Evaluation of safety interventions on risky driving behavior using data from a novel naturalistic driving experiment

Virginia, Petraki[1]*, Stella, Roussou[1], Christos, Katrakazas[1], Laurie, Brown[2], Rachel, Talbot[2], Md Rakibul Alam[3], Christelle, Al Haddad[3], Constantinos, Antoniou[3], Kris, Brijs[4], Muhammad, Adnan[4], Tom, Brijs[4], George Yannis[1]

[1]National Technical University of Athens, Department of Transportation Planning and Engineering, 5 Heroon Polytechniou str., 15773, Athens, Greece
[2]Transport Safety Research Centre, Loughborough University, Loughborough LE11 3TU, United Kingdom
[3]Technical University of Munich, Chair of Transportation Systems Engineering, Arcisstrasse 21, 80333, Munich, Germany
[4]UHasselt, School for Transportation Sciences, Transportation Research Institute (IMOB), Agoralaan, 3590 - Diepenbeek, Belgium

Abstract

This paper aims to evaluate the H2020 project i-DREAMS safety interventions impact on risky driving with a specific focus on speeding events. In this framework, a negative binomial model is developed to examine the correlations between 'high' severity speeding events per 100 km where the driver exceeds the proposed speed limit, the safety intervention schemes, and other risky driving factors. Additionally, a Friedman test is conducted to further explore the differences in risky driving behavior among the different intervention schemes. The findings highlight the positive impact of combining real-time and post-trip interventions, in reducing 'high' speeding events. Moreover, it is revealed that the presence of harsh acceleration, deceleration, and steering, and fatigue events amplifies the frequency of speeding. Overall, these findings emphasize the efficacy of specific intervention schemes and highlight the importance of addressing multiple risk factors simultaneously to enhance driver behavior and ensure road safety.

Keywords: *on-road field trials, risky driving behaviour, safety interventions, Friedman test.*

1. Introduction

Road crashes constitute a major and growing social problem internationally, accounting for approximately 1.3 million fatalities and being the eighth leading cause of death globally (WHO, 2022). Considering that the primary cause of road crashes is attributed to driving behaviour factors (Singh, 2018), the analysis of driver behaviour can lead to the improvement of road safety and more generally to the promotion of sustainable mobility (Mantouka et al., 2020; Huang et al., 2018; Sagberg et al., 2015). Driving behavior comprises a large number of factors that have been found to contribute to road crashes (Dingus et al., 2016). Among other factors, risky behavior can include driving while impaired, driving too fast for the conditions, tailgating, unsafe passing or lane changing (Kaiser et al., 2020).

Naturalistic driving studies have been extensively documented in the literature, as effective and accurate means of assessing driving behaviour (Singh et al., 2021). The naturalistic driving approach has considerable added value over more traditional methods as it ensures continuous, automatic and standardized data collection (Toledo and Shiftan, 2016; Wegman and Bos, 2015). Considering the exploitation of new connected technologies and the adaptation of big data in recent decades, automotive telematics and driver monitoring systems were introduced to provide safety interventions as well as feedback to the driver; the main objective of safety interventions is to improve driving behaviour (Zaira and Hadikusumo, 2017).

Evidence from several driving studies confirms the positive contribution of using real-time and post-trip interventions to reduce risky driving behaviors. One study by Payyanadan et al. (2017) found that providing interventions to older drivers resulted in a reduction of route risk by 2.9% per week and a decrease in speeding frequency by 0.9% per week. Another study by Toledo and Shiftan (2016) concluded that full post-trip feedback led to an 8% reduction in safety events. However, the positive effects tended to decline after a few weeks. Gamification features were found to have a positive impact on user retention and sustainable behavioral change (Musicant & Lotan, 2016). Additionally, studies by Toledo et al. (2008) and Donmez et al. (2008) showed that real-time and post-trip interventions led to significant reductions in crash rates and improved driving behavior.

Considering the importance of post-trip and real time interventions, the overall aim of the European Union's Horizon 2020 i-DREAMS project is to set up a platform and system that provides timely interventions to keep drivers in a safe driving area. Specifically, i-DREAMS aims to setup a framework for the definition, development and validation of a context-aware 'Safety Tolerance Zone (STZ)' for driving. The experimental design of the i-DREAMS on-road study consists of four phases, the baseline phase during which the driving behaviour is monitored without receiving any interventions in case of risky driving, and the other three phases during which during which real-time and post-trip interventions are provided to the drivers.

Within this context, this paper aims to assess the impact of i-DREAMS safety interventions on risky driving behavior. To capture risky driving behaviour, speeding events during which crash risk is further increased if no preventative action taken by driver, were investigated. 4,633 trips from a sample of 25 German drivers were analyzed to develop a negative binomial regression model for depicting the correlations between the high speeding among the different safety interventions and other risky driving factors such as harsh acceleration and braking, steering, and fatigue. Then, a Friedman test was used to determine if there is a statistically significant difference on speeding events among the Phases.

Following the introduction, this paper is structured as follows: section two outlines the methodology employed to address the research objectives of this study. It encompasses the experimental design of the i-DREAMS naturalistic driving experiment, the dataset description, and the statistical analysis methods utilized. Section three presents the analysis results, while section four consolidates the conclusions drawn from this research and proposes paths for future investigations.

2. Methodological background

2.1 The i-DREAMS naturalistic driving experiment

The i-DREAMS field trials took place in five European countries: Belgium, Greece, Germany, Portugal and the United Kingdom, focusing on both private and professional drivers for four different transport modes: cars, trucks, buses and rail. The main focus of the i-DREAMS on-road trials was on assisting drivers in maintaining their driving in STZ level 1, by monitoring their driving behaviour and by implementing real-time and post-trip interventions. The purpose of the i-DREAMS interventions is to effectively increase driver safety by supporting drivers in their driving task. The experimental design of the i-DREAMS on-road study is displayed in the following figure and consists of four phases.

Phase 1
- **Intervention: NO**, a reference period after the installation of i-DREAMS system to monitor driving behaviour without interventions
- **Duration**: 4 weeks

Phase 2
- **Intervention**: **YES,** a monitoring period during which only in vehice real-time warnings provided using adaptive ADAS
- **Duration**: 4 weeks

Phase 3
- **Intervention**: **YES**, a monitoring period during which in addition to the real-time in vehicle warnings, drivers received feedback on their driving performance through the app
- **Duration**: 4 weeks

Phase 4
- **Intervention**: **YES**, a monitoring period during which in-vehicle real-time interventions were active along with feedback and at the same time gamification elements
- **Duration**: 6 weeks

Figure 1: *The i-DREAMS on-road experiment interventions*

Phase 1 was the baseline phase of the experiment during which driving behaviour was monitored without receiving any interventions in case of detection of risky driving events. The ultimate goal of the collection of baseline measurements was the comparison of the driving behavior without receiving any interventions with the driving behavior when receiving safety interventions. This baseline measurement is important for the validity and reliability of the on-road trials as it allows to establish the possible effects of the interventions on driving behaviour. The duration of the baseline stage was 4 weeks.

The next phase (Phase 2) was a four-week period during which real-time interventions were implemented using an in-vehicle warning system which belongs to the category of adaptive ADAS. It is noted that the adaptive ADAS use flexible thresholds to determine the status of the STZ. The STZ defines three risk levels that a driver can be in, which are presented in the following table.

Table 1: *Phases of the STZ*

STZ level	Driving Phase	Description	Interventions
1	Normal driving phase	Crash risk is minimal	no real-time interventions were necessary
2	Danger phase	Risk of crash increases as internal /external events occur	a visual warning like a message is presented and audible warning
3	Avoidable crash phase	Crash risk is further increased if no preventative action taken by driver	a more intrusive instruction signal (e.g., visual warnings like flashes and auditory warnings like beeps) is provided

The fundamental goal of the i-DREAMS platform is to keep the driver in the normal driving phase for as long as possible and, where this is not possible, to prevent the transition from the danger to the avoidable accident phase.

During Phase 3, a combination of real-time and post-trip interventions were provided to the drivers. The i-DREAMS post-trip interventions can be qualified as digital-or internet-based interventions via app, and are to be understood as combining e-coaching with virtual coaching. For four weeks, drivers received real-time feedback through in-vehicle warnings combined with post-trip feedback in the smartphone app. During the last phase (Phase 4) which lasted six weeks, gamification features were additionally provided to the drivers. The difference with the previous phase lied in the fact that drivers were rewarded or receive benefits when they kept applying safe driving behaviour as well as a competitive element introduced with the leader board function.

2.2 The data

The i-DREAMS naturalistic driving experiment collected data concerning a variety of factors about Safety Promoting Goals (SPGs) and Performance Objectives (PO). SPGs encompass driving behaviors linked to safety outcomes, categorized into vehicle control, speed management, road sharing, and driver fitness. POs are specific actions or behavioral parameters necessary to achieve the SPGs (Brijs et al., 2020).

In the framework of this paper, it must be noted that PO and SPG events are presented in the following two severity levels ‘medium severity’, and ‘high severity’, which correspond to the ‘Danger’ and ‘Avoidable crash’ driving phases of the STZ. It is highlighted that the driving phase of the STZ is determined in function of flexible thresholds instead of so-called ‘fixed thresholds’.

In the case of Germany, there were limitations with the installations, resulting in a lack of 'road sharing' data. Additionally, only two German drivers had valid distraction data, which was insufficient for analysis. As a result, the analysis focuses on 'vehicle control,' 'speeding,' and 'fatigue' data. To accurately analyze 'speeding' events, a post-processing step was performed. The i-DREAMS recorded system occasionally misidentified speed limit signs, leading to false positives and false negatives. GPS data from each trip was used to map-match and determine the correct speed limit, allowing identification of speeding events based on the recorded vehicle speed at each GPS point.

The dataset utilized in this research comprises driving data captured by the i-DREAMS sensors during the German on-road field trials. Specifically, a total of 4,633 trips from a sample of 25 passenger car drivers were analyzed, covering the period from February to September 2022. Before starting the analysis, data was cleaned removing trips that were ‘outside phase’, excluding drivers who did not have trip data in all four phases, removing the trips that were outliers (defined as the mean +/- three standard deviations), and excluding the trips with a distance of less than 1km.

To provide a comprehensive overview, the following table presents descriptive statistics for each variable considered in this analysis. It must be noted that events results are presented for ‘high severity’, ‘medium severity’, and ‘total’ (medium + high) events. The total number of events is calculated as the sum of events for each PO.

Table 2: *Descriptive statistics for events per 100km*

Variable	Severity	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	STD
Speeding	Total	0	16	40	53	73	608	54
	Medium	0	0	6	14	19	295	22
	High	0	9	28	40	56	473	45
Vehicle Control	Total	0	27	67	95	131	1,193	101
	Medium	0	25	61	84	117	994	87
	High	0	0	0	11	12	304	23
Acceleration	Total	0	0	14	35	44	846	62
	Medium	0	0	13	29	38	819	51
	High	0	0	0	5	0	304	17
Deceleration	Total	0	0	0	4	0	188	13
	Medium	0	0	0	4	0	130	11
	High	0	0	0	1	0	94	4
Steering	Total	0	8	33	56	77	650	70
	Medium	0	7	31	51	71	650	63
	High	0	0	0	5	0	254	13
Fatigue	Total	0	0	0	0	0	59	1
	Medium	0	0	0	0	0	59	1
	High	0	0	0	0	0	2	0
Total	Total	0	59	115	148	204	1,492	130
	Medium	0	34	73	98	135	1,094	93
	High	0	13	37	50	70	481	53
Distance (km)/trip	NA	1.00	3.94	7.94	15.82	14.82	380.59	29.94
Duration (sec)/trip	NA	61.00	429.00	758.50	1,091.80	1,313.80	14,637	1253

In analyzing the data, several observations emerged regarding the nature of risky driving events and trip characteristics. For most variables, the occurrence of 'medium' severity events outnumbered 'high' severity events. This pattern is expected as drivers typically progress through the 'danger' phase before reaching the 'avoidable accident phase'. However, it's important to note that this trend differs for 'speeding' events. In the case of speeding, the maximum severity level assigned to each instance was determined through post-processing. Consequently, 'medium' events for speeding are only recorded if the driver did not subsequently experience a 'high' event.

Looking specifically at vehicle control events, it was found that 'deceleration' events accounted for a minimal proportion compared to 'acceleration' and 'steering' events. This discrepancy can be attributed to the calculation methodology. While the algorithms were developed based on relevant literature, harsh braking did not appear to trigger events in the same manner as harsh acceleration, leading to a lower incidence of 'deceleration' events.

In analyzing fatigue events, it became evident that their occurrence was relatively scarce. This can be attributed to multiple factors. Firstly, drivers sometimes forgot to wear the heart rate monitor bracelet, impacting the collection of relevant data. Additionally, technical issues occasionally prevented the connection of the bracelet to the i-DREAMS system. Lastly, it is worth noting that fatigue severe enough to be a safety risk is itself a rare event.

2.3 Statistical Analysis

2.3.1 Negative Binomial Regression

Since events data belong to the count data category, and more specifically to non-negative count data, linear regression modelling is inappropriate, and other approaches such as Poisson regression, negative binomial, zero-inflated Poisson regression and negative binomial regression have become the state-of-the-art in modelling such data (Washington et al., 2010). When overdispersed data are present, the negative binomial model can be used to overcome this issue. However, when the mean equals variance, the Poisson model is used. The most common relationship between explanatory variables and the Poisson parameter is the log-linear model,

$$\lambda i = e^{\beta \iota} \quad (1)$$

The negative binomial model is derived by rewriting Eq. (1) such that, for each observation i,

$$\lambda i = e^{\beta X \iota + \varepsilon i} \quad (2)$$

where EXP(εi) is a gamma-distributed error term with mean 1 and variance α (Washington et al., 2020).

In the present dataset there are repeated measurements (trips) over the same units (users-drivers) resulting to dependencies between the observations. These repeated measurements may affect the accuracy of the modelling results. On that purpose, a random effects modelling approach shall be used, in order to capture the random heterogeneity due to differences between drivers. To consider random effects in a negative binomial model, Eq. (2) is rewritten as,

$$\lambda ij = e^{\beta X \iota + \varepsilon i} e^{\eta j} \quad (3)$$

where λ_{ij} is the expected number of events for observation i (trips) belonging to group j (e.g., drivers), and η_j is a random effect for observation group j (drivers).

2.3.2 Friedman test

A Friedman test (Friedman, 1937) was conducted to determine if there is a statistically significant difference on speeding events among the different i-DREAMS Phases. The Friedman test is a non-parametric statistical test used to compare multiple related groups and is particularly useful when the data violates the assumptions of parametric tests, such as the repeated measures ANOVA, due to non-normality or when the data is measured on an ordinal scale.

3. Results and Discussion

3.1 Negative Binomial Regression Model

The objective of this research is the quantification and evaluation of the impact of safety interventions on risky driving behavior. In particular, the ‘high’ severity speeding events per 100 km recorded during the avoidable accident phase (STZ level 3) are taken into account as a representative indicator of risky driving behavior considering the variable of interest. Therefore, a zero-inflated negative binomial regression model is developed to describe the effect of the i-DREAMS interventions and the other examined risky driving indicators (e.g., vehicle control and fatigue) on ‘high’ severity speeding events. Specifically, the considered explanatory variables include the i-DREAMS Phase of the naturalistic driving experiment, the distance per trip, the ‘high’ and ‘medium’ severity events per 100 km recorded for vehicle control, the ‘high’ and ‘medium’ severity events per 100 km recorded for fatigue. The final and best fitting model results appear in the following table.

***Table 3:** Zero-inflated Negative Binomial regression model results for 'high' severity speeding events*

Conditional model:	**Estimate**	**Std. Error**	**z value**	**Pr(>|z|)**	
(Intercept)	3.617	0.070	51.620	< 2e-16	***
Phase 2 (ref. level: Phase 1 - Baseline)	-0.005	0.030	-0.150	0.880	
Phase 3 (ref. level: Phase 1 - Baseline)	-0.072	0.031	-2.340	0.020	*
Phase 4 (ref. level: Phase 1 - Baseline)	-0.053	0.029	-1.840	0.065	.
Distance/trip	-0.012	0.000	-26.530	< 2e-16	***
total_acceleration_events per 100 km	0.002	0.000	8.840	< 2e-16	***
total_deceleration_events per 100 km	0.005	0.001	6.060	0.000	***
total_steering_events per 100 km	0.003	0.000	15.260	< 2e-16	***
high_fatigue_events per 100 km	2.017	0.422	4.770	0.000	***
medium_fatigue_events per 100 km	0.017	0.006	2.840	0.005	**

Zero-inflation model:	**Estimate**	**Std. Error**	**z value**	**Pr(>|z|)**	
(Intercept)	-1.475	0.038	-38.610	<2e-16	***
Log-likelihood of the model	-18,942.3				

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Variables are considered statistically significant at the typical 95% level and 90% level, except of Phase 2 which seems to be insignificant. Also, the developed model shows a significant likelihood ratio test at the 95% level, indicating an adequate fit. It should be noted that the final selection of the results of the model was made after several configuration considerations of the many possible combinations of variables, which are not presented here for brevity. The primary method of selection of the optimal models was the maximization of the natural logarithm of the likelihood function, followed by the utilization of the Akaike Criterion Information (AIC).

The regression model results validate the positive impact of i-DREAMS real-time and post-trip interventions on improving driving behavior by reducing 'high' speeding events. Specifically, the events during which the driver exceeds the proposed speed limit, are decreasing significantly by providing a combination of real-time and post-trip interventions (Phase 3) as well as by adding gamification features (Phase 4) compared to no interventions (Phase 1). This finding can be considered in line with a few past studies regarding the positive effect of real-time and post-trip interventions on speeding events (Hickman and Geller, 2005; Zhao and Wu, 20131; Payyanadan et al., 2017). However, it should be noted that while providing only real-time interventions has a positive impact on safety by reducing speeding events, the effect is not statistically significant.

A statistically significant correlation between the distance of the trip and risky driving behavior is depicted. Specifically, it is observed that longer trips have a notable impact on increasing 'high' speeding events, thereby contributing to more risky driving behavior. This finding aligns with previous studies in the literature (Kontaxi et al., 2021) and is logical considering the extended duration of the journey. Additionally, a higher frequency of 'medium' and 'high' severity events recorded for vehicle control, such as harsh acceleration, harsh deceleration, and harsh steering events, has a positive impact on the occurrence of 'high' speeding events. Furthermore, the presence of 'medium' and 'high' severity fatigue events significantly augments the frequency of 'high' speeding events. This result is reasonable as all examined variables indicate risky driving behavior. The increased occurrence of such events amplifies the likelihood of engaging in speeding behaviors, further accentuating the risk factor involved.

3.2 Friedman test

A Friedman test is conducted as a follow-up analysis to explore further the differences in risky driving behavior among the four phases of the experiment. It is particularly suitable when the data violates the assumption of normality, as is the case with the 'high' speeding data in this study. It is important to note that the Friedman test itself does not provide specific information about which Phases differ significantly from each other. Therefore, post-hoc test is conducted to further examine the specific pairwise differences between the Phases. In the following figure the results of Friedman and post-hoc tests are summarized and visualized.

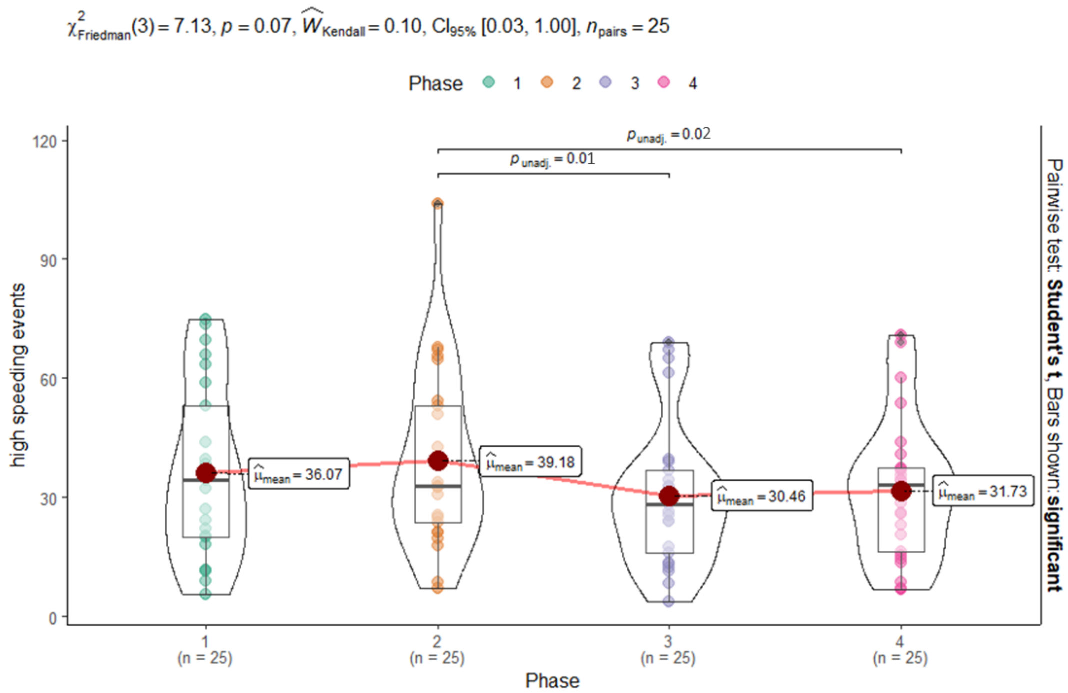

Figure 2: *Friedman test results*

Based on the Friedman test results, there is a statistically significant difference in the 'high' speeding events recorded during the i-DREAMS field trial in Germany $\chi^2_{Friedman}(df=3) = 7.13$, p = 0.07. Additionally, the effect size $W_{Kendall} = 0.10$ with 95% CI [0.03-1] turned out to be substantial. Post-hoc analysis with the Wilcoxon signed-rank test with no correction is used for multiple comparisons. Median recorded 'high' speeding events were 36.07, 39.18, 30.46 and 31.73 for Phase 1 to Phase 4 respectively. There was a statistically significant decrease of high speeding events in Phase 3 vs. Phase 2 (p = 0.01) and in Phase 4 vs. Phase 2 (p=0.02). In other words, the Friedman test reveals a significant decrease in events recorded for high severity speeding when real-time in vehicle warnings and feedback through a smartphone app are provided, and when in-vehicle real-time interventions are active along with feedback and at the same time gamification elements, compared to Phase 2, during which only real-time interventions are provided.

4. Conclusion

The objective of this study was to assess the effectiveness of the i-DREAMS interventions on risky driving behavior, specifically focusing on 'high' severity speeding. The i-DREAMS project aims to establish a framework for the definition, development and validation of a context-aware 'STZ' for driving. The dataset used comprises the recorded events of various risky driving factors per 100 km, involving 25 drivers participating in the German on-road field trial and captured by i-DREAMS sensors.

For the purposes of the analysis a zero-inflated negative binomial regression model was developed to depict the correlations between the 'high' severity speeding events with the real-time and post-trip interventions and other risky driving parameters. Following the development of the regression model, a Friedman test was employed to identify statistically significant differences in speeding among the four intervention schemes (Phase 1-4) of the i-DREAMS experiment. Numerous valuable observations and results pertaining to the impact of i-DREAMS interventions, trip characteristics, and various risky driving parameters on 'high' severity speeding events were obtained.

This study showed that real-time feedback using an adaptive ADAS system and post-trip feedback using a telematics mobile app, had significant positive effects in addressing risky driving behavior, particularly 'high' speeding events. More precisely, the findings highlight the positive impact of combining real-time and post-trip interventions, along with the incorporation of gamification features, in reducing events during which drivers exceed the speed limit. However, the study also reveals that the impact of providing only real-time interventions is positive but not statistically significant in improving safety. Furthermore, the analysis underscores the influence of trip distance on risky driving behavior, with longer trips being associated with a higher occurrence of 'high' severity speeding events. This emphasizes the need for targeted interventions and awareness campaigns for drivers engaging in extended journeys.

Moreover, the study highlights the correlation between vehicle control events (such as harsh acceleration, deceleration, and steering) and the occurrence of 'high' speeding events. Additionally, the presence of 'medium' and 'high' severity fatigue events amplifies the frequency of the speeding, emphasizing the significance of addressing fatigue-related factors in interventions targeting risky driving behaviors.

Looking ahead, future investigations could explore additional factors that contribute to speeding, such as weather conditions, seat belt usage, drug abuse, and alcohol consumption. Integrating real-time data collection and analysis mechanisms into existing interventions can provide immediate insights into these risk factors and enable proactive interventions. Also, expanding the STZ to encompass other modes and users is crucial. While this study focused on risky driving behavior of passenger car drivers, it is essential to extend this framework to accommodate Powered Two Wheelers, cyclists, and pedestrians.

Overall, these findings emphasize the efficacy of specific intervention schemes and highlight the importance of addressing multiple risk factors simultaneously to enhance driver behavior and ensure safer road conditions. This study lays a solid foundation for future research endeavors to further enhance the understanding of effective safety interventions for mitigating risky driving behaviors, ultimately striving towards creating safer road environments for all motorists.

Acknowledgements

Part of this work has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 814761.

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