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

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Abstract

Background: Advances in smartphone technology are rapid, constantly evolving and revealing new possibilities for data collection, interconnection and analysis in road safety. Furthermore, it is becoming easier to provide direct feedback and trip analysis to drivers about their driving performance regarding road safety, features which are capable of reducing road crash numbers and the corresponding casualties.

Aim: In view of these developments, the objective of the current research is to exploit large-scale trip data from smartphone sensors in order to identify the impacts of driver feedback on various key performance indicators, namely speeding, harsh braking and harsh acceleration events.

Methodology: Within the framework of BeSmart Project, a multimodal 200-driver ongoing naturalistic experiment was set to be conducted, consisting 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 differences in driver performance are going to be evaluated with descriptive and analytic means.

Results: The Covid-19 pandemic swept throughout the globe in an unprecedented surge as the experiment was underway, and the number of participants and corresponding trips was unexpectedly reduced. Furthermore, a critical mass of 65 drivers retained a high enough number of trips (≥40) that was sufficient for more robust statistical analysis. The identified trends were as follows: (i) There is an overall improvement of driving behavior from Phase 1 to Phase 2. (ii) The Covid-19 pandemic and the subsequent lockdown measures greatly reduced trips. (iii) There is a platooning in driver behavior in subsequent phases. (iv) There is an improvement of driving behavior during the Competition phase. (v) There is a relapse towards worse driving behavior as soon as the Competitions phase is completed.

Conclusions: From the execution of the BeSmart experiment, it becomes evident that driving behavior can be evaluated and communicated to drivers. The influence of feedback appears to fluctuate and platoon across the various experimental phases, though it appears that there are some relapse effects for drivers towards the end of the experiment.

Keywords:
road safety; driver monitoring; driver behaviour; smartphone application; feedback effects

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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].

Distracted driving, as one of the most important human factors that influence crash risk, has been attracting the attention of researchers the past decades. Mobile phone use (handheld or hands-free) and complex conversation (at mobile phone or with passengers) appear to be the most critical in-vehicle distraction factors [7]. Given that mobile usage is an inevitable part of everyday driving process and is expected to increase over the years [8], its impact on driving behavior in traffic and road safety is particularly crucial and merits further investigation. The literature so far has showed that when drivers are using mobile phones while driving, several impacts manifest on their behavior expressed in terms of loss of control, response to incidents, or crash occurrence [9, 10].

Speeding has also been the subject of extensive research in the transportation field. Excess and inappropriate speed are responsible for a high proportion of the mortality and morbidity that result from road crashes [11, 12]. In high-income countries, speed contributes to about 30% of deaths on the road, while in some low-income and middle-income countries, speed is estimated to be the main contributory factor in about half of all road crashes [13]. Elvik et al. [14] engaged in relevant research by first questioning whether speed is still as important for road safety as it was in the past, taking into account the penetration of constantly evolving vehicle safety systems in the global automotive market. After reviewing recent research studies regarding the impact of speed on road safety, they conclude that speed remains an important risk factor both for crash occurrence and for injury severity.

Furthermore, apart from speeding and distracted driving, more recent studies highlight the importance of investigating the phenomenon of harsh events in greater detail, as they have been associated with driving risk assessment, risk level correlation and classification [15, 16, 17]. This is because harsh driving events, such as harsh accelerations and harsh brakings, indicate an overall aggressive and unsafe driving behavior; unsafe distance from adjacent vehicles, possible near misses, lack of concentration, increased reaction time, poor driving judgement or low level of experience. From a research scope, during recent years harsh or safety-critical events have been adopted as crash surrogate measures and the understanding of related opportunities and challenges in their interpretation is under increased examination (e.g. [18, 19]).

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 [20].

Smartphones are equipped with a variety of sensors, such as motion sensors (e.g. accelerometer and gyroscope), position sensors (e.g. magnetometer), global navigation satellite system (GNSS) receivers, environmental sensors (barometers, photometers, and thermometers), microphone, cameras, etc. As a result, the exploitation of the various sensors for the purpose of transportation and road safety research allows for continuous, inexpensive and fast data collection, with plenty of studies confirming and even improving the reliability of smartphone measurement data implementing state-of-the-art machine learning and big data algorithms [21, 22]. Vlahogianni and Barmpounakis [23] examined the use of smartphones as an alternative for driving behavior analysis and they concluded that the smartphone-based algorithms may accurately detect four distinct patterns (braking, acceleration, left cornering and right cornering) with an average accuracy comparable to other popular detection approaches based on data collected using a fixed position device.

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 [24, 25, 26] 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 [27] as well as eco-driving [28, 29]. 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 [30]. Toledo and Shiftan [31] 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.

2. Data Collection

2.1 The BeSmart Application

In order to achieve the research aim, a smartphone application developed by OSeven was exploited to investigate the driver feedback effect on driving behavior.

2.2 Experimental Design

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 [33].

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.

A variety of different metadata are eventually calculated, including indicatively the following exposure indicators:

- Total distance (mileage)
- Driving duration
- Type(s) of the road network used (given by GPS position and integration with map providers e.g. Google, OSM)
- Time of the day driving (rush hours, risky hours)

The driving behavior indicators that are also calculated from the data include indicatively:

- Speeding (duration of speeding, speed limit exceedance etc.)
- Number and severity of harsh events
- Harsh braking (longitudinal acceleration)
- Harsh acceleration (longitudinal acceleration)
- Distraction from mobile phone use (mobile phone use is considered any type of phone use by the driver e.g. talking, texting etc.).

3. Methodology

3.1 Structural Equation Models (SEM)

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 question groups and then investigate their correlations with the four risky PTW rider behaviors. 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. As per the aforementioned, SEM have been applied to model psychological factors, personality and attitudes with self-reported behaviors of motorcyclists [34, 35].

Additional examples include the use of SEM to connect anxiety, reward sensitivity and sensation seeking propensity with unsafe driving [36, 37] or perception of risk and driving tasks on road safety attitudes of drivers [38, 39]. The underlying mathematical structure of SEMs can be defined as follows [40]:

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

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

The reader is also referred to studies for further details on SEM methodology. Several goodness-of-fit metrics are commonly used, including v2 (chi-squared), the goodness-of-fit index (GFI), the (standardized) root-mean-square residual ((S)RMR), the comparative fit index (CFI) and the Tucker-Lewis Index (TLI). Such criteria are based on differences between the observed and modelled variance–covariance matrices. Values less than 0.07 for SRMR and RMSEA and more than 0.90 for CFI and TLI are generally accepted as indications of very good overall model fit. As a note, the topic of SEM goodness-of-fit metrics has been a matter of previous scientific debate.

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. Demographic information regarding the drivers' gender and age are shown in Table 1.

Table 1. Overview of the selected sample

	Age groups			
	<25	25-55	>55	Total%
Male	0	27	3	46%
Female	3	31	1	54%
Total %	5%	89%	6%	100%

Table 2. 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%

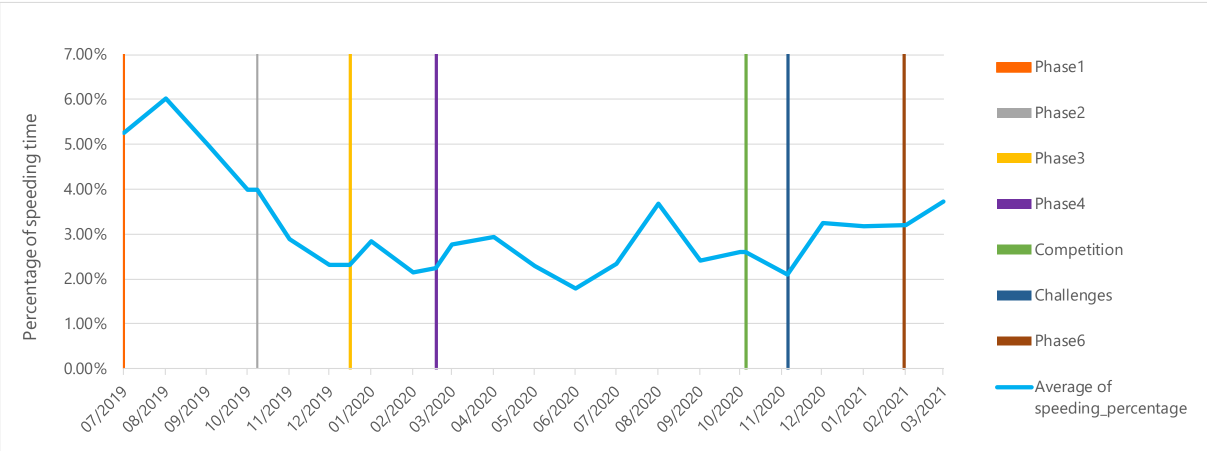

Figure 2: Average percentage of time exceeding the speed limits of car drivers throughout the experiment

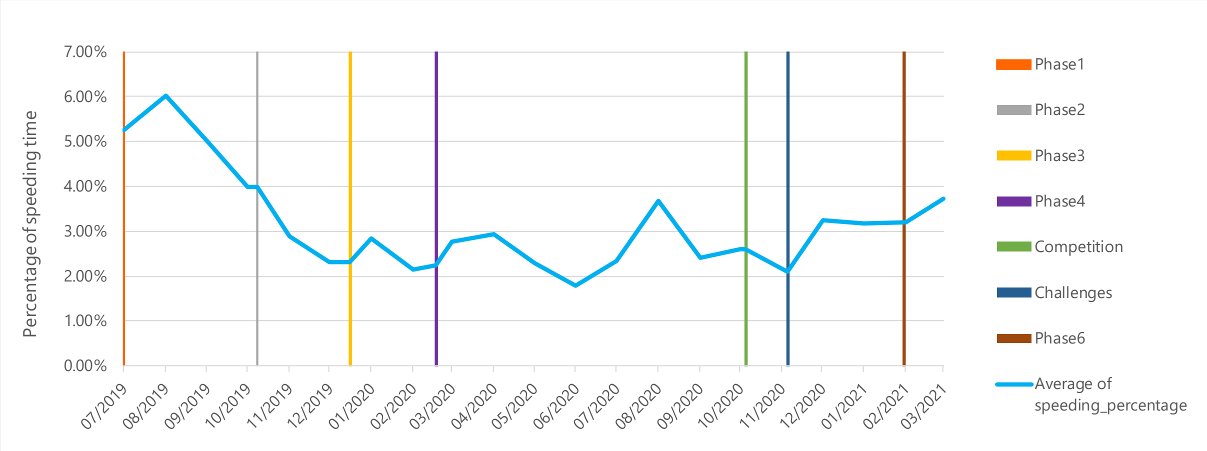

Figure 3: Average speed exceeding of the speed limits of car drivers throughout the experiment

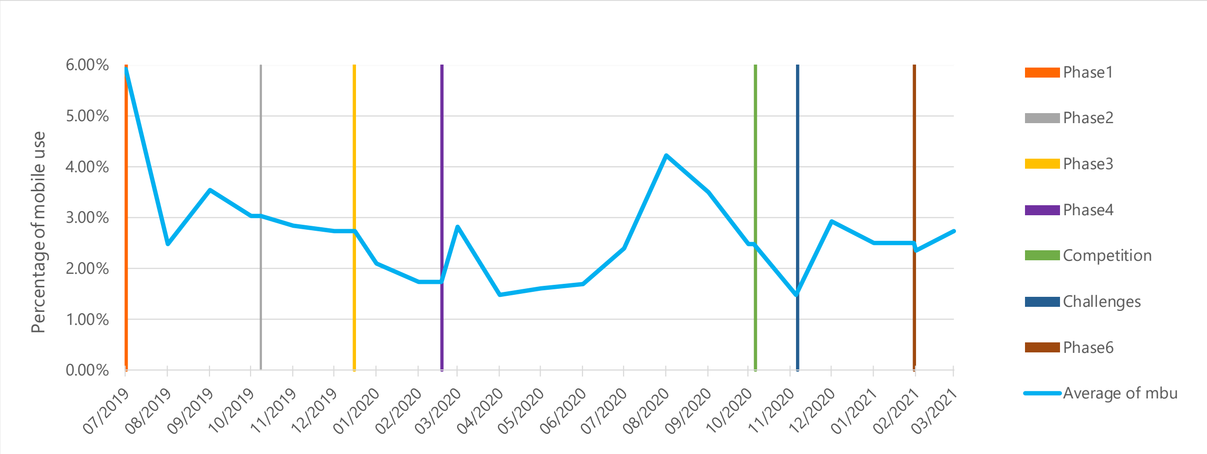

Figure 4: Average percentage of mobile phone use of car drivers throughout the experiment

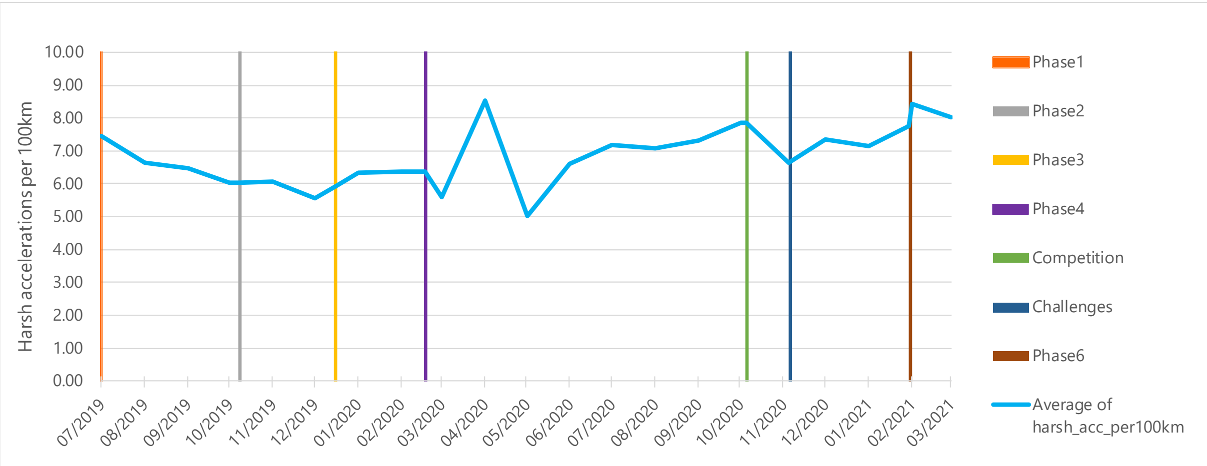

Figure 5: Average number of harsh accelerations per 100km of car drivers throughout the experiment

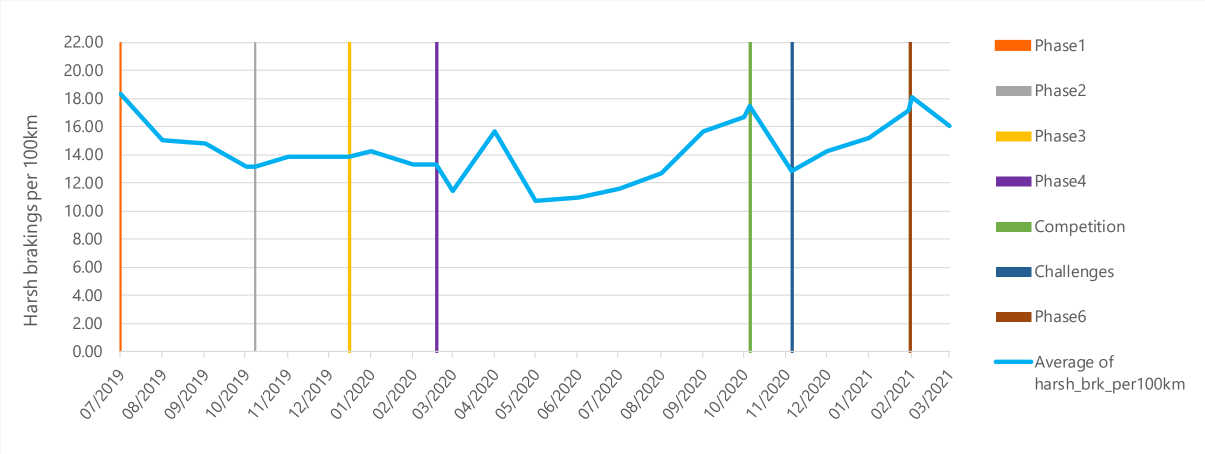

Figure 6: Average number of harsh decelerations per 100km of car drivers throughout the experiment

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. Furthermore, care was taken to avoid model misspecification based on both the appropriateness of the proposed underlying theoretical structure and on the produced outcomes – for instance, models producing negative variance values for observed and latent variable were discarded as cases of poor/illogical model fit. 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 3; 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 7; 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 3: 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

SEM Components		Parameters	Estimate	S.E.	z-value	P(>|z|)
		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			

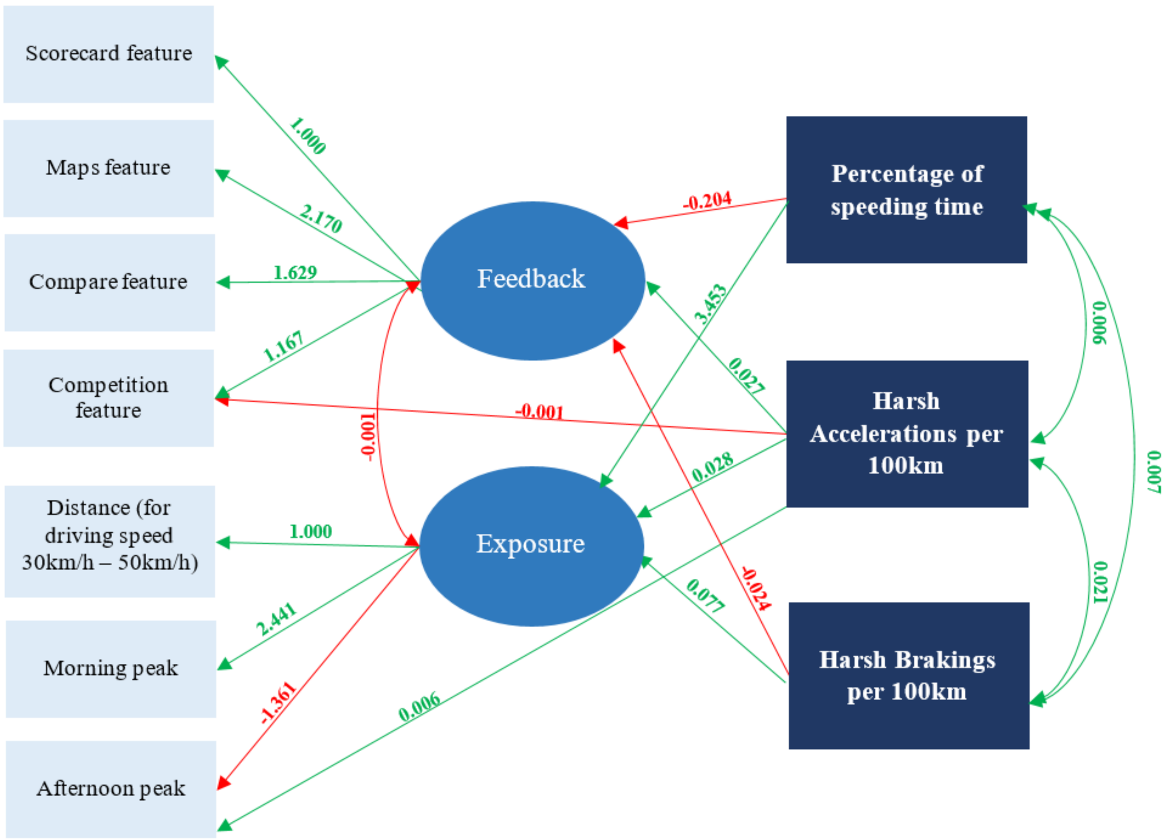

Figure 4: Path diagram of SEM model for percentage of speeding time, harsh accelerations per 100km and harsh brakings per 100km

5. Conclusions

The experiment conducted through the BeSmart project makes it clear that driver hazard can now be accurately assessed from real-time driving experiments, as they are considered more appropriate for assessing driving behavior. This is due to the fact that driving behavior is recorded under normal driving conditions and without any influence from external parameters, such as the presence of a researcher, prior knowledge of drivers in the experiment or the ability of participants to observe or predict road safety entanglements or even and real-time accidents. In addition, if drivers are monitored for an appropriate period of time, driving under real conditions will not change due to the fact that drivers know they are being recorded.

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.

More specifically, the research questions asked in this research project are the following:

- Identification of critical risk factors for driver behavior and safety via mobile phones
- Investigation of the effect of speed (improper speed, speeding, etc.), sudden events (sudden acceleration, sudden braking) and mobile phone use while driving in road safety
- Investigate the influence of feedback on the driver in driving behavior and its evolution over time

In conclusion, the indicative results that result from the analyzes applied during the project, are the following:

- For the first time, an overall improvement in driver behavior is observed through the feedback of information using a mobile phone.
- The biggest improvements in driving behavior are observed during the appearance of the User Score Card and during the Competition.
- Regarding car drivers. and professional drivers, speeding, appears to be the most improved indicator of driver behavior as 30% of drivers saw a reduction of more than 50%
- For the vulnerable group of motorcyclists, the number of sudden accelerations appears to be the most improved risk factor, with an average reduction of 30% for all riders.

The ultimate goal of providing feedback to drivers is to activate the process of learning and self-assessment of drivers and to enable them to gradually improve their performance and monitor their progress. This is a very important process, as it will have a significant impact on the human factor while driving, which is the main cause of road accidents, in order to avoid these accident situations and ultimately reduce the total number of accidents. This process may include establishing detailed cause-and-effect relationships between aggressive driving and risk, information on improving road safety valuable to insurance companies, fleet management applications, and determining the geographical location of hazards. points on the road network or can be a tool for objective proof of driving behavior, in order for a user to receive some benefit from his insurance company or to obtain a driver's license after revocation.

In view of the above conclusions, BeSmart contribution appears to be particularly important in the synthesis of driver behavior and risk. In particular, the importance of recording driver behavior is emphasized: for the first time, monitoring of all vehicles and especially of vulnerable groups on the road network (two-wheelers) is achieved. In addition, BeSmart contribution to driver training and support is enhanced by improving driver behavior, raising awareness among other road users, and providing continuous feedback to drivers to avoid impact reduction over time and developing a better road safety culture for all road users.

In addition, significant benefits to society are expected to be achieved, as stakeholders, including policy makers and industry, could rely on results and recommendations on risk factors deemed critical to safe driving.

Ethics approval

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

Acknowledgment

The authors would like to thank OSeven Telematics, London, UK for providing all necessary data exploited to accomplish this study.

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