Discovering the influence of feedback on driver behavior through a multiphase experiment based on a smartphone application

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Extended Abstract

1. Introduction

Measuring driving efficiency has been the focus of many studies in driving behavior literature in the past [1, 2]. From a road safety perspective, it is extremely significant to identify the parameters that affect driving behavior and therefore crash risk. It is only when these parameters are quantified that proper road safety measures can be effectively taken.

There is a significant number of risk factors affecting crash probability identified in literature. The most important risk factors recognized in the literature [3, 4] are human factors (speeding, distracted driving, driving under the influence of alcohol and other psychoactive substances etc.), unsafe road infrastructure, unsafe vehicles and inadequate law enforcement of traffic laws. Among them, human factors are likely to be the most crucial cause of road traffic fatalities and injuries every year and therefore the importance of studying how these factors can affect crash risk is high [5]. The predominance of human factors as crash causes is indicated by the respective percentage, which has been estimated to amount to up to 94% [6].

The importance of driver monitoring is progressively established in the transportation field; despite that, researchers have been struggling with the difficulty of collecting accurate real-time driving data by adopting low-cost collection and processing methods. In that environment, the high penetration rate of smartphones and social networks nowadays provide new opportunities and features to monitor and analyze driver behavior. Apart from the wide smartphone application capabilities and the low cost and ease of use in data collection, experiments under naturalistic conditions with the use of smartphones allow for drivers to be recorded under normal driving conditions and without any influence from external parameters, resulting at being considered as one of the most appropriate methods for the assessment of driving behavior [7].

Many studies have shown promising results using data collected through smartphone sensors under naturalistic driving conditions. By conducting naturalistic driving experiments by means of mobile phone, researchers aim either at examining the effect of various driving behavior indicators on driver performance and cash risk [8,9,10] or at identifying aggressive and dangerous driving profiles through a clustering approach. Going one step further, smartphones have proven to be an extremely useful feedback tool, allowing drivers to get informed about their weak points in regards with safety, namely speeding and aggressive driving style [11] as well as eco-driving [12]. The ultimate objective when providing feedback to drivers is to trigger their learning and self-assessment process and enable them to gradually improve their performance and monitor their evolution [13]. Toledo and Shiftan [14] found that feedback can lead to a reduction of 8% in safety incidents, and 3–10% in fuel consumption, with a higher reduction obtained for large vehicles.

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2. Data Collection

Within the framework of BeSmart Project, a 230 - driver naturalistic experiment spanning 21 months was conducted from July 2019 to March 2021. The experiment consisted of different driver types, namely car drivers, professional van drivers and PTW riders. In the present paper the car drivers who constituted the majority of the experiment sample are examined.

The objectives of the experiment include primarily the identification of critical risk factors through driver monitoring via an innovative smartphone application, and subsequently, the development of driver feedback features allowing to inform, notify and motivate the drivers to improve their critical skills and reduce their driving errors and therefore their crash risk. The experiment consisted of 6 different phases differing in the type of feedback provided to drivers. These phases were defined as follows:
Phase 1, where initially only the trip list and characterization were accessible to the application user.
Phase 2, where a Scorecard was introduced enabling scoring per trip.
Phase 3, where a Maps and Highlights were introduced providing further information per trip.
Phase 4, where Comparisons between drivers were enabled and added.
Phase 5, where Competitions were conducted with prizes for safe driving.
Phase 6, where the application reverted to Phase 1 and all additional feedback was removed from the drivers.

The first two phases of the experiment has already been analysed at previous studies with interesting findings both for car drivers (Kontaxi et al., 2021b) and motorcyclists (Kontaxi et al., 2021a), quantifying the positive telematics impact on driver behavior. The differences in driver performance are going to be evaluated with descriptive and analytic means.

In order to achieve the research objective, an innovative smartphone application was developed aiming at the assessment and improvement of driver behavior and safety. The application is developed by OSeven (www.oseven.io), aiming to record driver behavior using the hardware sensors of the smartphone device. Furthermore, a variety of APIs is exploited to read sensor data and temporarily store them to the smartphone's database before transmitting them to the central (back-end) database. Data collected from the application has been utilised in earlier research papers which also feature additional details regarding the application [15].

The standard procedure that is followed every time a new trip is recorded by the application is clearly presented in Figure 1. The data collected are highly disaggregated in space and time. Once stored in the backend cloud server, they are converted into meaningful driving behavior and safety indicators, using signal processing, Machine Learning (ML) algorithms, Data fusion and Big Data algorithms. This is achieved by using state-of-the-art technologies and procedures, which operate in compliance with standing Greek and European personal data protection legislation (GDPR).

Figure 1. The OSeven data flow system.

3. Methodology

The present analysis aims to examine the impact of feedback to driver behavior, i.e. in which ways driving risk factors are influenced by driver feedback.

Structural Equation Modelling belongs to the model family of latent variable analysis; it is a multivariate technique which can support multiple-input and multiple-output modelling. In the context of the present study, SEM provides an appropriate vehicle to formulate several unobserved constructs in the form of latent variables from the respective feedback phases. SEM is a well-known methodology with wide applications. Several studies have utilized it to model complex interrelationships typically involving unobserved concepts expressed as latent variables, with applications in the traffic engineering and road safety domains as well. The underlying mathematical structure of SEMs can be defined as follows [16]:

$$\eta = \beta\,\eta + \gamma\,\xi + \varepsilon \qquad \text{Eq. (1)}$$

where:
η is a vector expressing the dependent variables
ξ is a vector expressing the independent variables
ε is a vector expressing the regression error term
β is a vector expressing the regression coefficients for the dependent variables
γ is a vector expressing the regression coefficients for the independent variables

4. Results

Overall, during the 12-months experiment 106,776 trips were recorded from a sample of 200 drivers. . However, for the present analysis it was decided that the final sample should consist of drivers who have participated equally in both phases only. An additional criterion was set; all drivers chosen to be included in the analysis were required to have driven at least for 40 trips. This number approximately equals the typical monthly number of working trips for a driver assuming that each driver drives 2 trips per day for 5 working days per week. This number is reasonable to filter out drivers for which there are not enough observations, and it is also the 'industrial' criterion set by OSeven to start providing driver evaluation. As a result, from the 147 car drivers, 65 were ultimately selected creating a large dataset of 21,167 trips. Descriptive statistics of the per trip values of the variables recorded during the experiment are shown in Table 1.

Table 1. Descriptive statistics of the per trip values of the variables recorded during the experiment

Experiment Phases	Percentage of mobile use	Harsh accelerations per 100km	Harsh brakings per 100km	Speed above the speed limits	Percentage of speeding time
Phase1	3.85%	6.42	15.78	3.89km/h	5.32%
Phase 2	2.84%	6.26	13.74	3.19 km/h	3.12%
Phase 3	2.08%	6.26	13.94	2.31 km/h	2.60%
Phase 4	2.28%	6.96	12.54	2.34 km/h	2.45%
Phase 5/ Competition	2.19%	6.24	12.14	1.85 km/h	2.13%
Phase 5/ Challenges	2.41%	8.11	17.18	2.30 km/h	3.21%
Phase 6	2.48%	8.26	16.34	2.60 km/h	3.34%

The results of SEM analysis are presented in this section, showcasing only the final models. Apart from the previously aforementioned hard goodness-of-fit measures, the produced coefficient estimates were also checked to ensure that reasonable results are obtained based on their interpretation. During the modelling process it became apparent that certain model structures fitted the experiment data much more reasonably than others based on the following criteria; only the best overall models are presented herein. For variations within each different latent variable structure, model attempts were conducted with the backwards elimination technique. All statistical analyses were conducted in R-studio (R Core Team, 2013) and SEM analysis in particular utilized the lavaan R package. Ultimately, the proposed SEM structure retained two latent unobserved variables:

- Feedback, expressing the influence of the different features of the smartphone app during the different phases of the experiment, namely Scorecard feature, Maps feature, Compare feature, Competition feature and Challenges.
- Exposure, expressing the influence of the exposure metrics, namely Distance (for driving speed 30km/h – 50km/h), Morning peak and Afternoon peak.

Following SEM calibration, the produced model results are presented on Table 2; statistically significant p-values (≤0.05) are shown in bold. All of the four examined goodness of fit measure values and the signs of the parameter estimated coefficients suggest excellent model fit. As an additional verification, the model AIC was the minimum reached within the examined combinations, and no negative variances were calculated by the model, which would suggest misspecification (variance outputs are not shown here for brevity). It is also important to note that several variables were scaled linearly by factors of 10 to reduce variance discrepancies and to allow better model fit without hindering the coefficient interpretation.

Lastly, several covariances of the measured variables have been integrated in the model by an iterative process which involved comparing the observed and fitted covariance correlations. The largest shown differences were then addressed by including the relevant covariance pair in the model, provided that there were no major prohibitions from the underlying theoretical standpoint. This process aided in improving model fit.

The path diagram of the present model is presented on Figure 2; green arrows denote positive correlations, while red arrows denote negative correlations. Several useful insights can be obtained from the produced SEM model results. First and foremost, it appears that driver feedback during the experiment does have a statistically significant influence on the three examined indicators of the driving behavior risk factors. This means that the insertion of the smartphone application features can improve drivers behavior. Regarding the exposure latent variable, it seems that the exposure risk factors tend to increase the risky driving behavior.

Table 2: SEM model of Percentage of speeding time, Harsh Brakings per 100km & Harsh Accelerations per 100km

SEM Components		**Parameters**	**Estimate**	**S.E.**	**z-value**	**P(>|z|)**
Latent Variables	Feedback	Scorecard feature	1.000	–	–	–
		Maps feature	2.076	0.014	148.640	0.000
		Compare feature	1.646	0.010	157.864	0.000
		Competition feature	1.215	0.029	41.754	0.000
		Challenges feature	2.053	0.038	54.447	0.000
	Exposure	Distance_(for driving speed 30km/h – 50km/h)	1.000	–	–	–
		Morning peak	2.473	0.350	7.072	0.000
		Afternoon peak	-1.360	0.129	-10.579	0.000
Regressions	Percentage of speeding time	Intercept	0.409	0.003	138.941	0.000
		Exposure	0.326	0.043	7.627	0.000
		Feedback	-0.214	0.014	-15.655	0.000
	Harsh Accelerations per 100km	Intercept	0.099	0.001	95.037	0.000
		Exposure	0.028	0.010	2.769	0.006
		Feedback	0.026	0.004	6.493	0.000
		Competition feature	-0.001	0.000	-2.748	0.000
		Afternoon peak	0.006	0.002	3.095	0.002
	Harsh Brakings per 100km	Intercept	0.184	0.001	158.258	0.000
		Exposure	0.077	0.014	5.542	0.000
		Feedback	-0.027	0.005	-4.976	0.000
Covariances	Percentage of speeding time	Harsh Brakings per 100km	0.007	0.001	7.686	0.000
	Harsh Accelerations per 100km	Percentage of speeding time	0.006	0.001	9.526	0.000
	Harsh Brakings per 100km	Harsh Accelerations per 100km	0.021	0.000	75.739	0.000
	Feedback	Exposure	-0.001	0.000	-5.558	0.000
Goodness-of-fit measures		CFI	0.940			
		TLI	0.944			
		RMSEA	0.049			0.845
		SRMR	0.025			

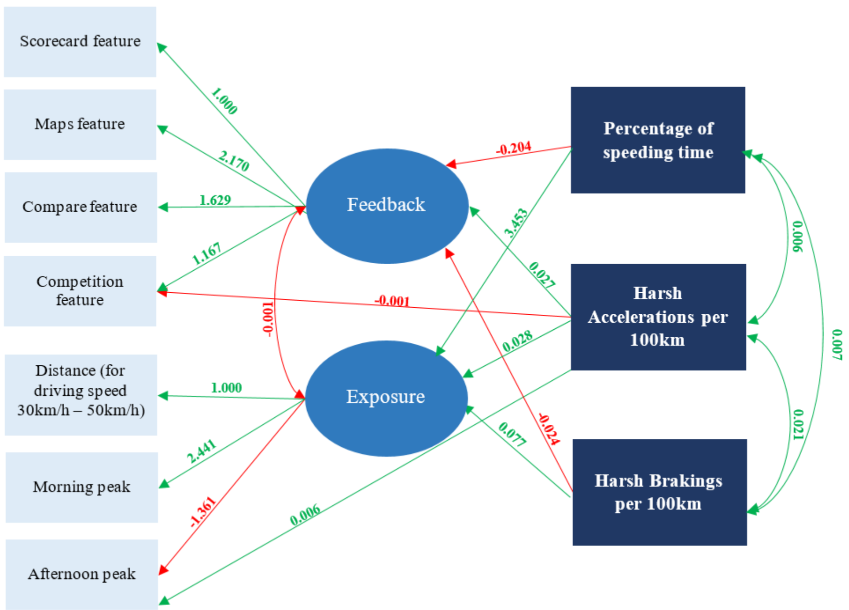

Figure 2: Path diagram of SEM model for percentage of speeding time, harsh accelerations per 100km and harsh brakings per 100km

5. Conclusions

In summary, the findings of the analyses show that both speeding, harsh events, and driver distraction reduce driving performance and lead to a high risk of accident. Therefore, it is extremely important to record drivers and measure various aspects of driving performance in order to evaluate and improve driving behavior and safety. Rapid technological advances, especially in telematics and Big Data analytics, as well as the increasing penetration and use of information technology by drivers (eg smartphones), provide new capabilities for monitoring and analyzing driving behavior. In this context, the BeSmart application on smart phones, has managed to create the driver's security "imprint" while at the same time has developed measures that allow information, feedback, motivation and training of drivers, in order to improve their skills. and reduce their mistakes and the risk of getting involved in an accident.

Ethics approval

This study was conducted with the approval of the National Technical University of Athens – NTUA Ethics Committee

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