavioral variables such as hard braking, speeding, swerving, and unbelted driving, which are critical indicators of unsafe driving practices. These systems also monitor environmental variables, including road conditions, traffic density, and operational factors like load type and trip length. By enabling continuous monitoring over extended periods, often several months, these systems provide fleet managers with actionable data to identify driving trends and high-risk behaviors, facilitating targeted safety interventions and operational improvements.

Vision-based monitoring systems are highly effective in capturing physiological variables such as blink rate, eye movement, and facial expressions, which are key indicators of fatigue and distraction. Additionally, these systems monitor behavioral variables like lane position, steering smoothness, and gaze patterns, reflecting driver attention and precision. Vision-based systems also track environmental variables, such as traffic density, road conditions, and visibility, offering real-time and contextualized insights into driver behavior across diverse scenarios, including both daytime and nighttime operations.

ADASs primarily monitor behavioral variables, including reaction time, braking distance, deceleration patterns, and headway distance, to evaluate driver responsiveness and safety. These systems also capture environmental variables such as vehicle speed, proximity to other vehicles, and collision risks. By operating continuously in real-world conditions, ADASs enhance situational awareness and enable proactive safety interventions. Through the integration of driver behavior data with external environmental information, ADAS technologies play a pivotal role in accident prevention and the overall improvement of road safety.

Data logging and event recording systems focus on capturing detailed behavioral variables such as speeding, harsh braking, and acceleration patterns, which are essential for identifying unsafe practices. These systems also monitor environmental variables like road conditions, weather, and operational settings. Continuous data logging facilitates

comprehensive post-trip evaluations and long-term trend analyses, making these systems indispensable for fleet management, regulatory compliance, and identifying areas for safety enhancement.

Connectivity and communication systems emphasize monitoring behavioral variables such as driver compliance with connected vehicle warnings, responses to advisory speed limits, and interactions with cooperative systems. They also track environmental variables, including real-time weather updates, road closures, and traffic conditions. By integrating real-world data with simulation-based training, these systems ensure adaptability across diverse operational environments, delivering dynamic and context-sensitive safety recommendations.

By systematically integrating physiological, behavioral, and environmental metrics, these monitoring technologies provide a holistic approach to improving road safety and driver performance. Each technology offers specialized capabilities, contributing valuable data for targeted interventions. Together, they form a robust framework for enhancing the safety, efficiency, and sustainability of modern transportation systems.

4. Discussion

This section presents an analysis of the findings from the systematic review on monitoring technologies for truck drivers, with a focus on key insights, methodological strengths and limitations, policy implications, and directions for future research. By synthesizing evidence across diverse studies, the discussion aims to deepen understanding of how these technologies contribute to improving driver safety and reducing risky behaviors.

4.1. Key Findings

This review synthesizes findings from 40 peer-reviewed studies investigating the use of monitoring technologies to improve truck driver safety. Across the literature, a wide range of technologies was employed to monitor physiological, behavioral, and environmental indicators associated with risky driving behaviors and safety outcomes.

Wearable devices, such as wristbands and physiological sensors, were frequently used to detect fatigue and stress through measures including heart rate variability, electrodermal activity, and blink rate (Section 3.3.1). These systems enabled early detection of driver impairment and offered non-intrusive alternatives to visual monitoring, particularly valuable in low-light or high-distraction environments.

In-vehicle monitoring systems and telematics platforms were widely applied to track behavioral indicators such as speeding, abrupt braking, and unsafe lane changes (Section 3.3.2). When combined with real-time feedback mechanisms, these systems were associated with measurable reductions in risky behaviors. The integration of GPS and telemetric data also enabled the classification of driving styles and the identification of high-risk operational patterns.

Vision-based systems were used to monitor distraction and fatigue through facial analysis, eye movement, and head position (Section 3.3.3). While these systems offered detailed driver-state insights, their performance was often affected by environmental factors such as poor lighting, glare, or sensor occlusion.

Advanced driver assistance systems, including forward collision warning and lane departure warning functions, were also examined (Section 3.3.4). Some studies applied machine learning to personalize alert thresholds, which helped reduce false alarms and improve alignment with individual driver behavior. These results highlight the benefit of adapting system outputs to context-specific risk factors.

Data logging and event recording systems, such as ELDs and EDRs, supported driver safety by enabling compliance monitoring and post-trip behavior evaluation (Section 3.3.5).

Studies reported reductions in hours-of-service violations, fatigue, and speeding events, particularly when these technologies were combined with structured feedback and training. However, some unintended effects, such as the displacement of risky behaviors to unmonitored driving contexts, were also observed.

Connectivity and communication systems, including V2V and V2I technologies, facilitated real-time safety communication (Section 3.3.6). These systems supported applications such as hazard warnings, cooperative overtaking, and variable speed limit advisories. While drivers generally responded positively to connected vehicle alerts, limitations in system usability, interface design, and reliability under mixed-traffic conditions were noted.

The technologies reviewed monitored a broad array of variables (Section 3.4). Physiological measures included heart rate, skin conductance, and eye behavior to assess fatigue and stress. Behavioral variables, such as lane position, speed variation, braking intensity, and off-road glances, were key indicators of driver risk. Environmental factors such as road type, traffic conditions, and weather were also incorporated to improve the contextual relevance and accuracy of safety assessments. Together, these dimensions enabled a more holistic understanding of driver state and behavior.

Despite these promising outcomes, several challenges persist. As illustrated in Figure 3, most studies were conducted in high-income countries, limiting the global applicability of results. In addition, high implementation costs, data privacy concerns, limited system adaptability, and insufficient sample diversity were consistently identified across studies. These factors affect both the scalability and acceptability of monitoring technologies in real-world operations.

4.2. Strengths and Limitations

This systematic review identified several strengths in the current body of research on monitoring technologies. The integration of naturalistic driving data and real-time monitoring allowed for detailed insights into driver behaviors under realistic conditions. Multi-faceted approaches, combining physiological, behavioral, and environmental data, proved particularly effective in capturing complex interactions contributing to safety risks. Advances in machine learning and artificial intelligence further enhanced the adaptability and precision of monitoring systems, allowing for personalized feedback tailored to specific drivers and contexts.

However, this review also identified several limitations that constrain the generalizability and applicability of the findings. First, many studies were geographically concentrated in regions with advanced infrastructure and regulatory environments, limiting the transferability of findings to contexts with different road conditions, cultural attitudes, and policy frameworks. The underrepresentation of low- and middle-income regions, where truck driver safety is often a critical concern, highlights the need for broader geographic inclusion in future research.

Second, small sample sizes and short study durations were common methodological limitations. These factors reduce statistical power and limit the ability to draw reliable conclusions about the long-term effectiveness of monitoring technologies. In addition, shorter study periods often fail to capture sustained behavioral changes or account for the possibility that drivers may become desensitized to monitoring systems over time. A further concern is the limited diversity of study samples, particularly in terms of age, gender, cultural background, geographic context, and driving experience, which restricts the adaptability of monitoring technologies to different user groups. Systems developed and validated on relatively homogeneous populations may not perform consistently across varied real-world scenarios. Addressing this issue requires greater emphasis on heterogeneous sampling strategies and cross-context validation.

Third, high implementation costs remain a considerable obstacle, especially for small and medium-sized fleet operators. The deployment of advanced monitoring systems typically requires substantial upfront investment in hardware, software integration, and ongoing maintenance. These financial constraints can limit the adoption of safety-enhancing technologies, particularly in resource-constrained regions or among operators with limited access to funding, subsidies, or incentive mechanisms. Addressing this barrier will require targeted efforts to develop cost-efficient solutions, such as modular system design, open-source platforms, and scalable deployment models.

Fourth, many monitoring systems, particularly those relying on vision-based sensors or physiological signal detection, are sensitive to external environmental conditions. Factors such as poor lighting, glare, precipitation, and road surface variability may distort data accuracy and compromise system reliability in real-world applications. These challenges highlight the need for more robust and adaptable system designs, as well as validation studies conducted under varied environmental scenarios to ensure consistent performance.

Fifth, false alarms in systems such as FCW technologies emerged as a significant issue. High rates of false alerts can lead to driver frustration, reduced trust in the technology, and eventual disengagement. Improving algorithmic precision and ensuring that system responses align closely with actual driving conditions will be essential to enhancing usability and acceptance.

Sixth, privacy concerns continue to present a substantial challenge, particularly in the case of video-based monitoring systems. Many drivers express discomfort with continuous surveillance, raising both ethical and legal issues surrounding data protection and consent. While several studies proposed privacy-preserving alternatives, such as non-visual monitoring methods, these approaches require broader validation and implementation to ensure wider acceptance and compliance.

Finally, the absence of standardized evaluation frameworks across studies limits the comparability of results and the ability to assess the relative effectiveness of different technologies. Inconsistencies in methodologies, performance metrics, and outcome measures hinder the formation of a cohesive evidence base and complicate the identification of best practices. This lack of standardization poses ongoing challenges for policymakers and industry stakeholders seeking to adopt and scale effective monitoring systems in a consistent and evidence-driven manner.

4.3. Policy Implications

The findings of this review have significant implications for policymakers and industry stakeholders. Addressing barriers such as privacy concerns and usability challenges is critical to enhancing the adoption and effectiveness of monitoring technologies. Regulatory frameworks should prioritize the development of adaptive systems that align with individual driver behaviors and preferences, as these are essential for fostering trust and compliance among drivers.

Policies promoting data anonymization and the adoption of non-invasive monitoring solutions are crucial for mitigating privacy concerns and driver resistance. Additionally, the establishment of standardized evaluation frameworks would enable consistent and robust assessments of monitoring technologies, facilitating evidence-based decision-making. Policymakers should also consider financial incentives to encourage the adoption of advanced monitoring systems, particularly in high-risk sectors, where safety improvements can have significant societal and economic benefits. Collaboration between technology developers, fleet operators, and regulatory agencies will be essential to ensure that innovations address practical needs and industry goals.

4.4. Future Research

Future research should address the gaps and limitations identified in this review to strengthen the evidence base for monitoring technologies. Longitudinal studies with larger and more diverse populations are needed to evaluate the long-term impacts of these systems on driver behavior and safety outcomes. Additionally, innovative, non-invasive monitoring methods, such as non-visual fatigue detection systems and wearable devices equipped with physiological sensors (e.g., heart rate variability, skin conductance, or eye-tracking capabilities), should be further explored to offer privacy-preserving and user-friendly solutions.

Developing standardized metrics and methodologies for evaluating monitoring technologies is essential to enable robust comparisons and identify best practices. Comparative studies assessing cost-effectiveness, scalability, and long-term feasibility will provide valuable insights for stakeholders. In particular, future investigations should explore affordable and scalable solutions, including the use of commercially available devices (e.g., smartphones or smartwatches), open-source platforms, and cloud-based data processing, all of which can reduce hardware demands and total cost of ownership.

Moreover, research into policy frameworks and financial mechanisms, such as public-private partnerships, government subsidies, tax incentives, or insurance discounts linked to safety technology adoption, could inform strategies to overcome financial barriers, especially for small and medium-sized enterprises. Collaborative models, including shared service platforms and subscription-based implementations, may also offer practical alternatives in cost-sensitive settings.

In addition, future work should explore the integration of multiple and diverse data sources, such as facial fatigue indicators, cockpit audio, physiological signals, and vehicle telemetry, to support more comprehensive and context-aware assessments of driving behavior. Combining these complementary inputs can provide a richer understanding of both driver state and environmental context, which is essential for accurately identifying risk patterns. Adaptive algorithms, particularly those based on deep learning techniques, offer strong potential for processing such complex data and dynamically detecting risky behaviors. These approaches can enhance system responsiveness, improve behavioral sensitivity, and support the development of individualized, data-driven safety interventions.

Beyond technical and economic considerations, future studies should also examine the broader human and organizational implications of monitoring technologies. This includes evaluating their impact on driver well-being, stress levels, and job satisfaction, which are essential for long-term adoption and behavioral change. Addressing these research priorities will contribute to optimizing the design and implementation of monitoring systems and promoting their effective integration into the trucking industry, ultimately supporting safer roads and improved outcomes for all stakeholders.

5. Conclusions

This systematic review examines the role of monitoring technologies in improving truck driver safety, highlighting the diverse technologies, variables measured, and outcomes observed across the studies. The findings demonstrate that technologies such as wearable devices, in-vehicle cameras, telematics systems, and AI-driven analytics show promise in enhancing driver safety by monitoring fatigue, stress, distraction, and other critical driving behaviors. However, the effectiveness of these technologies varies, and challenges such as high implementation costs, privacy concerns, and driver acceptance remain significant barriers to widespread adoption.

Despite these challenges, the reviewed studies underscore the potential of these technologies to reduce risky driving behaviors and improve overall safety outcomes. The

evidence presented offers valuable insights into current trends in truck driver safety and provides a foundation for future research focused on addressing the identified gaps and optimizing the deployment of monitoring technologies. Further investigation is needed to refine these technologies, ensure their practical applicability in real-world settings, and enhance their integration into comprehensive safety management systems for the trucking industry.

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Abbreviations

The following abbreviations are used in this manuscript:

ADASs	Advanced driver assistance systems
ADHD	Attention deficit hyperactivity disorder
AI	Artificial intelligence
ANF	Autonomic nerve function
BSM	Basic safety message
C/VISs	Camera/video imaging systems
CD	Crash data
CV	Connected vehicle
CV-VSL	Connected vehicle-based variable speed limit
DMS	Driver monitoring systems
DSE	Driving simulator experiment
EDR	Event data recorder
EEG	Electroencephalographic
ELD	Electronic logging device
EOG	Electrooculographic
FCW	Forward collision warning
GPS	Global positioning system
HMI	Human-machine interface
HMW	Headway monitoring and warning
HOS	Hours-of-service
HRV	Heart rate variability
IVMS	In-vehicle monitoring systems

LDW	Lane departure warning
LKA	Lane-keeping assistance
ND	Naturalistic data
NR	Not reported
PPG	Photoplethysmography
PRISMA	Preferred reporting items for systematic reviews and meta-analyses
PROSPERO	International Prospective Register of Systematic Reviews
QS	Questionnaire survey
RQ	Research question
SCE	Safety-critical event
SLI	Speed limit indicators
V2I	Vehicle-to-infrastructure
V2V	Vehicle-to-vehicle
V2X	Vehicle-to-everything
VD	Videographic data

Appendix A

The Appendix includes two tables that provide additional detail on the reviewed studies. Table A1 summarizes each study's authorship, location, goals, methods, and main findings. Table A2 lists the monitoring technologies used, measured variables, monitoring frequency, and time frame of data collection.

Table A1. Summary of included studies.

Study	Institution, Country	Objective	Data Collection	Data Analysis	Main Findings
Ahlström and Anund (2024) [47]	Linköping University, Sweden	To investigate the development of sleepiness in truck drivers and test the feasibility of DDAW system validation	ND	ANCOVA, and ANOVA	Sleepiness was higher at night, increasing with distance. Nighttime tests effectively induced required drowsiness levels for DDAW validation, while daytime tests faced challenges.
Ahmed et al. (2019) [43]	University of Wyoming, United States	To develop and evaluate a connected vehicle (CV) training program with e-learning and hands-on simulator training modules	DSE	Descriptive statistics	A connected vehicle training program combining e-learning and driving simulation improved truck drivers' understanding and response to CV systems. Drivers reported enhanced safety awareness and adaptability to CV warnings.
Bao and Wang (2024) [32]	Tongji University, China	To optimize FCW algorithms based on truck driver behavior data	ND	K-means clustering, Linear Support Vector Machine, and Long Short-Term Memory	An optimized truck FCW algorithm improved safety by up to 5.1%, achieving 97.92% accuracy and a 1.73% false alarm rate by modeling driver response behaviors with machine learning.
Bell et al. (2017) [19]	National Institute for Occupational Safety and Health, United States	To evaluate IVMS feedback mechanisms on reducing risky driving behaviors	VD	Logistic regression and Generalized Estimating Equation	Supervisory coaching combined with in-cab warning lights significantly reduced risky driving behaviors among commercial drivers, achieving a 39% greater reduction compared to lights-only feedback. Instant feedback alone showed no significant improvement over the control group. Coaching was most effective in fostering safer driving habits.

Table A1. Cont.

Study	Institution, Country	Objective	Data Collection	Data Analysis	Main Findings
C. Zhang et al. (2024) [20]	Southeast University, China	To assess driving style variations and risky behaviors in truck drivers based on load condition	ND	K-means clustering, Principal Component Analysis, MANOVA, and ANOVA	Truck drivers exhibited distinct driving styles under no-load and heavy-load conditions, with aggressive driving more prevalent in no-load scenarios. Aggressive drivers under both conditions posed the highest safety risks, showing increased driving volatility and distraction. Most drivers demonstrated safe driving, highlighting the potential for targeted interventions to address high-risk behaviors.
Cai et al. (2022) [21]	Sun Yat-sen University, China	To model the effect of fatigue and rest breaks on safety-critical events (SCEs)	ND	Bayesian hierarchical models, Non-homogeneous Poisson process, and Jump Power Law Process	Hard braking was more likely early in driving shifts, while collision mitigation system activations increased later. Rest breaks reduced the intensity of severe safety-critical events but had limited impact on less critical events. Driver heterogeneity accounted for significant variability in safety-critical event occurrence, supporting personalized interventions.
Castritius et al. (2021) [48]	Johannes Gutenberg-Universität Mainz, Germany	To evaluate driver situation awareness and perceived sleepiness in semi-automated truck platooning using eye-tracking data	Interview, QS, and VD	Friedman ANOVA, Paired sample <i>t</i> -tests, and Descriptive statistics	Drivers in semi-automated platoon systems maintained similar situation awareness as manual driving, with leading truck drivers spending less time on the road ahead and more on the HMI. Decoupling scenarios in the following vehicle demanded the highest visual attention. Sleepiness ratings were low across all conditions, showing no significant differences between manual and platoon driving.
Crizzle et al. (2022) [39]	University of Saskatchewan, Canada	To compare fatigue, work environment, and perceptions of ELD users vs. non-users	Interview and QS	Descriptive statistics, Independent <i>t</i> -tests, Chi-square tests, and Thematic analysis	Electronic logging devices (ELDs) reduced fatigue, improved sleep quality, and decreased night driving among long-haul truck drivers (LHTDs). While ELDs reduced stress and prevented HOS violations, parking shortages and concerns over reduced income were significant drawbacks. Adjustments to HOS flexibility and payment models are recommended to address these challenges.
de Oliveira et al. (2020) [41]	Federal Institute of Education, Science and Technology of Southeastern Minas Gerais, Brazil	To assess the influence of event data recorders (EDR), training, and feedback procedures on improving safety, operational, and economic outcomes	ND	Data Envelopment Analysis, Statistical variance analysis, and Composite efficiency indices	Integrating event data recorder (EDR) systems with training and feedback reduced speeding events by 46.35% and speeding time by 81.17%, while improving fuel efficiency and operational performance. Combined interventions outperformed EDR alone, ensuring safety and cost-effectiveness.
E. Sun et al. (2010) [49]	University of Science and Technology Beijing, China	To develop a 3D-assisted driving system (3D-ADS) for enhanced safety and route guidance in surface mining operations	ND	System architecture analysis	The 3D Assisted Driving System (3D-ADS) integrates GPS, wireless networks, and Google Earth for real-time truck navigation in surface mines, enhancing safety in low-visibility conditions. The system reduces decision-making uncertainty, provides dynamic 3D mapping, and allows real-time route updates to optimize operational safety and efficiency.

Table A1. Cont.

Study	Institution, Country	Objective	Data Collection	Data Analysis	Main Findings
Elbaum et al. (2024) [35]	Ariel University, Israel	To assess whether ADHD-related risky driving behaviors generalize to professional drivers monitored by supervisors	ND	Generalized Linear Model, Poisson regression, and Relative Risk analysis	Professional drivers with ADHD exhibited a 113% higher rate of speeding violations and significantly more safety events (e.g., hard braking, swerving) compared to non-ADHD peers, despite supervisory monitoring.
Fank et al. (2021) [44]	Technical University of Munich, Germany	To analyze the usability and effectiveness of an HMI in facilitating cooperative truck overtaking maneuvers and assess driving behavior during system failures	DSE	Wilcoxon test; Descriptive statistics; NASA-TLX	An improved human-machine interface (HMI) for cooperative truck overtaking maneuvers enhanced usability but did not significantly increase cooperation rates. Automated cooperation requests reduced driver workload but maintained high trust and acceptance. Simulated system failures were not perceived as safety-critical, with drivers either aborting or adapting overtaking maneuvers depending on failure timing.
Ferreira et al. (2019) [29]	University of Porto, Portugal	To investigate the effect of journey characteristics on distraction and drowsiness alerts	ND	Generalized Linear Model and Negative Binomial regression	Continuous driving time increased distraction and drowsiness alerts, with a 10% increase in driving time leading to a 10% rise in distraction and 15% in drowsiness alerts. Journey duration reduced drowsiness alerts when frequent breaks were taken. Drowsiness risks were higher in companies with irregular schedules.
Fitch et al. (2011) [26]	Virginia Tech Transportation Institute, United States	To evaluate C/VIS in real-world trucking operations for safety-critical event (SCE) reduction	ND	Mixed Factors ANOVA and Descriptive Statistics	Camera/Video Imaging Systems (C/VIS) improved drivers' situational awareness but did not reduce Safety-Critical Events (SCEs). Drivers used C/VIS more at night and during right lane changes, with the advanced C/VIS rated higher due to features like infrared and rear-view cameras. Glare from commercial C/VIS monitors was reported as a drawback.
Giorgi et al. (2023) [16]	Sapienza University of Rome, Italy	To evaluate neurophysiological parameters for early mental fatigue detection	DSE and ND	Repeated measures ANOVA, Friedman test, and Post-hoc tests	Neurophysiological measures, particularly EEG, proved most effective for early detection of driver fatigue, showing timely sensitivity compared to ocular parameters, which responded later. Behavioral performance diverged, with some drivers exhibiting fatigue earlier than others. Findings support using multimodal monitoring systems to enhance user-centered AI in autonomous vehicles.
He et al. (2024) [28]	Tsinghua University, China	To develop a non-visual, privacy-preserving fatigue detection method	ND	Bidirectional LSTM with Attention mechanism	A non-visual fatigue detection system for truck drivers, integrating physiological, vehicular, and temporal features, achieved 99.21% accuracy and 83.21% F1-score. Key contributors to fatigue included reduced photoplethysmogram (PPG) signals, high vehicle loads (>70 t), nighttime driving, and extended driving times (>4 h). The method offers a privacy-preserving, robust alternative to visual-based detection.

Table A1. Cont.

Study	Institution, Country	Objective	Data Collection	Data Analysis	Main Findings
Hickman et al. (2017) [40]	Virginia Tech Transportation Institute, United States	To assess the safety benefits of electronic logging devices (ELDs) in reducing crashes and HOS violations	CD	Poisson regression model	Electronic logging devices (ELDs) reduced total crash rates by 11.7% and preventable crashes by 5.1%, while also lowering driving-related and non-driving-related HOS violations by 53% and 49%, respectively. ELD-equipped trucks demonstrated clear safety benefits, enhancing compliance with hours-of-service regulations and reducing fatigue-related risks.
Hickman et al. (2018) [50]	Virginia Tech Transportation Institute, United States	To compare the Large Truck Crash Causation Study (LTCCS) and Naturalistic Driving (ND) data for evaluating crash causation and exposure to risky behaviors, focusing on the associated factor “Following Too Closely.”	ND and CD	Synthetic odds ratio analysis	Truck drivers following too closely were 1.34 times more likely to crash, based on combined LTCCS and naturalistic driving data. FCW systems are recommended to mitigate this risk.
Horberry et al. (2022) [31]	Monash University Accident Research Centre, Australia	To design and evaluate a human-centered HMI to address fatigue and distraction in truck drivers	Interview	Thematic analysis and human-centered design iterative evaluation	A human-centered design process created a two-level fatigue and escalating distraction warning system with multimodal alerts. Drivers preferred tactile seat alerts, finding the system effective and user-friendly. On-road testing is advised to confirm safety benefits.
Ito et al. (2023) [17]	Hitachi Ltd., Japan	To predict collision risks using physiological and simple external data	ND and biometric measurement	Deep learning, Binary classification, Recall, and AUC evaluation	Using autonomic nerve function and external data, the model predicted truck collision risks 30 min ahead with 74.9% recall and 0.79 AUC. Integrating biometrics with driving state and environmental factors proved effective for real-time accident prevention.
Khoda Bakhshi and Ahmed (2022) [45]	University of Wyoming, United States	To investigate the use of kinematic-based surrogate measures of safety (K-SMoS) in detecting crash-prone conditions in a connected vehicle (CV) environment	DSE	Bayesian Extreme Value Analysis, and Generalized Extreme Value distribution fitting	Bayesian analysis detected crash-prone conditions with 81% accuracy, identifying steering derivatives as superior indicators. This highlights the potential of connected vehicle data for early crash detection.
Krum et al. (2019) [51]	Virginia Tech Transportation Institute, United States	To evaluate the effectiveness of emerging safety technologies for commercial trucks	Interview and ND	Descriptive statistics, Paired <i>t</i> -tests, and System performance metrics analysis	The blind spot system reduced lane change conflicts by 46%, while onboard monitoring lowered speeding and seatbelt violations by 37% and 56%, respectively. Findings emphasized benefits and refinement for real-world use.
Li et al. (2019) [25]	Chang'an University, China	To assess truck driver risk based on speed variation metrics using GPS data	ND	Descriptive statistics and K-means clustering	Speed variation analysis of 100 trucks revealed risky driving patterns, with frequent speed fluctuations linked to higher crash risks. GPS-based metrics show promise for fleet safety monitoring.

Table A1. Cont.

Study	Institution, Country	Objective	Data Collection	Data Analysis	Main Findings
Liu et al. (2019) [52]	Virginia Tech Transportation Institute, United States	To assess the impact of pre-shift sleep duration on truck driver performance during long shifts	ND and biometric measurement	Mixed Poisson process recurrent event model, Penalized B-splines, and Expectation-Maximization algorithm	Drivers with insufficient sleep (<7 h) experienced increased unintentional lane deviations (ULDs) after 8 h of driving, peaking in the 10th hour. Normal sleep (7–9 h) maintained the lowest ULD rates, while abundant sleep (>9 h) showed unexpected performance declines, possibly linked to insufficient breaks.
M. Sun et al. (2023) [30]	Research Institute of the Highway Ministry of Transport, China	To explore risk factors contributing to HAZMAT truck driver fatigue and distraction using driver monitoring systems (DMS) data and association rule mining	ND	Fisher's exact test, Association rule mining, and Apriori algorithm	Fatigue in HAZMAT truck drivers was strongly associated with speeds of 40–49 km/h, travel times of 3–6 h, clear weather, off-peak hours, and tangent road sections. Distracted driving correlated with speeds of 70–80 km/h, visibility >1000 m, nighttime hours (18:00–23:59), and freeway driving.
Martín de Diego et al. (2013) [22]	Universidad Rey Juan Carlos, Spain	To develop a methodology to measure driving risk based on hand activities and other driving variables	DSE	Genetic Algorithm optimization, Euclidean distance metric, and Risk model validation	The HARBI model detected risky hand activities with high accuracy, aligning with expert evaluations, demonstrating potential for mitigating manual driving distractions.
Matović et al. (2020) [23]	University of Novi Sad, Serbia	To evaluate how driving anger influences speeding behavior using GPS data	ND	Hierarchical multiple linear regression and Pearson's correlation analysis	Driving anger, particularly from hostile gestures and traffic obstructions, significantly increased speeding behavior among Serbian truck drivers. Younger drivers and tight schedules amplified speeding tendencies.
Mehdizadeh et al. (2021) [37]	Auburn University, United States	To predict safety-critical events (SCEs) using machine learning models based on kinematic, weather, and driver data	ND	Machine learning models, Logistic regression, and Area Under the Curve	Machine learning predicted truck Safety Critical Events with 76.5% accuracy 30 min ahead, highlighting SCElag7 and speed metrics as key predictors for real-time safety interventions.
Minusa et al. (2021) [18]	Hitachi Ltd., Japan	To analyze the impact of acute stress-induced fatigue on rear-end collision risks	ND and biometric measurement	Logistic quantile regression and Gradient Boosting Decision Tree	Acute stress-induced fatigue increased rear-end collision risk by elevating sympathetic and suppressing parasympathetic nerve activity during truck driving. Continuous monitoring of drivers' autonomic nerve function (ANF) can aid in stress detection and fatigue management, reducing collision risks.
Mizuno et al. (2020) [24]	RIKEN Center for Biosystems Dynamics Research, Japan	To analyze the correlation between fatigue and rear-end collision risk using ANF	ND and biometric measurement	Decision Tree Analysis, Pearson's correlation coefficient, and Welch's <i>t</i> -test	Fatigue-related sympathetic nerve overactivity in truck drivers' post-shift condition significantly increased rear-end collision risk during the following day's shift.
Mortazavi et al. (2009) [53]	University of California, United States	To evaluate the impact of drowsiness on driving performance variables and propose a detection system	DSE	ANOVA, Tukey's post-hoc test, and Regression analysis	Drowsiness significantly impacted commercial drivers' steering and lane-keeping, with increased variability in lateral position and steering corrections. Two degradation phases were identified: impaired control (zigzag driving) and dozing off (constant steering leading to lane departure). Steering metrics showed strong potential for drowsiness detection systems.

Table A1. Cont.

Study	Institution, Country	Objective	Data Collection	Data Analysis	Main Findings
Raddaoui and Ahmed (2020) [36]	University of Wyoming, United States	To assess the visual and cognitive demands of CV-based weather and work zone warnings	DSE and VD	Paired <i>t</i> -tests, Descriptive statistics, and Chi-squared test	Weather notifications in connected vehicle (CV) systems had minimal effects on truck drivers' visual workload, while work zone warnings (WZWs) significantly increased off-road glances and fragmentation of visual attention. WZW-induced prolonged glances raised distraction risks, prompting design modifications to simplify messages and reduce cognitive demands.
Roosendaal et al. (2020) [34]	Delft University of Technology, Netherlands	To compare the effectiveness and acceptance of three haptic lane-keeping assistance designs	Test track	Repeated-measures ANOVA, Tukey post-hoc tests, and Descriptive statistics	Continuous haptic lane-keeping assistance for trucks improved lane-centering and was preferred by drivers over bandwidth-based systems. All assistance types reduced lane departures during distraction, but continuous assistance showed higher usability and satisfaction.
Schindler and Bianchi Piccinini (2021) [38]	Chalmers University of Technology, Sweden	To evaluate driver behavior when encountering vulnerable road users (VRUs) at intersections	Test track	Paired-samples <i>t</i> -test, Descriptive statistics, Gaze analysis, and Time-to-Collision metrics	Truck drivers reduced speed and adjusted glances toward cyclists and pedestrians at intersections, emphasizing ADAS's potential to enhance VRU detection and warnings.
Scott et al. (2021) [42]	Michigan State University, United States	To evaluate the unintended consequences of the ELD mandate on unsafe driving behaviors and crashes	CD	Difference-in-Differences, Regression analysis, and Descriptive statistics	The electronic logging device (ELD) mandate reduced hours-of-service violations among small carriers by 43–47%. However, unsafe driving violations increased by 16.7–26%, with no significant crash reduction, suggesting displacement of risk to unmonitored behaviors.
Talebi et al. (2022) [27]	University of Utah, United States	To identify key factors driving fatigue and build a predictive model using operational data	ND	Machine learning model, SHAP analysis, and Confusion matrix evaluation	A machine learning model predicted truck driver fatigue with 99% accuracy, identifying employee ID, overtime, and truck state as key factors. Results support tailored fatigue management strategies.
Wege et al. (2013) [54]	Volvo Group Trucks Technology, Sweden	To assess visual attention allocation and brake reactions to B-FCW events	ND	ANOVA, Descriptive statistics, and Time-based glance behavior analysis	Brake-capacity forward collision warnings (B-FCW) systems prompted immediate braking and road focus but caused post-threat glances toward the warning source, suggesting redesigns to reduce distractions.
Wu et al. (2023) [33]	Research Institute of the Highway Ministry of Transport, China	To investigate the impacts of ADAS warnings on driving behavior and performance	ND	One-way ANOVA; Descriptive statistics; Median and average trend analysis	ADAS systems positively impacted truck driver behaviors, reducing lane departures by 28%, headway violations by 45%, and speeding alerts by 15%. While effective at high speeds, ADAS had minimal impact on low-speed rear-end collision prevention, underscoring its limitations in urban driving conditions.
X. Zhang et al. (2022) [13]	Tongji University, China	To analyze how travel characteristics, driving behaviors, and in-vehicle monitoring data influence crash risks	ND	Zero-inflated Poisson regression, Standardized Regression Coefficients, and Interaction term analysis	Yawning increased crash risk due to drowsiness, while smoking slightly reduced it by mitigating fatigue. Night driving and freeway speeds lowered risk, whereas urban roads and sunny conditions increased it.

Table A1. Cont.

Study	Institution, Country	Objective	Data Collection	Data Analysis	Main Findings
Yang et al. (2019) [46]	University of Wyoming, United States	To evaluate the effect of CV-based VSL warnings on speed compliance and variance	DSE	Two-sample <i>t</i> -test, Descriptive statistics, and Speed compliance analysis	Variable Speed Limits (VSLs) in connected vehicles reduced truck speed and variance under adverse weather, improving safety and preventing skidding, especially with limits below 55 mph.
Note: QS represents questionnaire survey; CD represents crash data; DSE represents driving simulator experiment; ND represents naturalistic data; VD represents videographic data.					

Table A2. Technologies and monitoring variables.

Study	Monitoring Technology	Physiological Variables	Behavioral Variables	Environmental Variables	Monitoring Frequency	Temporal Context
Ahlström and Anund (2024) [47]	Vision-based monitoring systems	Heart rate, heart rate variability, and blink duration	Lane position and Karolinska sleepiness scale	Time of day, traffic density, and road conditions	Continuous monitoring during real-world driving	Monitored during daytime (normal sleep) and nighttime (sleep deprivation)
Ahmed et al. (2019) [43]	Connectivity and communication systems	NR	Response to connected vehicle warnings	Weather conditions, road closures, and advisory speed limits	Continuous monitoring during training scenarios	Training included real-world and simulated adverse conditions (e.g., fog, icy roads)
Bao and Wang (2024) [32]	Advanced driver assistance systems	NR	Reaction time, braking distance, and deceleration	Speed, distance to the lead vehicle, and collision risk	Continuous monitoring during driving	Real-world operations, data collected over a year
Bell et al. (2017) [19]	In-vehicle monitoring systems	NR	Hard braking, speeding, swerving, and unbelted driving	Road conditions and operational sites	Continuous monitoring during operations	Pre-feedback baseline, intervention, post-feedback baseline
C. Zhang et al. (2024) [20]	In-vehicle monitoring systems	NR	Speed, volatility, acceleration, and braking patterns	Road conditions, traffic density, and load (heavy vs. no-load)	Continuous monitoring over three months	Trip-level data for heavy-load and no-load conditions
Cai et al. (2022) [21]	In-vehicle monitoring systems	NR	Hard braking, short headway, and collision mitigation	Precipitation, wind speed, and time of day	Continuous data collection (1–15 min interval)	Shifts and trips recorded over a year
Castritius et al. (2021) [48]	Vision-based monitoring systems	Blink duration and gaze fixation	Fixation shares on road, human–machine interface, and mirrors	Time of day, driving mode, and transition type	Continuous monitoring during driving	Daytime and nighttime platoon drives lasting two hours
Crizzle et al. (2022) [39]	Data logging and event recording systems	NR	Sleep quality and hours of service (HOS) compliance	Driving hours, night driving, and parking availability	Continuous logging of HOS and rest periods	Data collected over three months
de Oliveira et al. (2020) [41]	Data logging and event recording systems	NR	Speeding events, idle time, and engine economy zone performance	Road conditions and fleet characteristics	Continuous monitoring over 13 months	Data collected across baseline and three monitoring phases (hidden and conscious monitoring)
E. Sun et al. (2010) [49]	In-vehicle monitoring systems	NR	Route selection, collision avoidance, and task efficiency	Visibility, road geometry, and pit conditions	Continuous real-time monitoring during operations	Data collected during dynamic operational tasks
Elbaum et al. (2024) [35]	Advanced driver assistance systems	NR	Hard braking, abrupt turns, swerving, and speeding	Road type, time of day, and exposure (km driven)	Continuous monitoring during military transport tasks	Safety events measured over 2–60 months

Table A2. Cont.

Study	Monitoring Technology	Physiological Variables	Behavioral Variables	Environmental Variables	Monitoring Frequency	Temporal Context
Fank et al. (2021) [44]	Connectivity and communication systems	NR	Lane change, cooperation rates, and reaction to failures	Road conditions (lane availability, surrounding traffic behavior)	Continuous monitoring during driving simulation	Data collected during overtaking scenarios and system failure events
Ferreira et al. (2019) [29]	Vision-based monitoring systems	Eye state, facial movements	Distraction (e.g., texting, looking outside)	Time of day and journey duration	Continuous data collection per journey	Data collected over nine months
Fitch et al. (2011) [26]	Vision-based monitoring systems	NR	Lane-change behavior and forward glances	Day/night driving conditions, and traffic density	Continuous monitoring over four months	Baseline (no Camera/Video Imaging Systems) vs. Test (Camera/Video Imaging Systems-enabled) periods
Giorgi et al. (2023) [16]	Wearable monitoring devices	Heart rate, heart rate variability, blink duration, and electrodermal activity	Reaction times	Time of day and traffic-free simulation	Continuous monitoring during simulation tasks	High-demanding (15 min) + Monotonous (45 min) driving scenarios
He et al. (2024) [28]	Wearable monitoring devices and In-vehicle monitoring systems	Heart rate, galvanic skin response, and photoplethysmogram	Steering behavior, acceleration, and braking	Road slope, vehicle load, forward angle, and time of day	Continuous monitoring during trips (1-min intervals)	Natural driving dataset over one month
Hickman et al. (2017) [40]	Data logging and event recording systems	NR	Driving-related violations (e.g., exceeding hours), crash preventability, and HOS compliance	NR	Continuous data collection	Data collected before and after the Electronic Logging Device installation
Hickman et al. (2018) [50]	Vision-based monitoring systems	Sleep quantity and quality	Following too closely (tailgating), evasive maneuvers, and lane deviations	NR	Continuous data collection	Data collected before, during, and after driving events
Horberry et al. (2022) [31]	Vision-based monitoring systems	NR	Driver attention and response to warnings	Day/night driving, and cabin complexity	Continuous feedback during simulated driving scenarios	Iterative design evaluations across multiple stages
Ito et al. (2023) [17]	Wearable monitoring devices	Heart rate variability	Reaction time and cumulative driving duration	Weather, time of day, and speed	Continuous; 2-min intervals, combined into 30-min datasets	Driving shifts over three months
Khoda Bakhshi and Ahmed (2022) [45]	Connectivity and communication systems	NR	Instantaneous acceleration and the derivative of steering	Roadway geometry and adverse weather conditions	Continuous monitoring during simulations	Data collected under crash-prone and non-crash conditions
Krum et al. (2019) [51]	Vision-based monitoring systems	NR	Lane changes, speed violations, seatbelt use, and collisions	Weather, road conditions, and traffic density	Continuous monitoring during baseline and intervention periods	Baseline (2 months) vs. intervention (4 months)
Li et al. (2019) [25]	In-vehicle monitoring systems	NR	Speed variation, frequency, and amplitude	Road conditions on dedicated routes	Continuous monitoring over 30 days	Trips repeated over identical dedicated routes
Liu et al. (2019) [52]	In-vehicle monitoring systems	Total sleep duration and sleep patterns before shifts	Unintentional lane deviations	Time of day, driving hours, and environmental conditions	Continuous monitoring throughout driving shifts	Driving performance measured throughout 11-h shifts

Table A2. Cont.

Study	Monitoring Technology	Physiological Variables	Behavioral Variables	Environmental Variables	Monitoring Frequency	Temporal Context
M. Sun et al. (2023) [30]	Vision-based monitoring systems	NR	Fatigue and distraction warnings, acceleration, speed, and horizontal alignment	Visibility, weather, road type, and time of day	Continuous data collection from in-cab monitoring system	Data captured during active driving sessions
Martín de Diego et al. (2013) [22]	In-vehicle monitoring systems	NR	Hand position, lane invasion, speed, and steering wheel angle	Traffic and road variables, including lane conditions and road slope	Continuous data during simulations	Data recorded during driving sessions
Matović et al. (2020) [23]	In-vehicle monitoring systems	NR	Speed violations and speeding index	Urban, rural, and motorway zones	Continuous, second-by-second data	6-month monitoring period
Mehdizadeh et al. (2021) [37]	Advanced driver assistance systems	Reaction times and cumulative driving time	Speed, hard braking, and headway distance	Weather conditions and traffic density	Continuous monitoring during trips	30 min trip segments over a year
Minusa et al. (2021) [18]	Wearable monitoring devices	Sympathetic and parasympathetic nerve activities	Speed, acceleration, and inter-vehicle distance	Weather, time of day, and road conditions	Continuous; data sampled every 20 s	Driving shifts of up to three months
Mizuno et al. (2020) [24]	In-vehicle monitoring systems	Sympathetic and parasympathetic nerve activities, and heart rate variability	Rear-end collision	Weather, traffic, and road conditions	Continuous data collection across eight months	Daily pre-/post-shift conditions, 8 months of driving
Mortazavi et al. (2009) [53]	In-vehicle monitoring systems	Eye closure and subjective drowsiness rating	Steering angle, lateral position, and lane keeping	Simulated highway driving conditions	Continuous monitoring during simulated scenarios	Morning (alert) and night (drowsy) driving sessions
Raddaoui and Ahmed (2020) [36]	Advanced driver assistance systems	Eye glance duration, fixation, and dwell time	Glance distribution and off-road glance duration	Adverse weather (fog) and work zones (lane closures)	Continuous monitoring during simulation	Weather warnings (clear visibility) vs. work zone warnings (low visibility)
Roozendaal et al. (2020) [34]	Advanced driver assistance systems	NR	Lateral position, lane departure frequency, and control activity	Lane geometry and traffic density	Continuous monitoring across three laps per trial	Distracted vs. non-distracted driving with different assistance designs
Schindler and Bianchi Piccinini (2021) [38]	Advanced driver assistance systems	NR	Speed profiles and stopping behavior	Simulated intersection conditions	Continuous data collection during test laps	6 test laps per driver
Scott et al. (2021) [42]	Data logging and event recording systems	NR	Speeding, lane changes, and aggressive driving	Traffic density and weather conditions	Continuous; monitored during all driving hours	Pre- and post-mandate implementation periods
Talebi et al. (2022) [27]	Vision-based monitoring systems	Eye closure and sleep-related metrics	Operational events and cycle rates	Time of shift, work schedules, operational delays	Continuous monitoring during shifts over four years	Events classified as “low” or “critical” fatigue
Wege et al. (2013) [54]	Advanced driver assistance systems	NR	Glance direction, brake pedal position	Roadway and lead vehicle dynamics	Continuous monitoring before and after collision warnings	30 s before and 15 s after collision events
Wu et al. (2023) [33]	Advanced driver assistance systems	NR	Lane departure, headway, speeding, and collision avoidance	Weather, road geometry, and traffic density	Continuous monitoring over 12 weeks	Blind Test (4 weeks), Training (1 week), Practical Test (8 weeks)

Table A2. Cont.

Study	Monitoring Technology	Physiological Variables	Behavioral Variables	Environmental Variables	Monitoring Frequency	Temporal Context
X. Zhang et al. (2022) [13]	Advanced driver assistance systems	Yawning, smoking, and fatigue	Speed, insufficient headway, and phone use	Weather, and time of day	Continuous, recorded every 30 s	One-year real-world operations
Yang et al. (2019) [46]	Connectivity and communication systems	NR	Speed compliance and reaction to speed limits	Weather conditions (snow, icy surfaces)	Continuous during simulation	Baseline (no Variable Speed Limit) vs. Connected Vehicle system with Variable Speed Limit test scenario

Note: NR represents not reported.

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