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Systematic Review

The Mind-Wandering Phenomenon While Driving: A Systematic Review

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Abstract

Mind wandering (MW) is a significant safety risk in driving, yet research on its scope, underlying mechanisms, and mitigation strategies remains fragmented across disciplines. In this review guided by the PRISMA framework, we analyze findings from 64 empirical studies to address these factors. The presented study quantifies the prevalence of MW in naturalistic and simulated driving environments and shows its impact on driving behaviors. We document its negative effects on braking reaction times and lane-keeping consistency, and we assess recent advancements in objective detection methods, including EEG signatures, eye-tracking metrics, and physiological markers. We also identify key cognitive and contextual risk factors, including high perceived risk, route familiarity, and driver fatigue, which increase MW episodes. Also, we survey emergent countermeasures, such as haptic steering wheel alerts and adaptive cruise control perturbations, designed to sustain driver engagement. Despite these advancements, the MW research shows persistent challenges, including methodological heterogeneity that limits cross-study comparisons, a lack of real-world validation of detection algorithms, and a scarcity of long-term field trials of interventions. Our integrated synthesis, therefore, outlines a research agenda prioritizing harmonized measurement protocols, on-road algorithm deployment, and rigorous evaluation of countermeasures under naturalistic driving conditions.

Keywords: mind wandering; MW; driving; safety; systematic review; PRISMA

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1. Introduction

Road traffic crashes remain a leading cause of death and injury worldwide, and driver inattention contributes to a substantial and growing share of these incidents. Cognitive distractions occur when a driver's mental resources shift away from the primary driving task without visible signs of visual or manual neglect [1]. The integration of semi-automated systems in modern vehicles can lead to cognitive distractions and a phenomenon known as out-of-the-loop behavior, in which driver vigilance declines over time [2–4], heightening concern as many collisions in Level 2 partially automated vehicles stem from delayed or inappropriate takeover responses [4].

Mind wandering refers to the redirection of attention from driving toward self-generated thoughts that are unrelated to the driving task [5] and arises primarily under low arousal or monotonous driving conditions such as highway hypnosis, consistent with the Yerkes–Dodson law [6]. In practical terms these lapses in attention can impair vehicle control, delay detection of unsafe traffic conditions, and slow reactions to hazards. For example, recent field and simulation research has linked mind wandering to riskier driving behaviors in young male drivers [7], observed degraded braking dynamics in partially automated vehicles that may elevate rear-end collision risk [8], and reported frequent episodes during long highway drives under monotonous conditions [8]. Researchers have therefore explored systems that monitor driver behavior and physiology [9] as well as engaging tasks designed to sustain focus [7].

Unlike external distractions such as smartphone use, mind wandering is internally generated and inherently difficult to measure [10]. To capture its effects on driver engagement in both manual and partially automated contexts, investigators have employed immersive simulations, physiological recording methods, including electroencephalography, functional near-infrared spectroscopy, and heart rate variability, and on-road field studies [11,12].

This systematic review, conducted in accordance with PRISMA guidelines, examines 64 empirical studies to assess how often mind wandering occurs, its effects on driver behavior and safety, and strategies for mitigation. The literature is organized into five interrelated subthemes that together bridge foundational insight and practical application. Prevalence and characterization quantify the frequency of mind wandering and delineate its signature patterns across driving contexts. Behavioral and safety impacts examines how these attentional lapses translate into measurable risks, drawing on both simulator studies and real-world incident data. Detection and measurement reviews advances in sensing technologies and analytic methods for the real-time identification of mind wandering episodes. Cognitive and contextual factors explore the mental processes and situational variables that precipitate attention shifts behind the wheel. Mitigation and technological interventions evaluate both behavioral strategies and emerging in-vehicle systems designed to reduce the safety costs of mind wandering. Collectively, these themes provide a comprehensive framework for understanding and addressing driver mind wandering.

By systematically integrating findings across these domains, this review study clarifies areas of consensus and contention, identifies methodological and practical gaps, and proposes targeted directions for future research. By addressing these objectives, this review aims to facilitate the development of robust, user-centered systems designed to predict and mitigate mind wandering on today's roads.

Section 2 introduces the systematic review methodology based on the PRISMA framework employed in this study. Section 3 describes the process for screening the literature and selecting studies, detailing the criteria and steps taken to identify relevant studies. Section 4 synthesizes findings across five subthemes, offering a comprehensive analysis of the key research subjects emerging from the selected studies. Section 5, Discussion, interprets these consolidated insights, examines methodological and practical limitations, and identifies priorities for future research. Lastly, Section 6 presents the main conclusions and key implications of the study.

2. Materials and Methods

2.1. Search Strategy

The present paper included papers related to MW and driving. Two scientific databases were used to search the relevant studies: ProQuest and Scopus. The search was conducted on 31 December 2024. The combination of keywords was selected by the authors in the following way:

(("MW" OR "mind-wandering" OR "mind wander" OR "task-unrelated thoughts") AND driving).

The review was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) [13]. The full details of our systematic-review methodology are described in the Methods section. This review protocol was not prospectively registered in a public registry.

2.2. Eligibility Criteria

2.2.1. Inclusion Criteria

Studies that met the following criteria were included in the review:

- original research available in full text, published in peer reviewed journals or conference proceedings;
- articles published between 1 January 2010 and 10 October 2024;
- studies that examined the relation between MW and driving;
- papers published in English.

2.2.2. Exclusion Criteria

Studies were excluded from the review according to the following criteria:

- review articles, encyclopedia, book chapters, conference abstracts, editorials, short communications, case reports, and dissertations;
- studies published outside the selected time span;
- studies that were not written in the English language;
- studies which did not investigate the relationship between MW and driving.

2.3. Study Selection

The search results obtained from the two databases were exported into EndNote 20 software. First, the duplicates were removed from the total number of identified records. In the next step, two authors (R.G.B. and G.-D.V.) independently screened the records by title and abstract, and they excluded the articles that did not correspond to the previously established eligibility criteria. After removing the irrelevant papers, a new round of screening was performed by the same two reviewers using the full text of the remaining studies. Finally, the papers were checked again by the authors, and the conflicts between the two reviewers were resolved after discussions with the third author (F.G.).

2.4. Data Collection

A full-text review of the selected articles was conducted by one author (C.-C.P.) in order to extract relevant information. The following data items were extracted and included in a Microsoft Excel file: study aim, year of publication, country, source, participant demographics, measures, research design, findings, and limitations.

3. Results

Following the PRISMA guidelines (see Figure 1), our search across ProQuest (n = 1172) and Scopus (n = 1311) returned 2483 records in total. Of these, 406 were duplicated and were excluded, 112 were ineligible, and 25 were removed on the grounds that they did not meet the first eligibility criterion.

The remaining 1940 articles were screened by title and abstract to determine whether they satisfy the requirements imposed by the eligibility criteria. In this stage, 1716 articles were excluded. The remaining 224 articles were reviewed by full text, and 128 were excluded.

Finally, the 96 remaining studies were assessed for eligibility, and 32 items were excluded for the following reasons: 8 were not available in full text, 19 were not eligible in terms of content, and 5 were irrelevant to the analysis. Thus, 64 studies met the inclusion criteria and were selected for the quantitative analysis. An overview of the included studies is presented in Appendix A, detailing each study's authors, publication year, and country, as well as their methodologies, key findings, and suggested future directions.

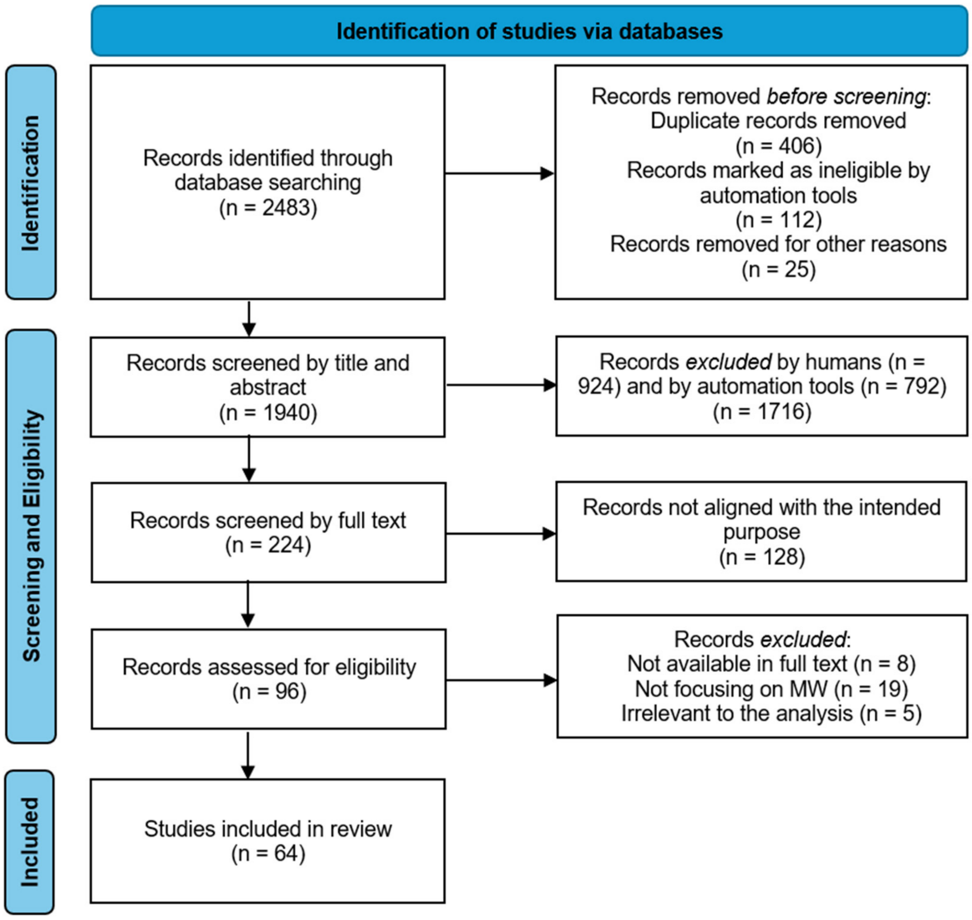

Figure 1. Flow chart of study selection process based on PRISMA.

3.1. Publication Trends

The annual distribution of publications on MW and driving shows a clear upward trend from 2010 to 2024 (see Figure 2). The field emerged slowly, with just one publication each in 2011 and 2012, followed by a gradual increase to two to four publications annually from 2013 to 2017. A notable spike occurred in 2018 with 11 publications, representing the highest annual output in the analyzed period. After 2018, publication numbers stabilized at five to seven papers per year from 2019 to 2023. Early 2024 already shows four publications, suggesting continued interest in the field.

Citation patterns reveal varying impacts across years. The highest citation counts were observed for publications from 2014 to 2015 (268 and 303 citations, respectively) and 2018 (282 citations), indicating these as particularly influential periods in the field. Earlier papers from 2011 to 2013 received moderate citation counts (130–194 citations), while more recent publications from 2019 onwards show lower citation numbers (6–98 citations), which is expected given their shorter time in the literature.

This publication pattern suggests three distinct phases in the field as follows:

- emergence (2010–2013): initial establishment with few but influential papers;
- growth (2014–2018): increased research activity and citation impact;
- consolidation (2019–2024): stable publication rate with emerging impact.

The overall trend indicates growing research interest in MW during driving, with the field maintaining consistent scholarly attention in recent years.

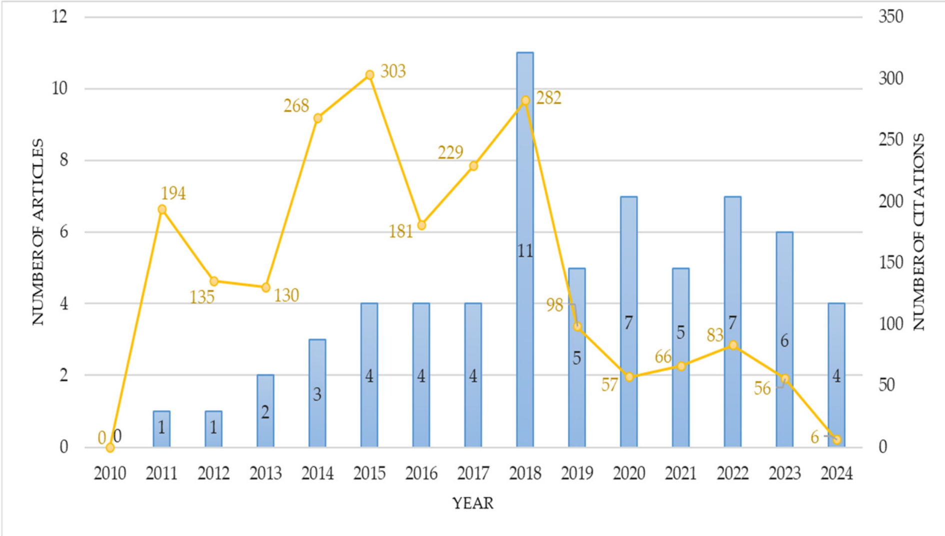

Figure 2. Publication trend of MW research in driving context (yearly distribution).

3.2. Results of Publications by Country

The analysis of publications based on country distribution reveals that research on MW in the context of driving has been conducted across 17 countries (Figure 3). The leading contributor is the United States (USA) with 18 publications, followed by France with 12 and Canada with 7. China and Australia share the fourth spot with four publications each, while Japan, New Zealand, and the United Kingdom (UK) each contributed three publications.

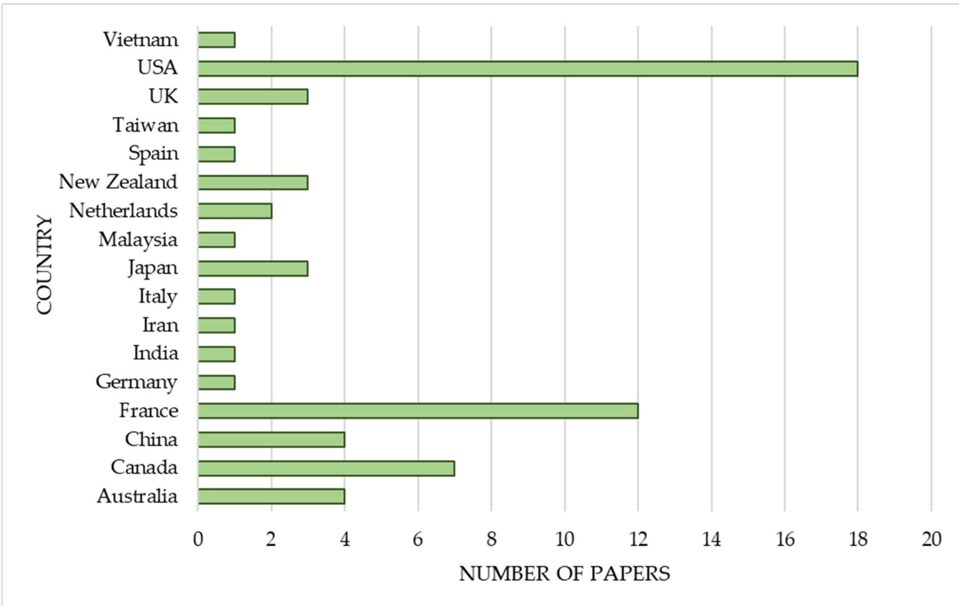

Figure 3. Bar chart of geographical distribution of publications on MW during driving.

Countries with two publications include the Netherlands, while the following countries have one publication each: Germany, India, Iran, Italy, Malaysia, Spain, Taiwan, and Vietnam. This geographical distribution underscores the global interest in understanding MW during driving, with the USA and France leading the research efforts.

3.3. Results of Publication Sources

The analysis of publication sources indicates a wide range of journals and conferences contributing to research on MW during driving (Figure 4). The top sources are *Transportation*

Research Part F with 10 publications, followed by *Accident Analysis and Prevention* with 9 publications.

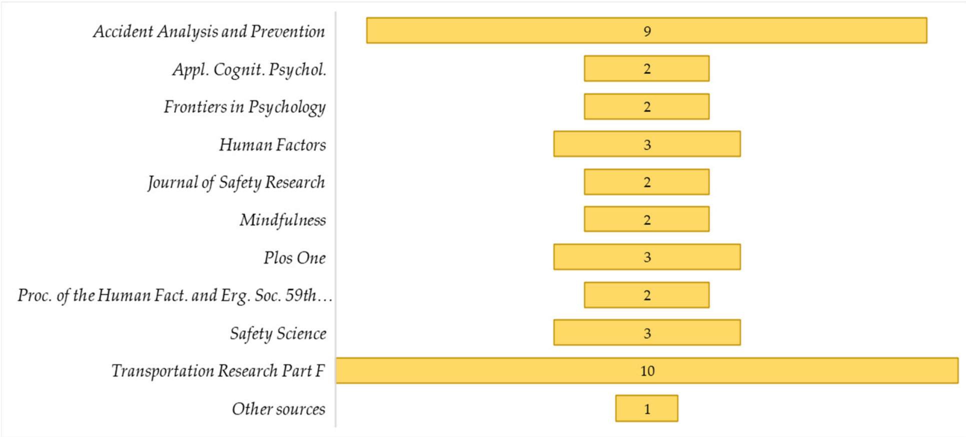

Figure 4. Distribution of publication sources for MW research in driving.

Several sources, including *Human Factors*, *Plos One*, and *Safety Science*, each contributed three publications. Journals such as *Applied Cognitive Psychology*, *Frontiers in Psychology*, *Journal of Safety Research*, *Mindfulness*, and the *Proceedings of the Human Factors and Ergonomics Society 59th Annual Meeting* (2015) each had two publications.

A small fraction (one publication) came from other sources, emphasizing the concentration of research in a few key journals and conferences. This distribution highlights the interdisciplinary nature of the topic, spanning fields like transportation, psychology, safety science, and human factors engineering.

4. Review

To structure our synthesis of the mind-wandering literature and highlight both what is known and where gaps remain, we organized the 64 papers into five thematic categories (see Figure 5). In this framework, each branch poses a guiding question—"How?", "What?", "When?", "Why?", and "Which?"—that maps directly onto one category. Prevalence and characterization ("How?") establish how often and in what forms mind wandering occurs in driving contexts, grounding the review in real-world and simulator data (e.g., ref. [14] reported off-task thought on 30–55% of on-road probes). Behavioral and safety impacts ("What?") quantify the performance costs and crash risks associated with these lapses, as simulator studies have shown 200–400 ms braking delays and increased lane deviations during mind wandering. Detection and measurement ("When?") bring together work on objective markers, such as electroencephalogram (EEG), eye-tracking, and physiological signals, to move beyond self-report and enable real-time identification of lapses (for instance, reduced P3 amplitudes during mind-wandering episodes). Cognitive and contextual factors ("Why?") examine the internal states and environmental conditions, such as risk perception, route familiarity, and fatigue, that trigger off-task thought, revealing, for example, how compensatory beliefs under high perceived risk foster mind wandering. Finally, mitigation and technological interventions ("Which?") survey the translation of these insights into countermeasures, from haptic alerts in simulators to adaptive automation strategies aimed at re-engaging attention.

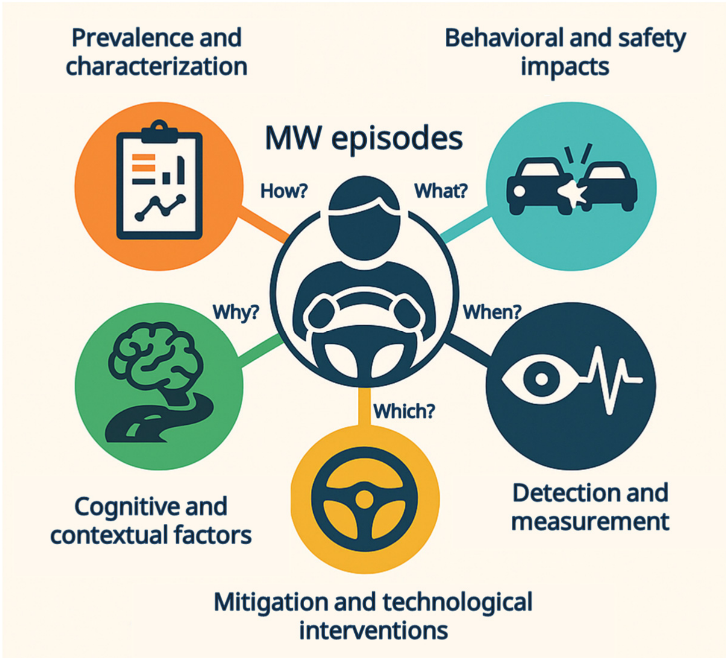

Figure 5. Conceptual framework of mind wandering in driving.

4.1. Prevalence and Characterization

MW is a common phenomenon in driving populations across both naturalistic and simulated environments. Surveys and on-road experience-sampling studies indicate that drivers acknowledge off-task thoughts on roughly 30–55% of randomly timed probes [14–16]. The study [17] reports that 85.2% of drivers reported at least one mind-wandering episode per trip, while [6] reported that over 60% of drivers estimated experiencing mind wandering in more than half of their familiar or low-demand drives. In simulated driving environments, which typically involve longer sections of low-demand driving, reported MW rates were even higher, with study Wotring [18] observing MW in up to 65% of thought probes. Reduced risks and monotonous scenarios experienced by the drivers in the artificial setting of the lab increase internal distraction [18,19].

Consistent characterization of MW patterns was identified across studies. MW is more prevalent in low-demand driving conditions (familiar routes, monotonous highways, in low-traffic conditions, and when driving alone) [16,17,20]. Fatigue and extended time on the driving task also contribute to increased MW [21,22]. Experienced drivers may experience MW more on familiar routes due to automated control [15], while sleep deprivation can increase MW [21]. The content of mind wandering often refers to personal concerns, planning, or cultural issues, as noted in studies involving both car drivers and motorcyclists [16]. MW is often activated by different sensory inputs from the driving conditions and can be rapidly interrupted by increased driving task demands [23].

Current research on MW prevalence and characterization while driving acknowledges some limitations. Many studies have been conducted in simulated environments, which may not fully replicate the complexities and risks of on-road driving [18,21]. On-road studies mainly use self-report measures, which may not capture unaware lapses in attention [15,17]. Future research should prioritize naturalistic driving settings to capture mind wandering as it occurs [6,17]. Integrating self-reports with objective measures, like eye-tracking or physiological indicators, could enhance the accuracy of MW detection [15,21]. Additionally, experimental designs are important to establish causal links between MW and driving performance and to evaluate interventions that can reduce MW [14,23].

4.2. Behavioral and Safety Impacts

MW can affect the ability to respond to dynamic road conditions, increasing crash risk. Numerous studies, most of which were conducted using driving simulators, have demonstrated that MW leads to measurable declines in driving performance. The study [24] shows that participants reporting off-task thoughts exhibited slower braking responses (by 200–300 milliseconds) and greater lane deviations (by 0.3–0.5 m) compared to when they were focused on the primary driving task. Also, drivers had slower reaction times to sudden braking events, higher mean vehicle speeds, and shorter headway distances from lead vehicles during MW episodes [25]. These results indicate that MW compromises a driver's ability to maintain safe following distances and respond quickly to crash risk. The study [26] used the Sustained Attention to Response Task (SART) to measure MW tendency and reported that subjects with a higher tendency for MW drove at faster average speeds in simulators, suggesting that they may engage in riskier driving behaviors. Related to the relevance of MW in semi-autonomous vehicles, the study [7] identified differences in braking patterns during MW episodes.

Related to the impact on crash risk, reviewed studies suggest that MW often occurs with other various contextual and individual factors, complicating its isolated impact on safety [18,27–29]. Wotring et al. [18] analyzed naturalistic crash data from the SHRP2 dataset, revealing that only the MW factor contributed in fewer than 1% of high-severity crashes, while cognitive distractions caused approximately 1.5% of those incidents. Here, "cognitive distraction" encompasses all shifts in mental focus, regardless of arousal level, whereas MW specifically involves internally generated thoughts during low-arousal or monotonous driving (e.g., highway hypnosis), consistent with the Yerkes–Dodson framework [5]. Not all secondary tasks during driving are equally unsafe. The study [28] proposed that engaging in trivia or quiz activities during driving might enhance driving performance under monotonous conditions by reducing the MW episodes. This result shows the complexity of distraction and how some secondary tasks may support driver engagement. Also, individual differences influence the effects of MW on driving safety. The study [27] reported that drivers with insomnia showed weaker lateral control during episodes of MW, with performance decrements more strongly correlated to cognitive scores than to sleep quality. Bernstein et al. [24] found that the impact of MW on driving was consistent across ADHD and non-ADHD groups, indicating that this phenomenon represents a universal risk. Developing and testing interventions to mitigate the effects of mind wandering, such as in-vehicle alerts or personalized assistance systems, is important for translating research findings into practical safety solutions [7]. Developing and testing interventions to address the effects of MW is important for improving driving safety.

4.3. Detection and Measurement

Studies that investigate MW detection used several methods that integrate self-reports, behavioral indicators, and physiological or neurophysiological measures. Self-reports are mainly based on auditory or visual cues and have been linked to slower response times, larger pupil dilations, and increased heart rate variability (HRV) [30,31]. A simulator-based study [32] used periodic auditory thought probes during monotonous driving tasks to collect self-reported MW, which appeared in 65.4% of probes. The authors identified distinct steering patterns associated with MW using principal component analysis (PCA) and t-distributed stochastic neighbor embedding (t-SNE) methods. The study [33] combined self-reports with driving performance metrics (speed and lane variability) and EEG data, finding that MW episodes were linked to reduced speed variability and increased alpha power. The disadvantage of self-reports is subjectivity and potential bias, with probes possibly disturbing natural MW flow [34].

Another approach focused on behavioral measures utilizing driving data (lane offset, steering ratio) to train personalized support vector machine (SVM) models that achieved up to 80% accuracy in detecting MW [35]. Also, machine learning techniques (SVM, random forests, and multilayer perceptrons) applied to time-series driving data from simulators achieved high classification accuracy of MW based on speed and brake pressure features [11]. Behavioral models are reported to struggle with inter-individual variability, rendering driver-independent detection elusive [35].

Neurophysiological methods use functional near-infrared spectroscopy (fNIRS) to identify decreased right frontal brain activity during MW in autonomous driving scenarios [36]. Also, the study [31] revealed reduced N1 and P3 amplitudes in EEG responses to visual cues, which correlated with prolonged braking reaction times. Neurophysiological methods, such as EEG and fNIRS, show improved precision in detecting MW episodes but require specialized equipment that is impractical for on-road use [31,36].

On-road study [37] explored MW in Level 2 automated vehicles, showing that drivers' familiarity with automation influenced event recall and that gaze dispersion widened during MW episodes. Also, another study [38] further demonstrated that heatmap-based gaze features on highways achieved 85.2% accuracy in classifying cognitive distraction.

Future research directions are focused on improving detection accuracy by combining behavioral, physiological, and neurophysiological signals in multimodal data [38,39]. Developing non-intrusive, real-time systems is another research direction, and studies [35,40] present adaptive, personalized algorithms deployable in vehicles.

4.4. Cognitive and Contextual Factors

Research in this category has identified internal and external factors that influence drivers MW. The driving environment is an important factor that influences MW episodes. The study [41] found that daily commutes on familiar routes can increase daydreaming and task-unrelated thoughts because the automated nature of routine driving demands less conscious attention. This study also shows that specific environmental factors (for example, passing a childhood home) can evoke autobiographical memories, leading to extended periods of internal focus. Road geometry is also important, with greater geometric variety improving lane-keeping performance and reducing vigilance decreases, in that way reducing MW episodes in monotonous environments [42]. In automated driving contexts, passive monitoring induces MW and passive fatigue, indicated by rising blink frequency and MW scores [43,44].

In addition to external factors, a driver's internal state can influence the prediction of MW. Cai et al. [45] found a direct correlation between self-reported sleepiness and the frequency of off-task episodes. Driving experience and mental cognitive workload also influence mind-wandering. The study [2] reported that novice drivers are less susceptible to MW episodes compared to experienced drivers because controlling the vehicle requires higher cognitive demands and reduces attentional drift. Zhou et al. [46] observed that in high-risk scenarios, drivers often rely on compensatory beliefs about their ability to manage the situation. These beliefs create a false sense of control, leading to an unintended liberation of cognitive resources and making drivers more susceptible to MW. Negative mood states have been shown to amplify MW frequency, leading to increased headway inconsistency and steering reversals in simulator settings [47]. A large survey of Australian and Italian drivers evidenced that personality traits such as neuroticism, extraversion, and conscientiousness facilitate unusual driving behaviors through MW tendencies [48]. The study [19] found that cognitive control mechanisms influence the experience of sleepiness signs among younger drivers, suggesting that they can either trigger or mitigate MW risks.

Methodological approaches in this area often combine self-report instruments (for example, Compensatory Beliefs Questionnaire and the Epworth Sleepiness Scale) with periodic thought probes. But differences in scale choice and probe timing influence the comparability of effect sizes across studies. To address this limitation, some studies have employed causal inference by using experimental manipulations (for example, scenario vignettes to modify participants' perceived risk [46]), adjusted session timing to induce varying levels of sleepiness [45], and post-drive interviews to gather data [41]. These findings show that MW is a complex phenomenon affected by the dynamic relationship between environmental familiarity, driver fatigue, cognitive load, and self-perception.

By elucidating the "why" behind driver mind wandering, this work provides critical inputs for both predictive models and proactive countermeasures. The final category will examine how these insights have been operationalized into technological and behavioral interventions.

4.5. Mitigation and Technological Interventions

Strategies to reduce MW episodes include two main approaches: real-time detection with in-vehicle alerts and behavioral interventions designed to increase driver engagement. Multimodal alert systems have been explored for the first strategy. The study [49] investigates the impact of MW on driver takeover performance in partially automated vehicles. The study was conducted using a high-fidelity simulator to evaluate the effectiveness of three types of alerts: auditory tones, visual dashboard icons, and haptic steering wheel vibrations. Their findings revealed that combining visual and tactile cues will be more effective than single-modality alerts in recovering drivers from MW and secondary-task distraction. Also, the study [34] introduced a predictive algorithm that integrated eye-tracking data with lane-position variance to activate a brief dashboard flash whenever the probability of MW exceeded 70%. Field testing of this system demonstrated a 150 ms reduction in reaction-time deficits and a 0.3 m decrease in lane deviations over the subsequent minute. The second strategy focuses on the use of adaptive driving aids to increase driver attention and mitigate distractions. Mohd et al. [50] investigated an adaptive cruise-control system that applies minor speed adjustments of approximately ± 2 km/h during low-demand driving segments. In naturalistic driving conditions, these small speed changes significantly reduced self-reported off-task thoughts by half and improved lane-keeping consistency. Also, early-stage brief notification on upcoming turns or landmarks shows potential in simulator studies.

Behavioral training and targeted messaging represent accessible, low-tech strategies for reducing mind wandering while driving. Amre and Steelman [2] provided pilot data showing that short educational modules related to risks of off-task thinking, combined with self-monitoring exercises (logging mind-wandering episodes during supervised drives) can lead to a 20% reduction in probe-caught MW within a week. The study [46] shows that the role of compensatory beliefs, or drivers' confidence that they can offset distraction through other safe behaviors influences MW. Safety messaging that opposes those beliefs could improve the driver's focus.

Although short-term improvements resulting from educational modules and safety aids appear promising, there is insufficient evidence to determine whether these benefits persist over longer periods or apply to various driving conditions. The development of adaptive alert systems that respond to individual drivers' attentional profiles could improve the efficacy of MW mitigation strategies.

5. Discussion

Based on the comprehensive synthesis presented in the previous chapter, we can now interpret the findings in a broader context. We examine the implications of cross-study trends, critically appraise methodological and conceptual gaps, and translate our insights into concrete recommendations for future research and practice in driver mind-wandering detection and intervention.

Experimental simulator studies consistently show that MW episodes are associated with measurable performance deficits: drivers' braking reaction times slow by approximately 200–300 ms, and lateral lane deviations increase by 0.3–0.5 m compared to on-task driving periods [24,25]. Trait MW propensity also correlates with riskier driving metrics, higher average speeds, and throttle pressures, observed in both ADHD and non-ADHD populations [24]. However, naturalistic crash analysis suggests that MW contributes to fewer than 1% of high-severity collisions, whereas broader cognitive distractions contribute to approximately 1.5% [18].

Objective methods for detecting MW have advanced rapidly in recent years. Behavior-based classifiers such as random forest models leveraging features like steering, speed, and brake pressure achieve up to 80% accuracy in simulators [11]. Electrophysiological markers, such as reduced N1/P3 amplitudes in EEG event-related potentials and hemodynamic changes in frontal fNIRS signals, show high precision in distinguishing MW from on-task states [31,36].

An important finding in MW mitigation is that engaging in secondary tasks (e.g., radio quizzes) can reduce MW frequency and improve lane-keeping performance under monotonous driving conditions [28]. Brief online mindfulness training has also shown potential to decrease MW rates and enhance "focus-related" steering patterns in young drivers [6].

The current body of work on driver mind wandering is constrained by its heavy reliance on small, homogeneous samples, often undergraduate students, tested in fixed-base or desktop simulators, which limits confidence that findings will generalize to real-world traffic environments [14]. Also, this research area lacks standardization, as studies employ diverse operational definitions for MW, varying thought-probe schedules, and inconsistent performance metrics. This methodological variability complicates cross-study comparisons and limits the feasibility of meaningful meta-analyses. Efforts to translate promising laboratory-derived detection algorithms, such as those based on EEG, fNIRS, or steering-pattern classifiers, into on-road applications present substantial challenges. Technical issues, including motion artifacts and sensor intrusiveness, remain important obstacles [11,31]. Finally, while some countermeasure trials (e.g., brief mindfulness training, engagement tasks) demonstrate short-term reductions in MW and improved safety in simulator-based studies, these interventions have rarely been tested in longitudinal or naturalistic settings. Their real-world efficacy, impact on crash effects, and driver acceptance remain mainly unknown [6].

Validating findings from controlled investigations and real-world applications necessitates expanding research beyond laboratory environments and student samples into large-scale, naturalistic settings. Future studies should employ harmonized operational definitions of MW, standardized probe intervals, and common safety metrics, such as braking latency and lane-keeping variability, to benchmark detection and intervention systems under real traffic conditions. Hybrid detection models that integrate behavioral indicators (steering dynamics and gaze dispersion) with physiological signals (heart rate variability and EEG) and contextual information (route familiarity and traffic density) promise to improve real-time identification of MW while mitigating lab-to-field artifacts. The development of adaptive countermeasures, ranging from dynamic engagement prompts to mindfulness protocols, requires rigorous evaluation through randomized, longitudinal experiments conducted in naturalistic driving environments. These experiments should assess the durability of interventions, their effects on crash rates, and driver acceptance. Finally, cross-disciplinary collaboration among cognitive neuroscientists, human factors engineers, and automotive designers will be important. Such collaborations, supported by open data repositories and standardized validation protocols, are important for co-designing non-intrusive, scalable systems capable of anticipating and mitigating driver mind wandering in everyday traffic.

6. Conclusions

This review synthesizes the mind-wandering literature into a coherent knowledge system that presents when, why, and how drivers' attention drifts and what can be done about it. By mapping 64 studies across prevalence, performance impacts, objective detection, cognitive and contextual triggers, and mitigation strategies, we provide a comprehensive overview of the field's current status and emerging directions.

This study presented several interconnected priorities that should be addressed to increase road safety. Rigorous on-road trials conducted over weeks or months are essential to validate laboratory-derived algorithms and countermeasures in real traffic conditions, as well as to evaluate drivers' habituation and acceptance. Also, standardizing thought-probe protocols, physiological and kinematic metrics, and performance indicators will facilitate robust comparisons and meta-analyses across studies.

To enhance real-time detection capabilities, future work should focus on improving the sensitivity and specificity of monitoring systems. This can be achieved by developing better signal filtering techniques and implementing calibration methods adapted to the physiological and behavioral characteristics of individual drivers. Furthermore, it is important to co-design interventions with drivers by iteratively refining alert modalities, thresholds, and training paradigms. This will help ensure that countermeasures reduce false positives, avoid annoyance, and accommodate individual cognitive profiles.

By aligning efforts related to standardized measurement, ecological validation, and user-centered design, the field can translate insights on attentional lapses into scalable, non-intrusive systems that sustain driver engagement and improve road safety through effective human–machine collaboration. However, this review is limited by the heterogeneity of study designs and mind-wandering measures, which complicates direct comparison across findings, and by the insufficiency of long-term, on-road validation data for detection algorithms and interventions.

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Abbreviations

The following abbreviations are used in this manuscript:

MW	Mind Wandering
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
EEG	Electroencephalogram
SART	Sustained Attention to Response Task
SHRP	Second Strategic Highway Research Program
ADHD	Attention-Deficit/Hyperactivity Disorder
HRV	Heart Rate Variability
PCA	Principal Component Analysis
t-SNE	t-distributed Stochastic Neighbor Embedding
SVM	Support Vector Machine
fNIRS	functional Near-InfraRed Spectroscopy

Appendix A

Table A1. Summary of included studies.

Author/s, Year, and Country	Methods	Main Findings	Future Directions
Albert et al., 2022 Canada [47]	Forty male drivers randomized to negative vs. neutral mood induction; T1/T2 simulator drives with thought probes, heart rate monitoring, and measures of speed, headway, steering, overtaking.	Negative mood increased MW frequency (OR 1.79) and, among high-rumination individuals, further amplified MW (OR 2.11); during MW, negative mood led to greater headway variability (d = 1.46) and more steering reversals (RR = 1.33).	Should include T1 HR, on-road replication, and alternate MW measures.
Albert et al., 2018 Canada [26]	N = 30 young male drivers; measured MW tendency via SART commission errors and DDFS; simulated drive recorded mean speed and eye-tracking vigilance.	Higher MW tendency (SART errors) predicted faster mean driving speed, confirming MW as a marker of risky driving; neither vigilance nor executive control capacity mediated or moderated this relationship.	Needs on-road replication; broader age/sex samples; exploration of other mediators (e.g., stress and fatigue).
Albert et al., 2023 Canada [6]	Double-blind RCT (n = 26 young drivers), brief online mindfulness vs. progressive muscle relaxation over 4–6 days; simulator drives with self-initiated and probe-cued MW reports.	Mindfulness training reduced overall MW in simulation, increased state mindfulness, and was associated with more “focus-related” steering behaviors; no group differences in adherence or attrition.	Needs definitive efficacy trials, on-road validation, and assessment of long-term adherence and real-world crash outcomes.
Alsaid et al., 2018 USA [32]	Nine participants completed 45 simulated drives with monotony; periodic auditory thought probes (30–90 s); extracted nine steering behavior features and applied PCA and t-SNE for dimensionality reduction.	MW was reported in 65.4% of probes; PCA revealed three broad clusters, t-SNE revealed finer subclusters differentiating MW vs. engagement; MW episodes exhibited distinct steering patterns (e.g., low mean and SD on straight segments).	Future work should integrate these features into real-time detection algorithms and validate in the field.

Table A1. *Cont.*

Author/s, Year, and Country	Methods	Main Findings	Future Directions
Amre & Steelman, 2023 USA [2]	80 licensed drivers (18–27 y) viewed a 15 min dash cam highway video under SAE L2 automation. Between subjects, drivers were assigned to keep either hands-on-wheel or eyes-on-road. A mid-video "glitch" (roadside mirror/reversed signage) tested change detection. Three thought probes assessed mind wandering. Eye tracking (Tobii Pro) recorded saccade amplitude, fixation duration, and entropy metrics (stationary gaze, dwell time, transition) across pre-, during-, and post-change epochs.	Keeping hands on the wheel led to fewer mind-wandering reports during the critical glitch segment (34% vs. 66%) and better detection of the mirror/reverse signage change (58% vs. 42%). Participants reporting mind wandering detected the change far less often (21% vs. 50%). Mind wandering and failed detections both correlated with reduced saccade amplitude and fixation duration, and increased gaze transition entropy.	Future research should employ higher fidelity simulation or on-road testing, integrate real-time physiological monitoring, and explore long-term adaptation.
Anderson et al., 2023 USA [51]	Sixteen night-shift workers drove 2 h on a closed loop after sleep vs. after shift; every 15 min self-rated KSS, sleepiness symptoms, likelihood of falling asleep; recorded lane deviations and emergency-brake events.	All subjective sleepiness ratings predicted severe driving events in the next 15 min (OR 1.76–2.4, AUC > 0.81), and certain symptoms (eye-closure, difficulty centering) predicted lane deviations (AUC 0.59–0.65). Drivers were reliably aware of drowsiness.	Future work should test interventions prompting drivers to stop and examine general-population samples.
Baldwin et al., 2017 USA [33]	Participants completed five days of 20 min monotonous freeway simulation, a cognitive depletion task, then the same 20 min drive in reverse. Auditory probes prompted self-report of MW; recorded driving performance (speed and lane variability) and EEG (alpha power) plus ERP (P3a) responses to probes.	Mind wandering frequency remained high and stable over days. Self-reported MW periods showed reduced speed and lane variability, increased EEG alpha power, and attenuated P3a amplitude to probe tones. Demonstrates that physiological and kinematic markers can reliably detect off-task states in continuous driving tasks.	Further work is needed to develop non-intrusive, real-time machine-learning classifiers integrating EEG and driving metrics, and to test in more varied driving scenarios.
Beninger et al., 2021 Canada [11]	Data from 117 drives by 39 participants in a high-fidelity, wraparound screen driving simulator. Extracted features from time series driving data (speed, accelerations, lane position, and brake pressure) using simple and feature extraction methods. Trained and compared SVM, random forest, and MLP to classify MW (vs. on-task) and predict hazard response times.	Random forest classifiers achieved the highest accuracy in detecting mind wandering from purely driving pattern data, and in predicting hazard response time significantly above baseline. Feature extraction representation further improved hazard response predictions. Demonstrates feasibility of non-invasive, machine-learning-based MW detection without self-report.	Future work should test classifiers with naturalistic driving data, integrate physiological signals for hybrid models, and assess robustness across different simulator platforms and driver populations.

Table A1. *Cont.*

Author/s, Year, and Country	Methods	Main Findings	Future Directions
Bernstein et al., 2019 USA [24]	87 participants (16 ADHD, 71 control) completed six laps on a PC-based Assetto Corsa simulator. Collected lap times, average/max/std of speed, tire-off counts, throttle/brake pressures; administered self-report questionnaires on driving behaviors, anger, ADHD symptoms, and mind wandering.	ADHD participants drove faster (higher ground speeds) and used throttle more aggressively. Across the full sample, greater self-reported mind wandering correlated with higher average and maximum throttle pressure and maximum speed, indicating a link between off-task thought and riskier driving metrics.	Future work should replicate on-road and explore real-time objective markers of off-task thought.
Berry et al., 2014 USA [52]	N = 32 per modality (visual vs. auditory) performed 10 runs of the Continuous Temporal Expectancy Task (CTET), detecting infrequent 1070 ms targets among 800 ms standards, with/without 30 s video distractors. Measured hit rates, false alarms, time-on-task declines, and correlated performance with self-reports of mind wandering, distractibility, and boredom.	Auditory CTET yielded higher precision and was less affected by sustained attention declines; distraction impacted both modalities equally. Individual differences: poor auditory performance linked to boredom; poor visual performance linked to distractibility. These modality-specific patterns illuminate facets of internal attention.	Future studies should adapt CTET insights to driving tasks, examine physiological correlations of modality-specific lapses, and test whether boredom- vs. distractibility-driven mind wandering differentially impact simulated driving performance.
Berthié et al., 2015 France [17]	Offline questionnaire completed by 191 ordinary drivers about their most recent trip: personal characteristics, contexts triggering MW, awareness, and content/emotional valence of thoughts. Collected trip type, road type, passenger presence, and self-reported % time spent mind wandering.	85.2% of drivers reported at least one MW episode, averaging 34.7% of trip time. MW was most frequent during low-demand contexts (familiar commutes, monotonous highways, and driving alone). Drivers typically became aware quickly, and thoughts were neutral, solution oriented private concerns. Findings support MW as functional planning state.	Next steps include real-time sampling (e.g., experience sampling in naturalistic or simulator settings) and linking MW frequency to objective driving performance metrics.
Burdett et al., 2016 New Zealand [22]	502 drivers (mean age 44.4 years) completed an online/paper questionnaire including MAAS, CFQ, DBQ, and custom items on MW frequency across various personal states (tired and stressed) and road contexts (familiar vs. unfamiliar, traffic density). Self-reported proportion of trip time spent MW was recorded.	85.2% reported at least one MW episode (mean 34.7% of trip time). MW was more likely on familiar roads and when tired. Individuals with higher MW reported lower trait mindfulness, more cognitive failures, and more driving violations and lapses.	Future studies should combine real-time sampling and objective driving metrics to validate and extend these findings across diverse driver populations and contexts.

Table A1. *Cont.*

Author/s, Year, and Country	Methods	Main Findings	Future Directions
Burdett et al., 2018 New Zealand [23]	Descriptive experience sampling with 11 female commuters (110 drives, 587 thought samples). Probes captured content categorized as driving-related vs. unrelated and by trigger (sensory vs. internal). Participants' focus state at each sample was recorded.	Commuters reported MW on 63% of samples, driving focus on 15–20%, and "no particular thought" on the remainder. Over half of MW episodes were sensory triggered, indicating habitual environmental scanning. MW was interrupted swiftly by increased task demands, suggesting focus shifts are dynamic in routine driving.	Future research should use larger, mixed gender samples, compare across trip types, and investigate how environmental triggers can be leveraged to design interventions that re-engage attention when MW risk is high.
Burdett et al., 2019 New Zealand [20]	Researcher-accompanied drives by 25 familiar-route drivers on a 25 km urban route. Thought samples taken at 15 predetermined road sections, categorized as mind wandering vs. driving focus (sensory- vs. internally-triggered). Five-year crash data on the same segments were also analyzed.	All drivers reported mind wandering; MW was more frequent at slower, quieter, less complex sections. Crash rate per section was highest at roundabouts—where MW was least reported—suggesting drivers allocate conscious focus to demanding contexts despite ubiquitous MW.	Needs replication with varied routes and larger samples, and experimental work to link MW sampling directly to crash risk and to inform targeted safety interventions.
Cai et al., 2024 Australia [45]	Sixteen younger (21–33 years) and 17 older (50–65 years) drivers completed two 2 h track drives under well-rested vs. sleep-deprived conditions. Every 15 min they rated sleepiness (KSS) and symptom frequency (SSQ); lane deviations and near-crash events were recorded by an instructor.	For younger drivers, all sleepiness symptoms (except mind wandering) strongly predicted near-crashes (AUC 0.78–1.00) and lane deviations (AUC 0.78–0.94). Older drivers' recollections predicted only severe impairment (AUC 0.86–0.94) for fewer symptoms. Drivers reliably perceived their drowsiness prior to impairment.	Future work should test open roads, broader populations, and examine interventions based on real-time symptom feedback (e.g., prompts to stop).
Cásedas et al., 2022 Spain [53]	N = 219 meditation-naïve adults completed the ANTI-Vea task, assessing phasic alertness, orienting, executive control, executive vigilance, and arousal vigilance. Dispositional mindfulness was measured via FFMQ; correlations (Kendall's τ) examined links between mindfulness facets and task performance.	Higher non-reactivity predicted faster reaction times and greater accuracy across attentional network trials. Higher total FFMQ and non-reactivity predicted faster RTs and fewer lapses in arousal vigilance; no associations with executive control or executive vigilance were found.	Future research should adapt these measures to real or simulated driving tasks, and test how dispositional mindfulness relates to on-road mind wandering and safety outcomes.
Cowley, 2013 USA [54]	118 undergraduates drove a fixed simulated route with 5 thought probes, self-classifying as on-task, off-task, mind wandering, or meta-unaware wandering. Measured speeding seconds and lane deviations in 14 s preceding each probe.	Meta-unaware mind wandering produced the highest mean lane deviations and second-highest speeding time; on-task periods had the lowest deviations and speeding. Suggests that lack of meta-awareness while wandering is particularly hazardous.	Future work should test diverse populations, varied scenarios, and incorporate physiological markers to detect meta-unaware wandering in real time.

Table A1. *Cont.*

Author/s, Year, and Country	Methods	Main Findings	Future Directions
Delhomme & Gheorghiu, 2021 France [55]	Face-to-face questionnaire of 515 French and non-French truck drivers at highway rest areas. Assessed perceived stress, organizational factors, mental health, and self-reported risky behaviors. Included items on mind wandering frequency and perceived driving difficulties. Structural Equation Modeling examined links among stress, mental health, mind wandering, and risky behavior.	Higher perceived stress predicted more risky driving behaviors. Organizational support and mental health were strongly linked to stress. Non-French drivers reported higher mind wandering and more driving difficulties than French drivers. Highlights mind wandering as a possible mechanism connecting stress to risky behaviors.	Future research should use real-time mind-wandering probes in naturalistic truck drives and longitudinal designs to assess directionality and intervention effects.
Dong et al., 2023 USA [49]	Planned human subjects study in a partial-automation simulator. Compared internal distraction (mind wandering) vs. external secondary tasks on takeover performance. Three takeover-request displays tested: visual only (V), tactile only (T), and combined visual + tactile (VT). Performance metrics: reaction time, takeover quality.	(Study protocol; empirical results pending.) Hypothesized that VT multimodal alerts will outperform single-modality displays in recovering drivers from mind wandering and secondary-task distraction. Expected mind wandering to degrade takeover times more than secondary tasks.	Future publication of empirical data is needed. Work should extend to on-road AV trials and incorporate physiological monitoring to predict mind wandering before takeover.
Farahmand & Boroujerdian, 2018 Iran [42]	45 min simulated drives on three highway layouts (low/moderate/high geometric variety). Measured steering wheel movements (SWM), SD of SWM (SDSWM), and lane position error (area between trajectory & centerline, ABTC).	Roads with moderate and high geometric variety improved lane-keeping by 11.3% and 20.6%, respectively (ABTC). Vigilance decreased over time (increased SWM and SDSWM), but deterioration was significantly lower on more varied geometry.	With no direct assessment of mind wandering, future research should add cognitive tools (e.g., thought probes and EEG) and conduct on-road validation in diverse environments.
Forest et al., 2021 France [56]	Prospective cross-sectional interviews with 1 200 drivers (459 serious vs. 741 nonserious accidents) at two French hospitals. Collected demographics, crash responsibility, alcohol/drug use (pictogram medications), sleepiness, distractions, and self-reported mind wandering at time of crash. Police reports matched for responsibility analyses.	Confirmed alcohol, motorcycle use, local roads, and psychotropic "pictogram" drugs increase serious crash risk (OR up to 3.64). Behavioral sleepiness (Epworth scale) did not predict accident severity; mind wandering at the time of crash was not a significant predictor once other factors were controlled.	Future studies should use naturalistic, real-time sampling (e.g., in-vehicle probes) to assess off-task thought leading to accidents.

Table A1. *Cont.*

Author/s, Year, and Country	Methods	Main Findings	Future Directions
Galéra et al., 2012 France [57]	Responsibility case–control in ED (*n* = 955 drivers). Classified thoughts pre-crash as task-unrelated (MW) or not, rated disruption (0–10). Responsibility scored via adapted Robertson-Drummer tool. Adjusted for confounders: demographics, crash characteristics, substance use, and external distraction.	Intense mind wandering (highly disruptive) was associated with responsibility for crash (17% vs. 9%; adjusted OR 2.12, 95% CI 1.37–3.28), demonstrating that pre-crash MW elevates culpability independent of external distractions and affect.	Future work should employ real-time MW probes in naturalistic or simulator settings linked to objective performance metrics.
Geden & Feng, 2015 USA [58]	25 licensed undergraduates completed simulated drives under low vs. high perceptual load (traffic, buildings, intersections). Thought probes at 30–90 s intervals; measured reaction times, visual scanning, braking speed, lane variation, and following distance.	Lower perceptual load drives elicited more mind wandering; task-unrelated thoughts yielded longer reaction times to sudden events. High load reduced MW frequency but did not eliminate performance costs when MW occurred.	Incorporate diverse driver populations, test ecological validity on-road, and explore physiological correlates to predict MW onset under varying load.
Geden et al., 2018 USA [59]	40 undergraduates drove two 65 km simulated scenarios (low vs. high perceptual load) with intermittent MW probes (~1/min). Applied generalized additive mixed models to assess effects of load and time-on-task on MW rate and vehicular control metrics (lateral/longitudinal velocity, acceleration).	Higher perceptual load significantly reduced MW rate. Driving duration exhibited nonlinear effects: MW costs on vehicular control fluctuated over time, whereas on-task performance declined linearly. Indicates both environment complexity and time modulate MW and safety.	Validate findings in naturalistic driving, include older and experienced drivers, and examine interventions adjusting environmental load dynamically.
Gil-Jardiné et al., 2017 France [14]	Responsibility case–control study in ED (*n* = 954 injured drivers). Assessed mind-wandering trait (DDFS, custom items) and state (disturbing thought just before crash) via structured interview. Crash responsibility scored via adapted Robertson–Drummer method.	Mind-wandering state (OR 2.51, 95% CI 1.64–3.83) and trait (OR 1.62, 95% CI 1.22–2.16) independently predicted crash responsibility, indicating both momentary and dispositional MW heighten crash risk.	Incorporate objective in-vehicle monitoring and test interventions targeting high-MW drivers.
Gresham et al., 2021 USA [60]	Validated the 19-item Attention-Related Driving Errors Scale (ARDES) in 81 adolescents (16–18 yrs). Conducted CFA for one- vs. three-factor (control, maneuvering, navigation) models; assessed construct validity via correlations with ARCES, CFQ, MAAS, ANT, and CPT performance.	ARDES exhibited good internal reliability and construct validity in adolescents; factor structure aligned with Michon's three-level model. ARDES scores correlated with performance-based attention measures, supporting its use for assessing endogenous inattention.	Future research should examine ARDES predictive power for on-road safety outcomes and integrate physiological markers.

Table A1. *Cont.*

Author/s, Year, and Country	Methods	Main Findings	Future Directions
He et al., 2011 USA [61]	Eighteen licensed drivers performed a car-following task in a high-fidelity driving simulator. Participants self-caught any MW episodes via a steering wheel button. Vehicle control metrics (headway and lane position) and eye movements (gaze distribution) recorded and compared between MW and on-task intervals.	During self-reported MW, drivers exhibited minimal deficits in vehicle control metrics but showed significantly narrower gaze dispersion—focusing more tightly on the lead vehicle—indicating reduced environmental monitoring and potential missed hazards.	Use randomized probes to capture unaware MW, test diverse driver demographics, and correlate gaze narrowing with actual hazard detection failures on the road.
Hidalgo-Muñoz et al., 2019 France [36]	fNIRS measured OxyHb in frontal, temporo-parietal, and occipital regions during manual and autonomous simulated driving, with/without an attentive listening secondary task. Mind-wandering self-reports collected; event-related hemodynamic responses to brake light cues analyzed.	Participants reported more mind wandering in autonomous vs. manual driving. Manual driving showed greater occipital and right temporo-parietal OxyHb increases to brake lights. During autonomous driving with listening, right frontal activity decreased, indicating attentional shift to secondary task over visual monitoring.	Future work should include on-road or higher fidelity settings, larger samples, and link hemodynamic changes to performance and real-world crash risk.
Huang et al., 2019 USA [30]	Twelve students drove a medium-fidelity simulator in a monotony-inducing highway scenario under partial automation. Eye tracking, pupilometry, GSR, and heart rate data recorded. Auditory tones served as warning signals; self-reports of mind wandering collected. Driving performance (speed and response time) and physiological metrics used to develop predictive models of MW.	Mind wandering is associated with slower response times to warning tones and higher driving speeds. Physiological markers (larger pupil dilations, increased heart rate variability, and higher skin resistance) correlated with MW episodes. A preliminary predictive model using driving years and response times achieved moderate accuracy in detecting MW.	Validate physiological predictors in diverse populations, test models in real-world driving, and integrate additional sensors (e.g., EEG) for improved MW detection.
Jana & Aron, 2022 USA [62]	Two within-subject stop-signal studies (n = 30 and n = 145) with intermittent probes classifying trials as on-task vs. MW. Behavioral stop-signal RT (SSRT) and trigger-failure rates estimated via computational modeling. Participants completed the Mind-Wandering Questionnaire post-task to relate trait and state MW.	During MW episodes, SSRT increased, and trigger-failure rates rose. Over 67% of variance in SSRT slowdown was explained by increased trigger failures, indicating that MW primarily impairs the initiation (“trigger”) of the inhibitory process rather than its execution. Trait MW correlated with probe-reported MW frequency.	Future studies should apply stop signal paradigms in driving contexts, examine physiological correlates of trigger failures, and test interventions to enhance trigger reliability in high stakes tasks like driving.

Table A1. *Cont.*

Author/s, Year, and Country	Methods	Main Findings	Future Directions
Körber et al., 2015 Germany [43]	Twenty participants completed a 42.5 min partially automated highway drive in a high-fidelity simulator. Secondary auditory oddball reaction time task (20% targets), eye tracking (blink frequency/duration, pupil diameter, PERCLOS), and Dundee Stress State Questionnaire subscales (Task Irrelevant/Relevant Thought) administered at start and end of drive.	No significant time-on-task effects on reaction times, but significant increases in blink frequency, blink duration, and PERCLOS over the drive. Mind wandering (Task-Irrelevant Thought) scores rose significantly, indicating that passive monitoring and monotony induce MW and passive fatigue even without active control demands.	Future work should link vigilance and MW measures to actual driving performance in on-road contexts, explore longer durations, and test countermeasures (e.g., variable automation engagement) to mitigate passive fatigue.
Laughland & Kvavilashvili, 2024 UK [41]	Single-case audio-recording method: first author recorded 674 IAMs across 20 familiar 30–40 min driving sessions. IAMs timestamped and coded by cue type (dynamic vs. static), chains (memory streams), and long-term priming from prior incidental stimuli.	IAMs occurred at ~34 per journey—far higher than previous estimates—with dynamic environmental cues triggering more IAMs than static ones. Memory chaining and long-term priming effects (up to several days) were prevalent, supporting a model where both immediate triggers and lasting primes govern IAM occurrence.	Replicate with larger, diverse driver samples, develop automated IAM detection, and examine IAMs' impact on driving safety and mind-wandering overlaps.
Lemercier et al., 2014 France [29]	Twenty participants encoded picture/word (retrospective) and picture/intention (prospective) pairs. In subsequent 30 km simulated highway drives, encoded pictures appeared on road-sign cues, prompting recall. Driving performance (speed micro-regulation, lateral position variability) and visual scanning metrics were recorded; subjective workload assessed post-drive.	Recall prompts led to significant reductions in speed and lateral micro-adjustments, narrowed visual scanning, and increased perceived workload, demonstrating that internally triggered distractive thoughts degrade driving control—particularly when recalling factual or intentional content.	Test varied thought content, use real-time thought probes, conduct on-road studies, and explore mitigation strategies (e.g., in-vehicle alerts) to counteract factual internal distraction.
Lin et al., 2021 China [40]	Questionnaire collected single-trip data (n = 190 drivers) on demographics, context (time, distance, purpose), and in-vehicle environment. Chi-square tests identified factors influencing MW frequency. Four ML algorithms (e.g., gradient boosting decision tree) were trained to predict MW occurrence using readily available variables; performance evaluated via confusion matrices, ROC curves, and AUC.	Identified key extrinsic/intrinsic predictors (e.g., driving experience, traffic density, and fatigue). Gradient boosting decision tree achieved highest AUC, with factor importance rankings matching questionnaire findings. Demonstrates feasibility of predicting MW from non-intrusive, easily collected data.	Future research should integrate driving performance and physiological data, test models in naturalistic settings, and evaluate interventions triggered by ML-based MW forecasts.

Table A1. *Cont.*

Author/s, Year, and Country	Methods	Main Findings	Future Directions
Lin et al., 2016 Taiwan [63]	Ten participants completed 60-min event-related lane-departure tasks in a 6-DOF driving simulator under two conditions: full sensory feedback (visual + motion) vs. visual-only. EEG was recorded and ICA/Granger causality analyzed pre-stimulus network dynamics among ACC, MCC, PCC, SMC, and ESC. Reaction times (RTs) to lateral perturbations were measured.	Removing motion feedback (low perceptual demand) shifted dominant causal hub from PCC→MCC, indicating greater default-mode activation during easier driving. PCC-dominated trials had RTs ~286 ms slower than MCC-dominated trials, linking default-mode dominance to performance lapses.	Future research should explore how sensory feedback and driver assistance systems influence attention in real-world driving and develop adaptive technologies using neural markers to monitor alertness.
Mohd Yusoff et al., 2024 Malaysia [50]	Multi-phase scale development: NGT with experts and nurses to identify themes; item pool generated and refined via expert review; EFA ($n \approx 442$ nurses) recovered six factors (violations, emotions, drowsiness, mind wandering, error, and carelessness); CFA confirmed factor structure and predictive validity via SEM.	The MyUDWC scale demonstrated good reliability and validity across six constructs, with "mind wandering" emerging as a distinct factor contributing to unsafe commuting behaviors. Provides a validated tool for assessing context-specific cognitive failures among nurses.	Future work should test MyUDWC's predictive power for crash risk, adapt for other commuter populations, and integrate with real-time MW detection systems for intervention development.
Mueller et al., 2022 USA [37]	On-road drives (1 h) in a Tesla/L2-equipped Mercedes-Benz with Autopilot on/off. Surprise events (oversized pink teddy bear overtakes) occurred thrice. Cameras recorded glance behavior; post-drive recall of events and self-reported mind wandering.	Familiarity with L2 systems improved recall of surprise events; unfamiliar drivers with automation on had poorer event detection. Better bear recall corresponded with wider gaze dispersion and higher self-reported mind wandering, indicating trade-offs between automation familiarity and environmental monitoring.	Future work should include larger, diverse samples, real-time MW probes, and performance outcome measures.
Musabini & Chetitah, 2020 France [38]	Collected eye gaze data from drivers on open highways under induced cognitive distraction. Generated image-based heatmaps of gaze dispersion on a virtual projection surface. Extracted features and trained SVM classifiers to distinguish distracted vs. neutral driving.	Heatmap features achieved 85.2% accuracy in classifying cognitive distraction from gaze dispersion alone, demonstrating that widened vs. narrowed gaze patterns reliably indicate mind-wandering episodes.	Expand sample size, integrate additional physiological and vehicular data, and validate models in varied driving contexts.
Nguyen et al., 2022 Vietnam [16]	Qualitative focus groups and in-depth interviews (*n* stakeholders) exploring perceived risk and underlying motives for risky behaviors—drink-riding, speeding, inattentive riding—among Vietnamese small-displacement motorcyclists.	Inattentiveness ("mind wandering") identified as one of four principal motives for risky riding; contextual barriers (e.g., cost of alternatives) and reactive pathways (e.g., thrill-seeking) jointly drive unintentional risk exposure.	Apply experience-sampling or naturalistic riding instrumentation to quantify mind wandering and link it to crash risk.

Table A1. *Cont.*

Author/s, Year, and Country	Methods	Main Findings	Future Directions
Nijboer et al., 2016 Netherlands [28]	Simulated driving under two traffic scenarios (no vs. substantial traffic) combined with four secondary tasks (radio quiz, passive listening, tablet use, and single-task driving). Measured driving quality via lateral deviation, speed/steering variability, overtaking consistency.	Tablet use (high cognitive/motor load) produced the worst driving performance; trivia and quiz tasks improved performance relative to single-task driving, suggesting engaged secondary tasks can reduce mind wandering and enhance attention under monotony.	Future studies should incorporate on-road trials and concurrent thought probes or physiological markers.
Nordhoff et al., 2023 Netherlands [44]	Semi-structured interviews (*n* = 103) with Tesla Autopilot and FSD Beta users. Explored driver state and behaviors (complacency, mind wandering, hands-off driving, and sleeping) and adaptation over time, including risky practices (steering wheel weights).	Experienced users exhibited complacency, mind wandering, or even sleeping when automation engaged; FSD Beta increased mental workload and stress due to system unpredictability; "knowing" and "unknowing" violations of intended use were common.	Future work should measure on-road behavior changes quantitatively and evaluate driver monitoring interventions.
Pepin et al., 2018 France [39]	20 volunteers performed two simulator sessions: unprompted MW self-reports (via button) and investigator cued Problem-Solving Thoughts (PST). Heart rate and oculometrics (e.g., fixation duration) were logged. A data triangulation approach compared MW vs. PST.	Both unintentional MW and intentional PST produced gaze fixity; MW, however, incurred additional cognitive cost when returning to task. Physiological signals (elevated HR) differed subtly between MW and PST, suggesting discriminable signatures for detection.	Combine probes with physiological classifiers and test the algorithm online in real-world driving.
Pepin et al., 2021 France [31]	Sixty participants completed 12 $\times$ 3 min simulator drives while EEG (64-channel) recorded event-related potentials to visual probes. After each drive, subjective attention levels were rated; the three highest ("on-task") and three lowest ("MW") sessions were contrasted.	Self-reported MW sessions exhibited significantly reduced N1 and P3 amplitudes in response to visual cues, alongside 150–300 ms longer brake reaction times. This confirms that MW disrupts early sensory processing and higher-order attentional allocation.	EEG artifacts in realistic driving require improved filtering. On-road ERP validation and integration with less intrusive sensors are needed for in-vehicle deployment.
Qu et al., 2015 China [8]	N = 295 Chinese drivers completed the 12-item Mind Wandering scale and the 28-item Dula Dangerous Driving Index (DDDI), plus demographics and self-reported crash/penalty history. Correlations and gender $\times$ MW interaction effects were analyzed via regression.	MW frequency positively correlated with all DDDI subscales (Risky, Aggressive, Emotional–Cognitive, and Drunk driving) and with higher self-reported accident involvement, penalty points, and fines. In high-MW drivers, males reported greater risky and emotional driving than females.	Future longitudinal studies with naturalistic MW sampling and official crash data linkage are recommended.

Table A1. *Cont.*

Author/s, Year, and Country	Methods	Main Findings	Future Directions
Rajendran & Balasubramanian, 2020 India [64]	21 healthy volunteers (mean age 22.6 ± 3.38 y, 11 ± 19 months driving experience) drove 22.36 km in a high-perceptual-load static simulator at two randomized speed limits (SL 1 = 40 mph, SL 2 = 70 mph). Mind wandering (MW) was captured via probe-caught method (Arduino-controlled 2250 Hz tones at 30, 60, 90, 60 s intervals) with button-press responses. Vehicle speeds were logged every 15 s, and speeds at 15 s and 5 s before each probe were extracted for MW vs. on-task periods. Variability in speed was tested via F-tests; Wilcoxon signed-rank tests compared mean speeds; linear regressions assessed speed as predictor of MW response time. A retrospective questionnaire probed MW sources and effects.	This study showed mind wandering as an influencer on vehicle speed variations and speed conditions as an influencer on the frequency of mind wandering. Therefore, mind wandering could act as a causal and effector. Frequency: MW occurred on 26% of probes at SL 1 and 22.5% at SL 2, supporting load theory of attention. Guilt due to mind wandering, reported as an effect may reduce people from mind wandering during their work, but due to its inevitable nature, rather than curbing its occurrence, managing its frequency might be a more practical solution.	Further research with more samples and collecting physiological signals are needed to verify the occurrence of perceptual decoupling during mind wandering.
Schnebelen et al., 2020 France [4]	18 min of SAE L2 automated driving in a fixed-base simulator. Gaze intersections with 13 predefined AOIs were recorded. Self-reports of mind wandering were regressed on static (time in AOI) and dynamic (transitions between AOIs) gaze indicators via PLS models.	Identified distinct visual strategies characterizing the out-of-the-loop state: reduced glances toward critical AOIs and fewer AOI transitions predicted higher self-reported mind wandering. These indicators can underpin real-time OOTL monitoring.	Field validation in real automated vehicles and integration with other sensors (e.g., heart rate) are needed.
Sridhar et al., 2024 USA [7]	Ten participants in a Level 1 automated driving simulator performed manual braking maneuvers under attentive vs. mind-wandering states. Data-driven conditional distribution embeddings characterized vehicle–human braking dynamics; Jaccard index compared feasible state regions for successful braking across states.	Statistically significant, participant-specific differences in braking profiles emerged between MW and attentive states. Heterogeneity suggests that partial-automation alerts and handover warnings must be personalized to individuals' attentional profiles.	Future work should expand sample size, test on varied automation levels, and integrate real-time MW detection to adapt braking assistance dynamically.

Table A1. *Cont.*

Author/s, Year, and Country	Methods	Main Findings	Future Directions
Steinberger et al., 2016 Australia [65]	Qualitative phenomenological study with 24 male drivers (18–25 y) in a highly immersive simulator. Semi-structured interviews explored antecedents to boredom, subjective experience, and coping strategies; thematic analysis identified situational and emotional factors.	Boredom triggers included low traffic, constant speed, and routine drives. Experience comprised frustration, vigilance lapses, mind wandering, "autopilot," and discomfort. Coping strategies were approach (speeding and risky maneuvers) and avoidance (phone use), both elevating crash risk.	Future research should test findings quantitatively, include female and older drivers, and develop interventions (e.g., in-vehicle engagement prompts) to mitigate boredom in both manual and automated driving contexts.
Techer et al., 2017 France [66]	33 participants completed two simulator drives (anger-induced vs. control), with EEG recording. Auditory and visual ERPs (N1, P3) were measured in response to alert tones and brake-light cues; lateral position variability and reaction times were logged.	Anger reduced visual N1 amplitude and increased lateral position standard deviation, indicating impaired perceptual processing and steering control; effects attributed to high arousal and mind-wandering induced by anger.	Future work should involve on-road testing, incorporate a wider range of cognitive and emotional states, and investigate adaptive assistance systems that respond to drivers' emotional conditions.
Tinella et al., 2022 Italy [48]	Online survey of 904 drivers (452 Australian and 452 Italian) measuring Big-Five personality, self-reported aberrant driving behaviors, and mind-wandering tendency; multi-group path analysis examined mediation of MW between personality traits and driving behavior across nationalities.	Mind-wandering tendency significantly mediated effects of neuroticism, extraversion, and conscientiousness on aberrant driving behaviors, with consistent patterns in both Australian and Italian samples.	Future research should employ real-time MW probes in driving contexts and integrate performance or physiological data to validate mediation effects.
Walker & Trick, 2018 Canada [21]	Participants completed three 20–25 min simulated drives with periodic thought probes asking if they were thinking of driving; measured driving speed, steering variability, hazard response times. Sustained attention was assessed via SART; sleep hours and self-rated focus difficulty collected before/after.	Self-rated difficulty focusing increased with time on task; reported MW rose non-significantly. Driving speed and steering variability increased over time. Hours of sleep best predicted MW propensity. SART performance did not predict MW or performance changes.	Future studies should include on-road tasks, larger samples, physiological measures of attention/fatigue, and examine causal direction between emotion and MW.
Watling & Watling, 2021 Australia [19]	N = 118 drivers (17–25 y) completed the Executive Function Index (EFI), Signs of Sleepiness Questionnaire (experienced signs and importance ratings), and demographics (age, hours driven/week). Linear regression assessed predictors of experienced sleepiness signs; correlations examined importance ratings.	Age, weekly driving exposure, and EFI subscales (organization, strategic planning, impulse control) positively predicted number of sleepiness signs experienced. Additionally, greater prior experience with signs correlated with higher importance ratings of those signs as sleepiness indicators.	There were no objective measures of sleepiness or driving performance. Future research should validate these relationships using physiological data and simulator or on-road performance metrics.

Table A1. *Cont.*

Author/s, Year, and Country	Methods	Main Findings	Future Directions
Weaver et al., 2022 USA [67]	Prescribed public road route driven twice by $n = 48$ drivers in a 2013 Cadillac SRX with and without ACC. Random auditory probes assessed mind wandering; CAN-bus recorded speed, gap distance, and steering variability; heart rate and EDA measured continuously.	ACC did not increase mind wandering overall; female drivers reported reduced mind wandering with ACC. ACC use tended to boost physiological arousal and improve lane-keeping and gap consistency, suggesting safety benefits for novice users.	Future work should examine experienced users, other ADAS levels, and link MW/physiology changes to crash risk in diverse traffic conditions.
Wotring et al., 2020 USA [18]	Analysis of 1139 Level 1–3 crashes from the SHRP2 NDS. Exclusionary filters removed cases with visual/manual distraction or impairment; remaining 172 high-severity crashes underwent multi-expert video reduction to identify cognitive disengagement (mind wandering/microsleep) as primary factor.	<1% of high-severity crashes had mind wandering/microsleep as sole contributing factor; ~1.5% due to purely cognitive distraction. Cognitive disengagement is relatively rare compared to visual/manual tasks in naturalistic crashes.	Future work should develop methods to detect combined factors and use physiological or in-vehicle monitoring for real-time MW detection.
Xu et al., 2022 China [27]	N = 42 (21 insomnia, 21 controls) in a within-subject simulator study. Two distraction tasks (no-distraction vs. instructed MW) and two scenarios (lane-keeping vs. lane-changing). Assessed longitudinal (speed, SD speed) and lateral (SD lane position) performance and correlated with sleep quality (PSQI) and cognition (MoCA).	In lane-keeping, MW×insomnia interaction increased longitudinal control variability; lateral control was weaker in insomnia group across tasks. In lane-changing, MW induced significant within-group performance declines. Performance correlated with cognitive scores, not sleep quality.	Include on-road validation, larger/clinical samples, and examine physiological correlations of MW in insomnia.
Yanko & Spalek, 2013 Canada [68]	Experiment 1: $n = 20$ undergraduates followed a lead vehicle on familiar vs. unfamiliar routes; sudden braking and pedestrian-onset events measured RT and collisions. Experiment 2 held headway constant and measured RT to central/peripheral events. Experiment 3 added a secondary focus task to eliminate effects.	Familiar drivers: shorter headways, slower RTs to braking and pedestrian events, and more collisions than unfamiliar drivers. When forced to focus (Exp 3), these familiarity effects vanished, implicating mind wandering/inattentional blindness on known routes.	Test diverse populations, varied driving contexts, and integrate objective MW probes or physiological measures to confirm inattention mechanisms on familiar routes.

Table A1. *Cont.*

Author/s, Year, and Country	Methods	Main Findings	Future Directions
Yanko & Spalek, 2014 Canada [25]	N = 17 undergraduates in a high-fidelity simulator followed a pace car at 30 m; random tonal probes required button-press for on-task vs. mind-wandering; pace car braked unpredictably (~60 events in 30 min); headway fixed by computer; measured brake RTs, vehicle velocity, and maintained headway distance in MW vs. on-task intervals.	During MW, participants had significantly slower reaction times to braking events, higher mean vehicle velocity, and shorter headway distances compared to on-task periods. Effects that mirror dual-task distraction and indicate elevated crash risk when attention drifts internally.	Include naturalistic on-road validation, physiological correlates (e.g., eye-tracking), and extend to varied driver demographics.
Yoshida et al., 2023 Japan [34]	Integrated a Sustained Attention to Response Task (SART) into a simulated car-following drive; *n* = 42 responded to high- vs. low-frequency SART stimuli amid driving, pressed brake upon lead-car brake light, then completed thought probes rating inattentiveness and mind-wandering separately on 7-point scales. Analyzed SART RT variability, brake RTs, and regression models.	Self-reported inattentiveness correlated significantly with SART RT variability and predicted longer brake RTs. Mind-wandering self-reports also related to braking delays. However, SART variability alone did not consistently detect MW state, highlighting difficulty of behavioral MW detection without self-report.	Future work should incorporate physiological monitoring (EEG/eye-tracking), expand to diverse populations, and refine non-intrusive real-time MW classifiers.
Young et al., 2018 UK [15]	Eye-tracking glasses on a driving instructor over 28 laps of the same 11.6 mi route; five road section analyses of fixation durations and off-road dwell time; calibration and data cleaning to exclude saccades and missing data.	Off-road dwell time increased with each repetition ($r > 0.50$); fixations on safety-relevant road features (e.g., speed signs and potential hazards) declined significantly in four of five sections as familiarity grew, indicating reduced external attention on highly practiced routes.	Include larger, diverse driver samples and link attention changes to real-world safety outcomes.
Young et al., 2019 Australia [69]	Online survey of *n* = 312 adult drivers assessing mindfulness via MAAS and frequency of engagement in 24 distracting activities (mobile phone, in-vehicle tech, daydreaming, and external stimuli); distraction items grouped into functional categories; correlations and regression analyses tested mindfulness as predictor of distraction engagement.	Trait mindfulness (MAAS) was negatively associated with frequency of nearly all distracting activities studied (phone use, daydreaming, and non-tech distractions), except passenger interaction, suggesting a single mindfulness intervention could reduce multiple types of distraction simultaneously.	Future longitudinal and experimental mindfulness interventions needed to confirm causal effects on real-world driving.

Table A1. *Cont.*

Author/s, Year, and Country	Methods	Main Findings	Future Directions
Zhang & Kumada, 2017 Japan [70]	N = 40 followed a lead vehicle at 20 m in a 25.3 km simulator; thought probes every minute to report mind-wandering; post-drive NASA-TLX administered for subjective workload; analyzed between-subjects correlation of TLX vs. mind-wandering frequency and within-session temporal trends of TLX and MW (trend analysis, correlation over task time).	Across individuals, higher TLX scores predicted fewer mind-wandering reports ($r = -0.459$, $p < 0.01$), supporting load theory's "spare capacity" concept. Temporally, both workload and MW frequency increased over time and were positively correlated within drives, indicating vigilance decrement drives MW and rising perceived workload.	Integrate real-time physiological measures, vary task load dynamically, and extend to on-road contexts to validate findings.
Zhang & Kumada, 2018 Japan [35]	40 licensed drivers in a medium-fidelity simulator performed a 25 min car-following task (25 km loop) at 80 km/h with random lead-car braking. Every minute, a tone prompted self-report of mind wandering vs. on-task. Four behavioral time-series (lane offset, steering ratio, pedal operation, and inter-vehicle distance) were logged at high frequency. Features (global and local statistical, autoregressive, wavelet, and ICA transforms) were extracted over sliding windows, then used to train and test supervised classifiers (SVM, decision tree, ensemble, KNN, discriminant analysis, and Naive Bayes) under driver-independent (leave-one-out) and driver-dependent cross-validation schemes.	Driver-independent models failed to generalize across individuals ($\kappa \approx 0$). Driver-dependent SVM models achieved up to ~80% accuracy for some drivers, demonstrating that personalized models based solely on driving behavior can detect mind wandering. Local (windowed) features were critical for within-driver performance, whereas global features alone were insufficient.	Incorporate physiological data (EEG, HRV, and eye-tracking), test in naturalistic settings, and develop adaptive, individualized online models.
Zhou et al., 2020 China [46]	Self-report questionnaires administered to 304 non-professional drivers (age 19–66 y). Scales measured: compensatory beliefs about distractive behaviors, perceived risk of each behavior, and frequency of distractive behaviors (including mobile phone use, in-vehicle interactions, and mind wandering). Factor analysis identified three components. Regression analyses tested how compensatory beliefs and risk perception predicted engagement in those behaviors.	Compensatory beliefs were a strong predictor of drivers' engagement in all three distractive behaviors, with the effect magnified for behaviors rated as higher risk (e.g., mobile-phone use). Mind wandering emerged as its own factor, and drivers who believed they could "make up" for distraction by other safe behaviors were more likely to mind-wander on the road.	Lacking objective safety data, future work should use naturalistic monitoring and experimentally test compensatory beliefs to assess their causal role in distraction.

Table A1. *Cont.*

Author/s, Year, and Country	Methods	Main Findings	Future Directions
Zimasa et al., 2019 UK [71]	40 experienced drivers (26 M, 14 F) in a high-fidelity hexapod simulator performed a car-following task under four induced moods (Neutral, Happy, Sad, and Angry), validated via self-report and physiological sensors (EDA and HR). Two forms of cognitive load questions (driving-related vs. non-driving-related) were posed mid-drive. Driving performance metrics (coherence, phase-shift, modulus, and time-headway) and eye-tracking measures (fixation duration and horizontal spread) were recorded and compared across mood/load conditions.	Negative moods (Sad/Angry) degraded car-following performance (lower coherence, greater phase-shift/modulus variability) and narrowed gaze spread vs. Neutral/Happy. Introducing driving-related cognitive-load questions partially "re-engaged" attention, improving performance and widening gaze under negative mood, whereas non-driving loads were less effective.	Future research should conduct on-road testing, manipulate task load intensity, and assess how long re-engagement effects last.

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