Effects of Fatigue on Driver Behavior in Urban and Highway Environments Using a Driving Simulator

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Abstract

Existing literature suggests that fatigue impacts driver behavior and road safety negatively. The present study aims to investigate the effects of fatigue, particularly due to a lack of sleep, on driver behavior and road safety in both urban and highway environments. A driving simulation experiment was conducted with 35 young drivers under controlled conditions. Participants drove in two phases: (i) well-rested and (ii) fatigued after sleep deprivation. The collected data were analyzed using linear regression models, to identify the effects of fatigue on key driving variables. The findings indicate that when fatigued, drivers exhibited increased speed and reaction time, shorter following distances, and reduced longitudinal acceleration. The effects were more noticeable in high-traffic conditions, where drivers showed a greater tendency to engage in risky behaviors. Drivers experiencing mild fatigue symptoms tended to underestimate them, leading to more aggressive driving behavior.

Keywords: *driver fatigue, driving simulator, urban roads, highways, reaction time, headway distance*

1. Introduction

Traffic crashes remain a major public health concern, contributing significantly to mortality and economic loss worldwide. According to the World Health Organization (WHO), road traffic crashes are responsible for approximately 1.19 million fatalities annually, making them one of the leading causes of premature death, particularly among young adults (World Health Organization, 2023). Beyond the human toll, the financial burden of traffic collisions is substantial, with associated costs estimated at around 3% of the global Gross Domestic Product (GDP).

Despite improvements in road safety measures and advancements in vehicle technology, driver-related factors continue to be a dominant cause of crashes, with fatigue strongly affecting performance (Williamson et al., 2011). Addressing driver fatigue has become a priority in road safety research, as it poses a serious threat to not only the driver but also passengers, pedestrians, and other road users. Fatigue-related crashes often result from prolonged driving hours, sleep deprivation, and circadian rhythm disruptions, all of which impair cognitive function, reduce reaction times, and increase the likelihood of critical errors on the road. Recent studies emphasize that drowsy driving significantly impairs cognitive and motor performance, affecting reaction times, decision-making abilities, and overall hazard perception. Research indicates that prolonged wakefulness can result in performance deficits comparable to those seen in individuals with elevated blood alcohol concentrations, highlighting the serious risks associated with fatigue-related driving (Lowrie &

Brownlow, 2020). Moreover, research highlights that night-time driving, extended work shifts, and long-haul trucking significantly increase the likelihood of fatigue-related crashes (G. Zhang et al., 2016).

Furthermore, recent research continues to highlight the significant impact of fatigue on driving performance, particularly in relation to reaction time, lane deviation, and overall road safety. Fatigue-related impairments have been shown to reduce a driver's ability to maintain lateral control, increase reaction times, and lead to more frequent lane departures, mimicking the effects of alcohol impairment (Costedoat et al., 2023). Studies using driving simulators have confirmed that sleep-deprived drivers experience significant performance deterioration, particularly in the morning and during long-haul trips (Caponecchia & Williamson, 2018). Furthermore, research has demonstrated that sleep deprivation of even two hours can substantially impair hazard perception and decision-making, leading to an increased risk of crashes (Lin et al., 2023).

Experimental studies have also indicated that commercial truck drivers and night-shift workers are particularly vulnerable to fatigue-related crashes due to prolonged wakefulness and extended duty hours (Liu et al., 2019). Physiological monitoring using EEG and ECG data has further validated that fatigue leads to reduced cognitive alertness and impaired motor responses, highlighting the need for real-time driver monitoring and intervention strategies (Wang et al., 2023). These studies emphasize the importance of fatigue management in reducing the incidence of traffic crashes and improving overall road safety.

This study aims to investigate the impact of fatigue due to sleep deprivation on driving behavior in both urban and highway environments, under varying traffic conditions. By utilizing a driving simulator, the study collects and analyzes data from a representative sample of drivers, integrating personal characteristics through survey responses. Through statistical modeling, specifically linear regression, key driving attributes such as average speed, reaction time, following distance, and acceleration are examined to quantify the effects of fatigue. The experimental approach includes scenarios where participants drive both well-rested and sleep-deprived, allowing for a comparative analysis of behavioral changes. The study contributes to road safety by offering data-driven insights into the risks associated with fatigued driving, supporting the development of targeted interventions to reduce crash risks and enhance driver awareness.

This paper is organized as follows. In the present section, a comprehensive review of the literature on fatigue-related driving risks and road safety is provided. Next, it outlines the research methodology in detail, including the theoretical underpinnings of the models, the experimental setup, and the data collection and processing protocols. Subsequently, the results are presented to quantify the influence of fatigue on driving behavior across different road environments. Finally, the study concludes with practical recommendations for mitigating the impact of fatigue on driving and enhancing road safety policies.

2. Materials and Methods

2.1 Driving Simulator Experiment

To examine the effects of fatigue on driving performance, a driving simulator experiment was conducted at the Department of Transportation Planning and Engineering of the National Technical University of Athens (NTUA). The study employed a FOERST Driving Simulator FP (**Figure 1**), which features three Full HD LCD screens, a realistic driving seat, and a motion-support base. With dimensions of 230 x 180 cm and a base width of 78 cm, the simulator provides a 170-degree field of view, ensuring an immersive driving experience.

Figure 1: *NTUA FOERST Driving Simulator*

The driving simulator functions as a highly advanced data acquisition system, enabling the precise monitoring of driver behavior and performance metrics. Throughout the experiment, the simulator captures up to 60 data points per second for each driving-related variable, ensuring high temporal resolution in data collection. These measurements are automatically processed and exported in text format, generating a distinct dataset for each participant, and driving scenario to facilitate systematic analysis.

The driving simulator experiment was conducted between late October and mid-November 2023, involving a total of 35 volunteer drivers (22 males, 13 females) aged 18 - 30 years. All participants held a valid driver's license and were divided into two age groups: 18 - 23 years (46%) and 24 - 30 years (54%), to examine differences in driving behavior based on experience.

The experiment involved two distinct driving environments: an urban road scenario (**Figure 2**), featuring one- and two-lane segments with low traffic, and a highway scenario (**Figure 3**), which included two- and three-lane road sections with both high- and low-traffic conditions. To introduce real-world unpredictability, unexpected events (e.g. a pedestrian crossing road) were fixed into the simulation, with one random event in the urban road scenario and two in the highway scenario, strategically placed to prevent participants from anticipating them. To prevent learning effects, scenario order was randomized for each participant. The data collected from the simulator along with the encoded questionnaire responses resulted in the development of a master table.

Figure 2: *Urban Road Scenario - Low traffic flow*

Figure 3: *Highway Road Scenario - Low traffic flow*

Additionally, the experiment was conducted in two phases. In the first, participants completed the driving scenarios (urban/low traffic and highway/low and high traffic) after adequate sleep, establishing a baseline performance. In the second phase, they returned to the simulator completing once more the driving scenarios without having slept the previous night, replicating the effects of sleep deprivation on driving ability. Furthermore, participants completed two phases of questionnaires and a familiarization drive prior to each experimental session to adapt to the simulator's controls and to collect relevant background data. The first questionnaire, administered before the initial (non-sleep-deprived) phase of the experiment, gathered information on participants' driving expertise (e.g., license issuance year, years of driving experience, average kilometers driven per day, number of driving days per week, etc.), driving behavior (e.g., frequency of driving while fatigued, behavioral changes when fatigued, perceived danger of fatigued driving, typical fatigue symptoms, etc.), crash history (e.g., number of accidents and whether fatigue was a factor), and basic demographic details (e.g., age, gender, etc.). The second questionnaire was completed before the sleep-deprived driving phase and focused on sleep-related variables (e.g. the number of hours slept the previous night, average sleep over the past week, whether any physically demanding activities were performed the previous day, current subjective fatigue level, etc.).

2.2 Statistical Modeling

To examine the effects of sleep deprivation on driving performance across different road environments, this study applies linear regression models to analyze key behavioral and performance indicators obtained through the driving simulator experiment. The aim is to estimate how fatigue, vehicle dynamics, and participant characteristics influence critical outcomes such as error rates, lateral control, and response timing. Linear regression was selected due to widespread use and proven effectiveness in behavioral modeling, where it enables the identification and quantification of variable relationships with high interpretability and statistical reliability. Regression-based approaches have also been applied, specifically, to analyze the impact of fatigue on driving behavior (Mahajan & Velaga, 2021). The method is particularly suitable for analyzing the continuous data captured by the simulator and enables rigorous evaluation of fatigue-related effects in both urban and highway driving conditions.

2.2.1 Regressions Model

The relationship between the dependent variables (e.g., average speed, reaction time) and the independent variables (e.g., fatigue condition, age group) was estimated using the standard form of the linear regression model (Eq. 1):

$y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \ldots + \beta_n X_{ni} + \varepsilon_i,$ **(1)**

Where:

- y_i: Observed value of the outcome variable for participant i
- X_{ni}: Independent variables
- β_0: Intercept
- β_n: Regression coefficients
- ε_i: Residual error

2.2.2 Evaluation Criteria

To ensure the validity and interpretability of the regression models, several statistical criteria were applied during the evaluation process. First, the statistical significance of each independent variable was assessed using the t-statistic, calculated as (Eq.2):

$ti = \frac{\beta_i}{s_{\beta i}},$ **(2)**

where β_i represents the estimated regression coefficient and $s_{\beta i}$ its standard error. Variables were considered statistically significant at the 95% confidence level ($p < 0.05$), with a 90% threshold ($p<0.10$) applied in marginal cases supported by theoretical relevance.

The overall predictive performance of each model was evaluated using the coefficient of determination (R^2), which quantifies the proportion of variance in the dependent variable explained by the model (Eq.3):

$$R^2 = \frac{SSR}{SST} = \frac{\sum_{i=1}^{n}(\widehat{Yi}-\overline{Y})^2}{\sum_{i=1}^{n}(Yi-\overline{Y})^2} = 1 - \frac{\sum_{i=1}^{n}(Yi-\widehat{Yi})^2}{\sum_{i=1}^{n}(Yi-\overline{Y})^2}, \quad \textbf{(3)}$$

Where:
- $\widehat{Yi}$ represents the model's predicted independent variable.
- $\bar{Y}$ represents the mean value of the independent variable Yi.

A higher R^2 value indicates stronger explanatory power and better model fit, with values approaching 1 suggesting a close alignment between observed and predicted outcomes.

2.2.3 Elasticity Analysis

In addition to interpreting the raw regression coefficients, elasticity analysis was conducted to assess the relative sensitivity of the dependent variable to proportional changes in each independent variable. Elasticity is calculated using the following expression (Eq. 4):

$$e_i = \left(\frac{\Delta Y_i}{\Delta X_i}\right)\left(\frac{X_i}{Y_i}\right), \quad \textbf{(4)}$$

This unitless measure provides a standardized index of effect size, making it especially useful for comparing the influence of predictors that are measured in different units or scales. In practical terms, elasticity indicates the percentage change in the outcome variable resulting from a 1% change in the predictor, offering more intuitive insights into variable impact.

3. Results

The statistical analysis focused on evaluating the effects of driver fatigue, behavioral adaptations, demographic characteristics, and environmental conditions on four key driving performance metrics: average speed, reaction time, headway distance, and longitudinal acceleration. The relationships between these outcomes and the selected predictors were modeled through multiple linear regression. Detailed regression results, including coefficient estimates, standard errors, t-values, p-values, and elasticity measures, are presented in order to capture the magnitude, direction, and statistical significance of these relationships, offering comprehensive insight into the factors affecting driving behavior and safety-relevant performance.

3.1 Average Speed Model

The Average Speed Model, defined by **Equation (5)**, quantifies the influence of fatigue, road type, duration of wakefulness, trip frequency, and fatigue-related behavioral changes on average driving speed:

Avg_Speed = 11.962 + 7.074 × fatigue + 49.526 × Ur_Hw + 0.763 × hrs_awake + 2.896 × routes_per_day + 3.107 × fatigue_driving_behavior_change, **(5)**

Where:
- **Avg_Speed**: Average speed (km/h).
- **fatigue**: Driver fatigue (1: driving with fatigue, 0: driving without fatigue).
- **Ur_Hw**: Driving environment (0: urban, 1: highway).

- **hrs_awake**: Number of hours since the driver last slept.
- **routes_per_day**: Number of daily trips in urban areas and highways (0: 0 trips, 1: 1 trip, 2: 2 trips, 3: 3 trips, 4: 4 trips, 5: 5 trips, 6: >5 trips).
- **fatigue_driving_behavior_change**: Average self-reported behavioral adaptations under fatigue (1: vehicle immobilization, 2: speed reduction, 3: speed increase, 4: driving near the road edge, 5: phone use or passenger interaction, 6: energy drink consumption, 7: window opening, 8: no behavioral change).

The regression estimates in **Table 2** demonstrate that driving on highways (Ur_Hw = 1) is the dominant predictor of higher average speeds, contributing an increase of 145.6% compared to urban roads. Fatigue driving is also associated with a statistical significant increase in speed by 20.8% ($\beta = 7.074$, $p = 0.015$), suggesting a behavioral tendency among fatigued drivers to adopt faster speeds, potentially as a maladaptive compensatory mechanism.

Significant effects were further observed for the number of daily trips (routes_per_day) and fatigue-related behavioral adaptations (fatigue_driving_behavior_change). Specifically, average speed increases by 8.5% with a higher number of trips per day, while fatigue-related behavior changes are associated with a marginal 0.1% increase in speed. Additionally, the number of hours awake (hrs_awake) exerted a measurable effect on speed ($\beta = 0.763$, $p = 0.011$), indicating the role of sleep deprivation in speed regulation.

The model explains approximately 69.3% of the variance in average speed ($R^2 = 0.693$; adjusted $R^2 = 0.683$), reflecting a moderate to good level of explanatory power. These results emphasize the combined influence of environmental conditions and fatigue-related factors on speed regulation.

Table 2: *Average Speed Model Prediction*

Independent Variables	βi	Std. Error	t Value	p-Value	e	e*
(Constant)	11.962	5.406	2.213	0.028*		
Discrete variables						
fatigue	7.074	2.881	2.456	0.015*	0.208	2.443
Ur_Hw	49.526	2.896	17.103	0.000***	1.456	17.104
routes_per_day	2.896	0.813	3.562	0.000***	0.085	1.000
Continuous variables						
hrs_awake	0.763	0.296	2.582	0.011*	0.000	2.111
fatigue_driving_behavior_change	3.107	0.754	4.119	0.000***	0.001	1.000
$R^2 = 0.693$						
Adjusted $R^2 = 0.683$						

* Significance at the 95% confidence level/*** 99.9%.

3.2 Reaction Time Model

The relationship between driver reaction time and influencing variables is expressed in **Equation (6)**:

Avg_ReactionTime = 0.939 + 0.226 × fatigue + 0.361 × Ur_Hw + 0.406 × gender + 0.116 × routes_per_day + 0.136 × intense_level_mle, **(6)**

Where:

- **Avg_ReactionTime:** Average reaction time (seconds).

- **fatigue:** Driver fatigue (1: driving with fatigue, 0: driving without fatigue).
- **Ur_Hw:** Driving environment (0: urban, 1: highway).
- **gender:** Gender (1: male, 2: female, 3: other).
- **routes_per_day**: Number of daily trips in urban areas and highways (0: 0 trips, 1: 1 trip, 2: 2 trips, 3: 3 trips, 4: 4 trips, 5: 5 trips, 6: >5 trips).
- **intense_level_mle:** Intensity level of exercise or manual labor performed by the driver during the day (1: none, 2: low, 3: moderate, 4: high, 5: very high).

As indicated in **Table 3**, fatigue significantly increases reaction time by 0.226 seconds ($p = 0.032$), 16.8% compared to non-fatigue driving, confirming the established link between cognitive impairment and fatigued driving. The gender variable also emerges as a significant predictor, with female participants displaying longer reaction times ($\beta = 0.406$, $p < 0.001$), 30.2% increased compared to males.

Driving on highways (Ur_Hw = 1) and higher daily trip frequency (routes_per_day) are both associated with delayed reaction times ($p = 0.006$ and $p = 0.005$, respectively). Furthermore, increased physical exertion during the day (intense_level_mle) contributes to slower reaction performance ($\beta = 0.136$, $p = 0.045$), reflecting the combined burden of physical and mental fatigue.

The model achieves an R^2 of 0.519 and an adjusted R^2 of 0.448, indicating moderate explanatory strength.

***Table 3:** Reaction Time Model Prediction*

Independent Variables	βi	Std. Error	t Value	p-Value	e	e*
(Constant)	0.939	0.143	6.586	0.000***		
			Discrete variables			
fatigue	0.226	0.101	2.237	0.032*	0.168	1.951
Ur_Hw	0.361	0.122	2.960	0.006**	0.268	3.110
gender	0.406	0.107	3.801	0.001***	0.302	3.500
routes_per_day	0.116	0.038	3.040	0.005**	0.086	1.000
intense_level_mle	0.136	0.065	2.077	0.045*	0.101	1.172
$R^2 = 0.519$						
Adjusted $R^2 = 0.448$						

* Significance at the 95% confidence level/**99%/*** 99.9%.

3.3 Headway Distance Model

Headway distance is modeled through **Equation (7)**, incorporating driver fatigue, environmental conditions, traffic density, age, and reported fatigue symptoms:

$$\text{Avg\_Hway} = 91.470 - 19.785 \times \text{fatigue} + 57.973 \times \text{Ur\_Hw} - 127.456 \times \text{Volume} + 2.395 \times \text{age} - 7.756 \times \text{fatigue\_driving\_symptoms}, \quad \textbf{(7)}$$

Where:

- **Avg_Hway:** Headway Distance (m).
- **fatigue:** 1: Driving with fatigue, or 0: without fatigue.
- **Ur_Hw:** Driving environment - 0: urban road, or 1: highway.
- **Volume:** Traffic volume - 0: low traffic, or 1: high traffic.
- **age:** Driver's age (years).

- **fatigue_driving_symptoms:** Self-reported fatigue symptoms experienced by drivers (mean of responses - e.g., 1: tendency to fall asleep, 2: lack of concentration, 3: yawning, 4: eye blinking, 5: no symptoms, 6: other).

Results presented in **Table 4** highlight the negative impact of fatigue on headway distance, with fatigued drivers maintaining 15.5% shorter following distances compared to non-fatigued drivers ($\beta = -19.785$, $p < 0.001$). Traffic volume exhibits the strongest influence, with high-volume conditions reducing headway distance by 100% ($p < 0.001$). Driving on highways (Ur_Hw = 1) is associated with a 45.5% increase in headway distance compared to urban driving conditions ($\beta = 57.973$, $p < 0.001$), suggesting that drivers allow for more space between vehicles in less dense traffic environments.

Additionally, older drivers tend to maintain longer headway distances, with each unit increase in age associated with an 8.4% increase in headway ($\beta = 2.395$, $p = 0.028$). In contrast, greater self-reported fatigue symptoms are linked to a 0.1% reduction in headway distance ($\beta = -7.756$, $p = 0.017$), further illustrating the behavioral impact of perceived fatigue.

The model explains approximately 70.5% of the variance in headway distance ($R^2 = 0.705$; adjusted $R^2 = 0.695$), indicating a good level of explanatory power for the observed relationships.

Table 4: *Headway Distance Model Prediction*

Independent Variables	**βi**	**Std. Error**	**t Value**	**p-Value**	**e**	**e***
(Constant)	91.470	25.889	3.533	0.001***		
Discrete variables						
fatigue	-19.785	5.148	-3.843	0.000***	-0.155	1.000
Ur_Hw	57.973	6.219	9.322	0.000***	0.455	-2.930
Volume	-127.456	6.832	-18.657	0.000***	-1.000	6.442
Continuous variables						
age	2.395	1.078	2.222	0.028*	0.000	8.449
fatigue_driving_symptoms	-7.756	3.220	-2.409	0.017*	-0.001	1.000
$R^2 = 0.705$						
Adjusted $R^2 = 0.695$						

* Significance at the 95% confidence level/*** 99.9%.

3.4 Longitudinal Acceleration Model

The Longitudinal Acceleration Model, formulated in **Equation (8)**, assesses the effects of fatigue, driving environment, driving experience, and fatigue symptoms on longitudinal acceleration control:

$$Avg\_AccLon = -0.359 - 0.102 \times fatigue + 0.233 \times Ur\_Hw - 0.019 \times years\_drive + 0.047 \times fatigue\_driving\_symptoms, \quad \textbf{(8)}$$

Where:

- **Avg_AccLon:** Average Longitudinal Acceleration (m/s^2).
- **fatigue:** 1: Driving with fatigue, or 0: without fatigue.
- **Ur_Hw:** Driving environment - 0: urban road, or 1: highway.
- **years_drive:** Driving experience in years.

- **fatigue_driving_symptoms:** Self-reported fatigue symptoms experienced by drivers (mean of responses - e.g., 1: tendency to fall asleep, 2: lack of concentration, 3: yawning, 4: eye blinking, 5: no symptoms, 6: other).

As reported in **Table 5**, fatigue is associated with a 33.8% reduction in longitudinal acceleration (β = -0.102, p < 0.001), while highway driving substantially increases it (β = 0.233, p < 0.001), indicating more cautious acceleration behavior under fatigued conditions. Conversely, driving on highways (Ur_Hw = 1) leads to a 76.9% increase in acceleration (β = 0.233, *p* < 0.001), reflecting the higher acceleration demands of highway environments.

Driving experience exerts a modest protective influence, with each additional year of driving associated with a 0.1% decrease in acceleration (β = 0.047, p = 0.007), suggesting an interaction between subjective fatigue perception and vehicle control behavior. Furthermore, fatigue symptoms are linked to a 0.2% increase in longitudinal acceleration (β = 0.047, p = 0.007), indicating that subjective fatigue perception may lead to subtle compensatory driving behavior, possibly reflecting decreased motor control or riskier tendencies under fatigue.

Despite these significant findings, the model's explanatory capacity remains moderate (R^2 = 0.367), indicating the potential role of additional unmeasured variables.

Table 5: *Longitudinal Acceleration Model Prediction*

Independent Variables	βi	Std. Error	t Value	p-Value	e	e*
(Constant)	-0.359	0.056	-6.384	0.000***		
Discrete variables						
fatigue	-0.102	0.028	-3.633	0.000***	-0.338	1.000
Ur_Hw	0.233	0.029	8.158	0.000***	0.769	-2.274
Continuous variables						
years_drive	-0.019	0.006	-3.292	0.001**	-0.001	1.494
fatigue_driving_symptoms	0.047	0.017	2.757	0.007**	0.002	1.000
R^2 = 0.367						
Adjusted R^2 = 0.354						

* Significance at the 95% confidence level/*99%/*** 99.9%.

4. Discussion

The analysis of the present study provides significant insights into the multifaceted effects of driver fatigue on key aspects of driving behavior, including average speed, reaction time, headway distance, and longitudinal acceleration. Through the application of linear regression models, the study quantitatively demonstrates that fatigue, induced by sleep deprivation, systematically degrades driving performance across these critical metrics.

A principal finding of this research is that fatigue is associated with increased driving speed. This outcome may reflect a behavioral tendency among fatigued drivers to engage in maladaptive compensatory strategies, such as accelerating in an attempt to reduce overall driving time. Such compensatory behaviors under fatigue have been previously observed in the literature, where cognitive impairments diminish risk perception and lead to inadequate self-regulation during driving tasks (Jirgl et al., 2024). The observed contribution of highway driving to higher speed levels is also consistent with prior studies showing that monotonous road environments with low geometric variety can exacerbate driver fatigue and reduce vigilance, thereby influencing speed regulation and performance (Farahmand & Boroujerdian, 2018). Equally important is the finding that fatigue significantly prolongs reaction time, confirming well-established evidence on the neurocognitive consequences of sleep deprivation. Reaction time is a critical component of hazard perception and collision avoidance, and its deterioration under fatigue mirrors or even exceeds the performance impairments documented in alcohol-impaired driving studies, suggesting comparable or greater levels of risk (Lowrie & Brownlow, 2020). The study also identifies demographic factors such as gender as significant contributors, with female drivers exhibiting longer reaction times on average. While this result aligns with certain strands of previous research, it remains an area where the influence of physiological, cognitive, and sociocultural factors requires further investigation.

The reduction in headway distance among fatigued drivers, another key outcome of this study, raises serious safety concerns. Maintaining an appropriate following distance is vital for collision prevention, particularly in congested environments where reaction time is critical. The finding that high traffic volume further exacerbates the reduction of headway distance is consistent with previous field studies on car-following behavior under fatigue conditions, which reported similar tendencies toward reduced time headway and greater variability in following distance (H. Zhang et al., 2016). The results regarding longitudinal acceleration reveal a somewhat more complex relationship. Fatigue was associated with decreased acceleration, possibly reflecting either impaired psychomotor control or deliberate defensive adjustments by fatigued drivers. However, the explanatory power of the longitudinal acceleration model was notably lower compared to the other models, suggesting that this aspect of driving behavior may be influenced by additional situational or emotional variables not accounted for in the current analysis. Previous work has similarly highlighted the sensitivity of longitudinal control to external factors such as road geometry, real-time traffic conditions, and psychological stressors (Xu et al., 2013).

An interesting aspect of the findings is the role of behavioral adaptations reported by participants as strategies to counteract fatigue, including speeding, window opening, or energy drink consumption. However, these adaptations were insufficient to neutralize the negative effects of fatigue on driving performance, confirming that self-regulation under fatigue is largely ineffective when it comes to maintaining safe driving behavior. This result reinforces calls from the literature for the integration of objective fatigue monitoring systems into vehicles, using physiological signals such as EEG or eye closure rates, to provide timely feedback and prevent fatigue-induced performance degradation (Wang et al., 2023).

Despite the strength of the results, several limitations should be acknowledged. The controlled simulator environment, while providing high experimental control, may not fully replicate the complexity of real-world driving scenarios. Additionally, self-reported fatigue symptoms and behavioral changes, though valuable, are inherently subject to bias. The sample was also limited to young adult drivers, which may restrict the generalizability of the findings to other age groups or professional driving populations. Despite these limitations, the study offers important implications for both road safety policy and fatigue management practices. The quantification of fatigue-related impairments across multiple driving metrics supports the development of targeted interventions, including maximum driving hour regulations, fatigue awareness training, and technological solutions such as in-vehicle alert systems. Furthermore, these results suggest that addressing fatigue should remain a central focus in efforts to reduce traffic-related injuries and fatalities, particularly in high-risk settings such as long-haul driving or shift work.

5. Conclusions

The analysis conducted in this study provides compelling evidence that driver fatigue significantly affects key driving performance indicators, including speed, reaction time, headway distance, and longitudinal acceleration. Specifically, fatigue leads to increased driving speeds, prolonged reaction times, reduced following distances, and alterations in acceleration behavior, all of which may elevate crash risk.

The models developed offer valuable insights into the mechanisms through which fatigue compromises road safety, confirming the detrimental influence of both subjective fatigue perception and objective behavioral adaptations. The inclusion of demographic and environmental variables further enhances the understanding of these dynamics.

These findings underscore the importance of effective fatigue monitoring and management strategies, such as limiting driving duration, implementing in-vehicle alert systems, and educating drivers about the risks associated with fatigued driving. Moreover, given that behavioral adaptations like speeding and headway reduction are insufficient to mitigate fatigue-related impairments, regulatory approaches focusing on maximum driving hours and compulsory rest periods remain critical.

Future research should aim to extend these findings through naturalistic driving studies that incorporate real-time physiological monitoring and behavioral tracking under diverse driving conditions. Such research could further clarify the interplay between fatigue, workload, emotional states, and environmental complexity, providing a deeper understanding of the mechanisms through which fatigue compromises road safety. Future research should explore additional moderating factors, including sleep quality, stress levels, and real-world traffic dynamics, to refine predictive models and enhance the generalizability of these results across different populations and driving scenarios.

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