Investigation of speeding and aggressive behavior of professional drivers on highways through an innovative smartphone application

Armira Kontaxi[1]*, Eleni Konstantina Frantzola[2], Apostolos Ziakopoulos[3], George Kostoulas[4], George Yannis[5]

[1] Τομέας Μεταφορών και Συγκοινωνιακής Υποδομής, Εθνικό Μετσόβιο Πολυτεχνείο
akontaxi@mail.ntua.gr
[2] OSeven Single Member Private Company, Greece
efrantzola@oseven.io
[3] Τομέας Μεταφορών και Συγκοινωνιακής Υποδομής, Εθνικό Μετσόβιο Πολυτεχνείο
apziak@central.ntua.gr
[4] OSeven Single Member Private Company, Greece
gkostoulas@oseven.io
[5] Τομέας Μεταφορών και Συγκοινωνιακής Υποδομής, Εθνικό Μετσόβιο Πολυτεχνείο
geyannis@central.ntua.gr

Abstract

Professional drivers constitute a high-risk road user group mainly due to the increased driving time and distance travelled, the heavy weight of vehicles and the special traffic and operating rules to be followed while driving. In that context, the objective of the present study is to: (i) explore the speeding and aggressive behavior of professional drivers based on detailed driving analytics collected by smartphone sensors, and (ii) investigate whether incentives in a social gamification scheme can improve driving behavior. For that purpose, high-resolution smartphone data collected from a naturalistic driving experiment with a sample of 19 professional drivers were utilized and analysed by means of Generalized Linear Mixed-Effects Models. The findings suggest that speeding and aggressive driving behavior are correlated both to exposure and behavioral driving indicators. Additionally, results capture and quantify the positive effects of awarding safe driving, thus providing needed impetus for larger-scale applications as well as relevant policy interventions.

Keywords: *road safety; professional drivers; driver monitoring; naturalistic experiment; smartphone application; speeding; harsh events*

Περίληψη

Οι επαγγελματίες οδηγοί ανήκουν στις ομάδες ευάλωτων οδηγών κυρίως λόγω της αυξημένης διάρκειας οδήγησης και διανυόμενης απόστασης, του μεγάλου βάρους των οχημάτων αλλά και των ειδικών κυκλοφοριακών κανόνων που πρέπει να ακολουθούν κατά την οδήγηση. Στόχο της παρούσας έρευνας αποτελεί η διερεύνηση: (i) της επικίνδυνης και επιθετικής οδήγησης με βάση αναλυτικά δεδομένα από αισθητήρες κινητών τηλεφώνων και (ii) της επιρροής των συστημάτων παροχής κινήτρων σε ένα πλαίσιο «κοινωνικού παιγνίου» στη βελτίωση της οδηγικής συμπεριφοράς. Για το σκοπό αυτό, δεδομένα υψηλής ανάλυσης που συλλέχθηκαν από πείραμα φυσικής οδήγησης 19 επαγγελματιών οδηγών αναλύθηκαν μέσω Μικτών Γενικευμένων Γραμμικών Μοντέλων. Τα αποτελέσματα δείχνουν ότι η υπερβολική ταχύτητα και η επιθετική συμπεριφορά σχετίζονται τόσο με δείκτες έκθεσης κινδύνου όσο και δείκτες συμπεριφοράς οδηγού. Επιπρόσθετα, τα ευρήματα της μελέτης ποσοτικοποιούν τα θετικά αποτελέσματα της επιβράβευσης της ασφαλούς οδήγησης, παρέχοντας την απαραίτητη ώθηση για εφαρμογές μεγαλύτερης κλίμακας καθώς και σχετικές πολιτικές παρεμβάσεις.

Λέξεις κλειδιά: οδική ασφάλεια, επαγγελματίες οδηγοί, καταγραφή οδηγού, πείραμα φυσικής οδήγησης, εφαρμογή κινητού τηλεφώνου, υπέρβαση ορίου ταχύτητας, απότομα συμβάντα

1. Introduction

1.1 Professional drivers

Road accidents are the leading cause of death from work-related accidents in industrialized countries. For truck, coach, and company car drivers, fatigue and speeding are the most common causes of accidents. (*Professional Drivers | Mobility and Transport*). Yuan et al., 2021 analysed the risk factors associated with truck-involved fatal crashes on various group of truck drivers. The findings revealed that extreme adverse weather, risky driving behavior (fatigue, driving under the influence of alcohol), the use of one or more trailing units, and trucks with heavy weights, were all linked to an increased risk of serious accidents. Uddin & Huynh (2017) examined injury severity in crashes with trucks, concluding that lighting conditions, age and gender of occupant, truck types, speed, and weather condition were found to be factors that have impact on injury severity. Brouwer et al. (2015) conducted a simulator experiment with 26 professional truck drivers to investigate the effectiveness of personalised feedback. Han & Zhao, 2020 investigated driving behavior of professional urban bus drivers in China.

1.2 Type of experiments

An experiment can be carried out mainly in two ways: in a naturalistic experiment, where actual conditions are used or in a simulator experiment, in a more secure and contained environment.

Driver monitoring through naturalistic driving is one of the most recognized developments in road safety. Approaches of that area include the use of high-end technological solutions, exploitation of On-Board Diagnostics (OBD) and smartphone data collection. The last approach has many proven advantages, including uninterrupted and rapid data collection and broad application capabilities, as well as lower costs per examined driver. Dahlinger et al. (2018) performed naturalistic experiments and collected data via smartphone. Elvik (2014) conducted naturalistic trials in several countries to evaluate the impact of rewards to drivers.

There is a variety of studies that used driving simulators for experiments (Dijksterhuis et al., 2015; Molloy et al., 2018; Zhao & Wu, 2012). Donmez et al. (2007) conducted a simulator study to investigate real time feedback on drivers. Mullen et al. (2015) used a driving simulator as a cost efficient and effective solution. Brouwer et al. (2015) and Yuan et al. (2021) both used a driving simulator experiment in order to evaluate truck drivers' behaviour.

1.3 Feedback through gamification

Gamification is the application of game-based design techniques and game-inspired mechanics (e.g. scoring and achievement measurement methods) to non-game contexts. It is a powerful tool that can be used to enable drivers to adopt improved driving behavior (behavior persuasion) (Rossetti et al., 2013). According to Toledo and Lotan (2006) safety-related scores calculated based on in-vehicle monitoring and given to drivers through personal web pages had a major positive impact on driver results. Elvik (2014) carried out a comprehensive analysis of experiments to reward safe and eco-driving and found that they were all successful in encouraging rewarded behaviors. Hamari et al. (2014) found that the effects of gamification (e.g. scores, competition, social pressure, incentives and rewards, tips and recommendations) are positive, although controlled by several factors such as the context in which it is applied as well as the profile of targeted users. Mantouka et al. (2019) found that economic rewards tend to have a major effect on users' willingness to use a mobile application for airports.

1.4 Objectives

The objective of the present study is: (i) to explore the speeding and aggressive behavior of professional drivers based on detailed driving analytics collected by smartphone sensors, and (ii) to investigate whether incentives in a social gamification scheme can improve driving behavior. For that purpose, high-resolution smartphone data collected from a naturalistic driving experiment with a sample of 25 professional drivers is utilised. Generalized Linear Mixed-Effects Models (GLMMs) with the Poisson function are estimated using high-level trip data of professional drivers, to estimate the percentage of driving time over the speed limit and the frequency (counts) of harsh-acceleration and harsh-braking events.

2. Data Collection

2.1 The BeSmart Application

In order to achieve the research objective, an innovative smartphone application developed by OSeven (www.oseven.io) for the purpose of the BeSmart research project was exploited aiming to record driver behavior using the hardware sensors smartphone devices. OSeven has also developed a seamless integration platform for collecting and transferring raw data and recognizing the driving behavior metrics via Machine Learning (ML) algorithms. After the end of each trip, the application transmits all data recorded to the central database of the OSeven backend office via an appropriate communication channel, such as a Wi-Fi network or cellular network (upon user's selection) e.g. 3G/4G (online options). The data collected are highly disaggregated in terms of space and time. The standard procedure that is followed every time a new trip is recorded by the application is showcased in Figure 1.

***Figure 1:** The OSeven data flow system*

The available exposure indicators include indicatively trip duration (seconds), total distance (mileage), type(s) of the road network used, given by GPS position and integration with map providers e.g. Google, OSM, (highway, rural or urban environment) and time of the day when driving. Moreover, the driving indicators associated with driving behavior consist of the following: speeding (distance and time of driving over the speed limit and the exceedance of the speed limit), driving aggressiveness, measured by the number and severity of harsh events (harsh brakings/accelerations) and mobile phone use while driving.

2.2. Experimental Design

Within the framework of BeSmart project, a naturalistic experiment was conducted with different participating driver types: car drivers, professional car drivers, and motorcyclist riders, who all installed the respective BeSmart driver / rider application on their smartphone devices.

In the present paper, the high-risk road user group of professional drivers is analyzed. The experiment consisted of different phases A and B differing in the type of feedback provided to drivers: a) personalized feedback with scorecards, statistics and reports, and b) incentives within a social gamification scheme, with personalized target setting, benchmarking and comparison with peers.

In Phase A, drivers were provided with personalized feedback; namely a trip list, a scorecard regarding their driving behavior and maps and highlights allowing them to identify their critical deficits and unsafe behaviors on the road network (Figure 2 - left). The respective feedback was provided to participant smartphones through the application, each time a trip was completed. More specifically, Figure 2 demonstrates the Scorecard which enables the per trip score on a 0-100 rating scale, as well as additional information with respect to the four driving behavior indicators (from the left to the right); speeding, mobile phone use, harsh breaking, harsh acceleration. Phase B consists of a 30-day competition with prizes for safe driving. The aim of the Competition is to highlight the safest drivers during the Competition, according to their performance through the use of the BeSmart application. The competition points were calculated as the sum of the points collected by the participant in each route within the competition. The points of each route are defined as the product of the distance traveled on the route on the driving behavior factor for the specific route.

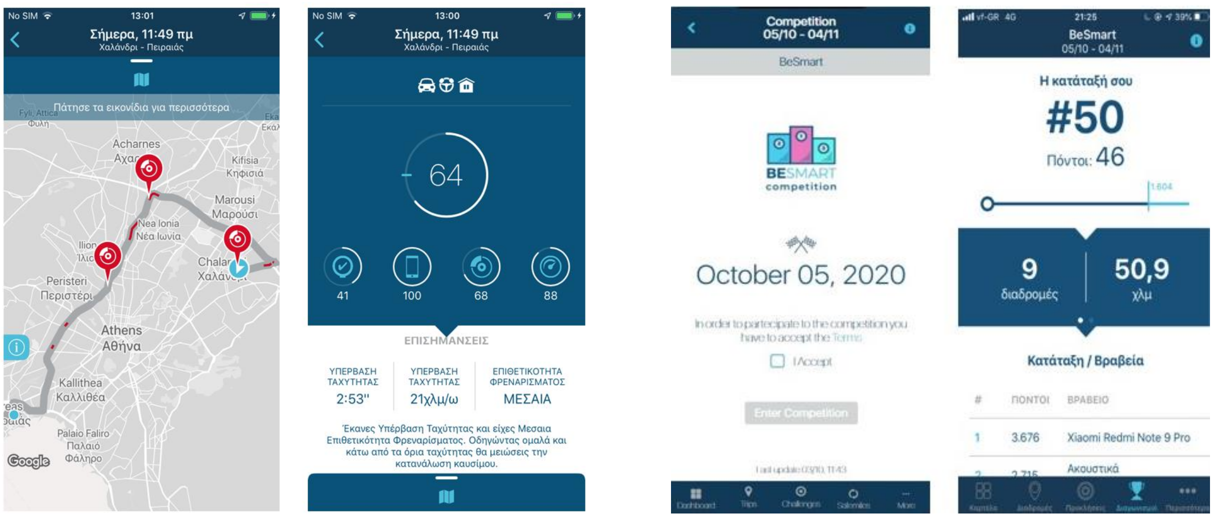

***Figure 2:** Example screenshots from the application features in Phase A – Baseline (left) and Phase B – Competition (right)*

2.3. Participants

Originally, 27 professional drivers volunteered to participate in the experiment and allow for monitoring their driving behavior through the respective smartphone application. However, for the present analysis it was decided that the final sample should consist only of drivers who have participated equally in both phases on terms of trips. An additional criterion was set; all drivers selected for the analysis were required to have driven for at least 20 trips. As a result, from the 27 professional drivers, 19 drivers (all male) were ultimately selected. The participants were aged between 25-34 (n=9), between 35-45 (n=9) and between 45- 54 (n=1). Detailed sample information is presented in Table 1.

***Table 1:** Participant panel description regarding driving and vehicle data (N=19)*

Driving experience (no of years)	Percentage %	Driven distance per year (km)	Percentage %	Engine size (cc)	Percentage %
<5	5.6	< 10.000	0.0	<1500cc	0.0
5 - 10	16.7	10.000 - 20.000	22.2	1500 - 1700cc	0.0
11 - 20	38.9	20.000 - 30.000	16.7	1701 - 1900cc	0.0
21 - 30	38.9	30.000 - 40.000	0.0	1901 - 2200cc	55.6
>30	0.0	> 40.000	61.1	> 2200cc	44.4
Total	100.0	Total	100.0	Total	100.0

3. Methodology

The variables of interest in the present analysis are the three following:

- The percentage of travelled time above the speed limits per trip
- The frequencies of harsh acceleration events per trip
- The frequencies of harsh braking events per trip

Since harsh events can be considered as instances similar to road crashes, but more frequent, a statistical method suitable for dealing with frequency data (in other words, count data) can be implemented. Therefore, Generalized Linear Models (GLMs) which are used when dealing with event count data (Lord & Mannering, 2010) were selected for the statistical analysis. Furthermore, after transforming the speeding percentage per trip to an integer, GLMs were again implemented with a Poisson data distribution. Although GLMs are known to be better used when dealing with frequency (count), after several other modelling attempts, it was concluded that they can serve to adequately model speeding percentages (by conversion of the decimals to integers). Therefore, they were selected as an appropriate methodology to interpret the impact of the independent variables on every aforementioned response variable.

The general form of the GLM models the log-odds via a linear predictor. Following McCulloch (2003), if y is the observed speeding percentage / frequencies of harsh events per trip i, and λ is the expected speeding percentage / frequencies of harsh events to be predicted, then the model is specified as:

$$y_i \sim Poisson(\lambda_i) \quad \textbf{(1)}$$

And the linear predictor is:

$$log(\lambda_i) = \beta_0 + \beta_n x_n + \varepsilon \quad \textbf{(2)}$$

Where β are the fixed-effect parameters (constant and coefficients) for n independent variables, and ε is the error term.

However, one may also consider that in the present dataset there are repeated measurements (trips) over the same units (drivers). Therefore, in order to capture personal driver traits, such as personality and experience, which affects their driving style, and thus the speeding percentage and harsh events they exhibit, random effects are introduced to GLMs in order to extend them as Generalized Linear Mixed-Effects Models (GLMMs). Random effects in GLMMs are expressed as random variable coefficients (random slopes) or random intercepts. For a GLMM containing a random intercept and a random slope for a single independent variable j of the total n, Eq. (2) would be formulated as:

$$log(\lambda_i) = \beta_{0i} + \beta_{ji}x_{ji} + \beta_{n-1}x_{n-1} + \varepsilon \tag{3}$$

Where β_{0i} and β_{ji} follow normal distributions centred at the value of their fixed counterparts:

$$\beta_{0i} \sim N(\beta_0, \sigma_{s,0}^2) \tag{4}$$

$$\boldsymbol{\beta_{ji} \sim N(\beta_j, \sigma_{s,j}^2)} \tag{5}$$

As McCulloch (2003) mentions, random effect models may use correlated independent variables as input, circumventing the limitations of traditional GLMs. Furthermore, it should be mentioned that for computational reasons during the GLMM fitting, the trip data underwent z-score scaling, a common standardization process which does not affect the obtained coefficients. Mathematically, for every parameter x with a mean $\bar{x}$ and a standard deviation S a scaled value is obtained:

$$x_{scaled} = (-\bar{x})/S \tag{6}$$

The best-fitting model which contains the more informative variable combination and explains the highest degree of variance per given dataset is selected as the one with the minimum Akaike Information Criterion (AIC). It is critical to note that the added value of any random effects is assessed by conducting a custom ANOVA (log-likelihood test) between the fixed effects GLM and any formulated GLMMs.

4. Results

Overall, during the two phases of the experiment a large dataset of 5,345 trips from a sample of 19 professional drivers were recorded. Before presenting the model development, it should be highlighted that the majority of professional drivers' trip distance was travelled on highways; namely 84% of the total travelled distance, while 12% and 3% were travelled in the rural and the urban environment, respectively (Figure 3). Taking that into consideration, in combination with the specific driving patterns noticed on highways, the authors decided to analyse explicitly the total of trips travelled on highways.

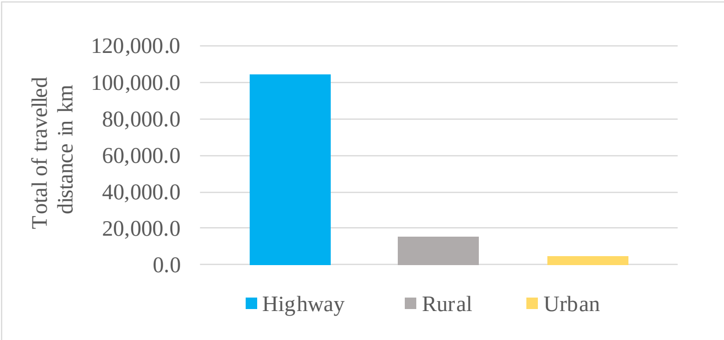

Figure 3: *Total of travelled distance in km per road type*

Furthermore, exploratory descriptive analysis of the data is implemented, allowing for an overview of the four driving indicators that are presented via the application during the two different phases, and the driven average speed as well. Particularly, the descriptive statistics of values of the respective variables are shown in Table 2 and they reveal some interesting first findings. It is obvious that all risk factors show a significant reduction when professional drivers participate in the competition phase, which constitutes an incentive for modelling the impact of rewarded safe driving in a social gamification framework.

Table 2. *Descriptive statistics of the per trip values on highways recorded for Phase A (Baseline) and Phase B (Competition)*

Variable	Baseline		Competition	
	Mean	Std. error	Mean	Std. error
Average speed [km/h]	72.72	0.26	66.09	0.42
Speeding percentage [%]	0.10	0. 006	0.01	0.003
Mobile use percentage [%]	1.72	0.004	0.71	0.007
Harsh accelerations [count]	0.08	0.03	0.02	0.04
Harsh brakings [count]	0.36	0.05	0.07	0.04

In order to model the expected speeding percentage as well as the frequency of events per trip for the participant drivers, models in a GLM framework were calibrated, as previously explained. Since the BeSmart application allows for a high resolution, big-data oriented collection scheme, it was attempted to include random effects in order to capture the unique driving behavior traits for each driver. This entails having a critical minimum sample of trips for each driver to achieve a meaningful outcome. Therefore, a screening was made among participant drivers, as described above, and drivers that had over 20 trips each were selected for the GLMM analysis.

GLMMs were fitted in R-studio (with the lme4 package) via maximum likelihood and using z-factor scaling. A number of models were tested with different configurations in the collected parameters in both fixed effects and random effects. The selected variables were chosen after taking into account the following: lowest Akaike Information Criterion (AIC) for dealing with the trade-off between the goodness of fit of the model and the simplicity of the model, high statistical significance of variables, low multicollinearity, and finally rational interpretation of their impact on the dependent variable. Table 2 provides a description of the variables selected.

***Table 3:** Description of the variables used in the analyses*

Variable	Description
Competition (binary dummy variable)	Competition phase (yes/no)
Trip Duration (continuous numerical variable)	Total trip duration (sec)
Harsh Accelerations (discrete numerical variable)	Number of harsh accelerations per trip
Weekend (binary dummy variable)	Trip realized during the weekend (yes/no)
Speeding Percentage (numerical variable)	Share of time over the speed limit per trip (%)
Harsh accelerations (discrete numerical variable)	Harsh acceleration events per trip (count)
Harsh brakings (discrete numerical variable)	Harsh braking events per trip (count)

4.1 Modeling Speeding

Based on the theoretical background of GLMM, after conducting log-likelihood test ANOVA comparisons, the most informative configuration of random effects included both random intercepts and random slopes in the GLMMs to capture unique rider traits. Table 3 provides a description of the results of mixed effect selection.

***Table 4:** Log-likelihood comparison of mixed effect selection for the speeding percentage model*

Model Family	Model Configuration	D.f.	Log Likelihood	χ^2	P(>χ^2)	Sig.
GLM	Fixed effects only [baseline]	4	-1655.9	–	–	–
GLMM	Fixed effects & Random Intercepts	5	-1504.8	302.19	<2e-16	***
GLMM	Fixed effects, Random Intercepts & Random Slopes	7	-1258.9	491.82	<2e-16	***

The final model was selected as the one with the lowest AIC value. Fixed effect results appear on Table 4. Modelling results reveal some interesting findings. The parameter of harsh accelerations have been determined as statistically significant and positively correlated with the percentage of speeding; the number of harsh accelerations seem to increase speeding percentage by a factor of 1.525, indicating the pattern of a stressful driving style. The exposure metric of trip duration is also found statistically significant, but negatively correlated with speeding percentage. In other words, the longer the trip distance the lower the probability of speeding while driving; by a factor of 0.002. In the same context, driving during the competition phase, reduces the probability of speeding by a factor of 0.225, revealing the impact of the gamification effect on the driving behavior improvement.

***Table 5:** GLMMs for the speeding percentage of 19 professional drivers (fixed effects)*

Trip characteristic	Estimate	s.e.	p-value	Sig.	Relative Risk Ratio
Intercept	-12.581	1.736	0.000	***	-
Competition	-1.492	0.339	0.000	***	0.225
Trip Duration	- 6.148	0.421	0.000	***	0.002
Harsh Acceleration	0.422	0.027	0.000	***	1.525

Significance codes: '***': 0.000 | '**': 0.001 | '*': 0.01 | '.': 0.05 | ' ': ≥ 0.1

4.2 Modelling harsh accelerations

On the same note, in order to model the frequency of harsh accelerations events, log-likelihood test ANOVA comparisons were conducted. As it is shown in Table 5, the most informative configuration of random effects was the inclusion of random intercepts in the GLMMs to capture unique driver traits (lowest LogLikelihood and highest χ^2). Table 5 provides a description of the results of mixed effect selection.

***Table 6:** Log-likelihood comparison of mixed effect selection for harsh acceleration model*

Model Family	Model Configuration	D.f.	Log Likelihood	χ^2	P(>χ^2)	Sig.
GLM	Fixed effects only [baseline]	4	-1198.8	–	–	–
GLMM	Fixed effects & Random Intercepts	5	-1156.8	83.91	<2e-16	***
GLMM	Fixed effects, Random Intercepts & Random Slopes	7	-1151.2	11.13	0.004	**

Results for the harsh acceleration model indicate that the exposure metrics of trip duration as well as driving during the weekend are statistically significant and correlated with the frequency of harsh events. More precisely, trip duration seems to increase the odds of harsh acceleration frequencies; 1 sec of driving time increases acceleration frequencies by 1.558 times. On the other hand, driving during the weekend compared to the weekdays seems to reduce the probability of a harsh acceleration occurrence while driving by a factor of 0.661. This finding can be explained by the different driving style over the week, indicating a less stressful one on the weekends. With respect to the impact of the competition on driving behavior, similar to the speeding model, it is found that drivers seem prone to reducing the frequency of harsh accelerations events when participating in social gamification scheme with prizes and awards; namely by a factor of 0.348.

***Table 7:** GLMMs for harsh accelerations of 19 professional drivers (fixed effects)*

Trip characteristic	Estimate	s.e.	p-value	Sig.	Relative Risk Ratio
Intercept	-3.531	0.341	0.000	***	-
Competition	-1.054	0.219	0.000	***	0.348
Trip Duration	0.444	0.026	0.000	***	1.558
Weekend	-0.414	0.175	0.000	*	0.661

Significance codes: '***': 0.000 | '**': 0.001 | '*': 0.01 | '.': 0.05 | ' ': ≥ 0.1

4.3 Modeling harsh brakings

Similar to harsh acceleration model, the inclusion of random intercepts was the most informative configuration of random effects in order to capture the unique driver traits. The log-likelihood test ANOVA comparisons are presented in Table 7. (lowest LogLikelihood and highest χ^2).

***Table 8:** Log-likelihood comparison of mixed effect selection for harsh braking model*

Model Family	Model Configuration	D.f.	Log Likelihood	χ^2	P(>χ^2)	Sig.
GLM	Fixed effects only [baseline]	4	-3324.6	–	–	–
GLMM	Fixed effects & Random Intercepts	5	-3093.4	462.38	<2e-16	***
GLMM	Fixed effects, Random Intercepts & Random Slopes	7	-3092.3	2.14	0.343	

With respect to harsh braking events model (Table 8), all the independent variables, both driving behavioral and exposure ones, seem to have effects that are similar to the ones they have on the harsh acceleration events. The occurred finding is more obvious when examining the relative risk ratio of every variable. Specifically, trip duration appears to increase the odds of harsh braking frequencies; 1 sec of driving time increases braking frequencies by 1.564 times On the other hand, similarly to the harsh acceleration models, the exposure parameter of the variable "weekend", was found to be negatively associated with the odds of higher harsh braking counts; corresponding to risk ratio of 0.748. Finally, once more, the competition seems to motivate drivers improve their performance adopting a less aggressive style, with lower frequencies of harsh brakings. Notably, driving during the competition phase, the probability of a harsh braking occurrence is reduced by a factor of 0.404.

Table 9: *GLMMs for harsh brakings of 19 professional drivers (fixed effects)*

Trip characteristic	Estimate	s.e.	p-value	Sig.	Relative Risk Ratio
Intercept	-2.384	-8.161	0.000	***	-
Competition	-0.907	-7.738	0.000	***	0.404
Trip Duration	0.447	45.106	0.000	***	1.564
Weekend	-0.290	-3.432	0.001	***	0.748

Significance codes: '***': 0.000 | '**': 0.001 | '*': 0.01 | '.': 0.05 | ' ': ≥ 0.1

5. Conclusions

This paper aimed: (i) to explore the speeding and aggressive behavior of professional drivers on based on detailed driving analytics collected by smartphone sensors, and (ii) to investigate whether incentives in a social gamification scheme can improve driving behavior. For that purpose, high-resolution smartphone data collected from a naturalistic driving experiment with a sample of 19 professional drivers were utilized. Using risk exposure and driving behavior indicators calculated from smartphone sensor data, statistical analyses were carried out for correlating the percentage of driving time over the speed limit, as well as the frequencies of harsh events, with other driving behavior indicators, namely by means of Generalized Linear Mixed-Effects Models.

The results from the interpretation of the estimated parameters of the models can be summarized as follows: Trip duration has a different impact on speeding (negative correlation) compared to harsh events (positive correlation), while driving during the weekends seems to reduce the frequency of harsh events; both accelerations and brakings. In addition, harsh accelerations are associated with the odds of someone exceeding the speed limits, outlining a pattern of an overall unsafe driving behavior.

Furthermore, the present research contributes a preliminary example of the quantitative documentation of the impact of encouraging rewarded behaviors on all the three examined human risk factors; speeding and aggressive behavior as expressed by the frequency of harsh accelerations and harsh brakings. Professional drivers constitute a high-risk road user group mainly due to the increased driving time and distance travelled. In that context, rewarding safe driving behavior and providing drivers with motivations and incentives within a social gamification scheme seems to have successful results. State-of-the-art interventions can include approaches for driver training and support through innovative driver behavior monitoring and feedback tools in a variety of ways; personalized feedback with scorecards as well as incentives within a social gamification scheme, with personalized target setting, benchmarking and comparison with peers.

Finally, future research will also focus on the analysis of different driving behavior parameters identified by the road safety literature as risk factors (e.g. mobile phone distraction) and their effect on driving performance and road safety. Furthermore, analyses per gender, age, crash history, self–assessment, driving experience and more demographic characteristics could be undertaken in order to capture any particular trends found in the categories of these parameters, possibly improving feedback processes, on the condition that this information can be provided while observing data protection laws.

6. Acknowledgements

This research is co-financed by the European Union - European Regional Development Fund (ERDF) and Greek national funds through the Operational Program "Competitiveness, Entrepreneurship and Innovation" (EPAnEK) of the National Strategic Reference Framework (NSRF) - Research Funding Program: BeSmart - Multi-modal driver behavior and safety support system on the basis of smartphone applications.

The research team would like to thank Nea Odos Company for supporting BeSmart project by providing its professional drivers as participants in the experiment.

6. References

Brouwer, R. F. T., Stuiver, A., Hof, T., Kroon, L., Pauwelussen, J., & Holleman, B. (2015). Personalised feedback and eco-driving: An explorative study. *Transportation Research Part C: Emerging Technologies*, *58*(PD), 760–771. https://doi.org/10.1016/j.trc.2015.04.027

Dahlinger, A., Tiefenbeck, V., Ryder, B., Gahr, B., Fleisch, E., & Wortmann, F. (2018). The impact of numerical vs. symbolic eco-driving feedback on fuel consumption – A randomized control field trial. *Transportation Research Part D: Transport and Environment*, *65*, 375–386. https://doi.org/10.1016/j.trd.2018.09.013

Dijksterhuis, C., Lewis-Evans, B., Jelijs, B., De Waard, D., Brookhuis, K., & Tucha, O. (2015). The impact of immediate or delayed feedback on driving behavior in a simulated Pay-As-You-Drive system. *Accident Analysis and Prevention*. https://doi.org/10.1016/j.aap.2014.11.017

Donmez, B., Boyle, L. N., & Lee, J. D. (2007). Safety implications of providing real-time feedback to distracted drivers. *Accident Analysis and Prevention*, *39*(3), 581–590. https://doi.org/10.1016/j.aap.2006.10.003

Elvik. (2014). Rewarding safe and environmentally sustainable driving: Systematic review of trials. *Transportation Research Record*, *2465*(0349), 1–7. https://doi.org/10.3141/2465-01

Hamari, J., Koivisto, J., & Sarsa, H. (2014). Does gamification work? - A literature review of empirical studies on gamification. *Proceedings of the Annual Hawaii International Conference on System Sciences*. https://doi.org/10.1109/HICSS.2014.377

Han, W., & Zhao, J. (2020). Driver behavior and traffic accident involvement among professional urban bus drivers in China. *Transportation Research Part F: Traffic Psychology and Behavior*, *74*, 184–197. https://doi.org/10.1016/j.trf.2020.08.007

Lord, D., & Mannering, F. (2010). The statistical analysis of crash-frequency data: a review and assessment of methodological alternatives. Transportation research part A: policy and practice, 44(5), 291-305.

Mantouka, E. G., Barmpounakis, E. N., Milioti, C. P., & Vlahogianni, E. I. (2019). Gamification in mobile applications: The case of airports. *Journal of Intelligent Transportation Systems: Technology, Planning, and Operations*, *23*(5), 417–426. https://doi.org/10.1080/15472450.2018.1473157

McCulloch, C. E. (2003). Generalized linear mixed models. In NSF-CBMS regional conference series in probability and statistics (pp. i-84). Institute of Mathematical Statistics and the American Statistical Association.

Molloy, O., Molesworth, B. R. C., & Williamson, A. (2018). Improving young drivers' speed management behavior through feedback: A cognitive training intervention. *Transportation Research Part F: Traffic Psychology and Behavior*, *54*, 324–337. https://doi.org/10.1016/j.trf.2018.02.010

Mullen, N. W., Maxwell, H., & Bédard, M. (2015). Decreasing driver speeding with feedback and a token economy. *Transportation Research Part F: Traffic Psychology and Behavior*, *28*, 77–85. https://doi.org/10.1016/j.trf.2014.11.008

Professional drivers | Mobility and transport. (n.d.). Retrieved May 12, 2021, from https://ec.europa.eu/transport/road_safety/users/professional-drivers_en

Rossetti, R. J. F., Almeida, J. E., Kokkinogenis, Z., & Goncalves, J. (2013). Playing transportation seriously: Applications of serious games to artificial transportation systems. *IEEE Intelligent Systems*, *28*(4), 107–113. https://doi.org/10.1109/MIS.2013.113

Toledo and Lotan. (2006). *In-Vehicle Data Recorder for Evaluation of Driving Behavior and Safety*. *1953*, 112–119.

Uddin, M., & Huynh, N. (2017). Truck-involved crashes injury severity analysis for different lighting conditions on rural and urban roadways. *Accident Analysis and Prevention*, *108*, 44–55. https://doi.org/10.1016/j.aap.2017.08.009

Yuan, Y., Yang, M., Guo, Y., Rasouli, S., Gan, Z., & Ren, Y. (2021). Risk factors associated with truck-involved fatal crash severity: Analyzing their impact for different groups of truck drivers. *Journal of Safety Research*, *76*, 154–165. https://doi.org/10.1016/j.jsr.2020.12.012

Zhao, G., & Wu, C. (2012). The effects of driver identity on driving safety in a retrospective feedback system. *Accident Analysis and Prevention*, *45*, 354–365. https://doi.org/10.1016/j.aap.2011.08.002