Investigation of the speeding behavior of motorcyclists through an innovative smartphone application

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Abstract

Objective: The objective of the present study is twofold: (i) to explore the riding behavior of motorcyclists while speeding, based on detailed riding analytics collected by smartphone sensors, and (ii) to investigate whether personalized feedback can improve motorcyclist behavior.

Methods: In order to achieve the objective, a naturalistic riding experiment with a sample of 13 motorcyclists based on a smartphone application developed within the framework of the BeSmart project was conducted. Using risk exposure and riding behavior indicators calculated from smartphone sensor data, Generalized Linear Mixed-Effects Models are calibrated to correlate the percentage of riding time over the speed limit with other riding behavior indicators. An overall model was developed for all trips, as well as separate models for the parts of trips realised on different road types (urban and rural).

Results: Results indicate that the parameters of trip duration, distance driven during risky hours, morning peak hours and the number of harsh accelerations are all determined as statistically significant and positively correlated with the percentage of speeding time. Additionally, the provision of rider feedback and riding during afternoon peak hours are statistically significant and correlated with decreased percentages of speeding time.

Conclusions: The outcomes of this study entail both scientific and social impacts. The present research contributes a preliminary example of the quantitative documentation of the impact of personalized rider feedback on one of the most important human risk factors; speeding. The ultimate objective when providing feedback to riders is to: (i) trigger their learning and self-assessment process, thus enabling them to gradually improve their performance and (ii) monitor the shift of riding behavior as the application provides feedback. The present results capture and quantify the positive effects of rider feedback, thus providing needed impetus for larger-scale applications as well as relevant policy interventions.

Keywords: road safety; motorcyclists; rider monitoring; naturalistic experiment; smartphone application; Generalized Linear Mixed-Effects Models

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INTRODUCTION

Motorcyclists constitute a vulnerable road user group with up to 30 times higher fatality rates compared to passenger cars (Johnson et al., 2008). In 2017, motorcyclists accounted for 18% of the total number of road deaths in the EU countries; specifically, about 3,850 users (riders and passengers) of motorcycles and about 600 riders of mopeds were killed in EU countries in road traffic accidents (European Commission, 2018). During 2017, Greece had the highest rate of motorcycle fatalities per million population in EU-28 Countries, 20.1 deaths, while the EU average was 7.5 fatalities per 1 million population (European Commission, 2018). Although motorcyclists represent approximately the 15% of total vehicles in Greece, they were involved in 36% of total road accidents in 2018 (ELSTAT, 2020).

Specific factors affecting the accident injury severity of motorcyclists have been determined in the literature: Albalate & Fernandez-Villadangos (2010) identified gender, excess speed, road width, and alcohol consumption as factors affecting powered two-wheeler (PTW) injury severity. Theofilatos & Ziakopoulos (2018) determined that traffic and speed variations increase PTW injury severity, while increased truck proportions in the traffic mix were found to relatively reduce injury severity, possibly due to behavioral adaptations on behalf of PTW riders.

Behavioral issues are major moderating factors to both frequency and severity of motorcycle accidents. Speeding, sensation seeking, aggressiveness, perceived risk, errors, violations and attitudes towards road safety are considered to be crucial behavioral risk factors (Vlahogianni et al., 2012; Theofilatos & Yannis, 2015). This is corroborated by a related in-depth accident investigation as well. Using data collected from 500 accidents involving PTWs and bicycles, Ziakopoulos et al. (2018) found speeding to be a contributing factor to both accident frequency and severity. Another in-depth accident study using the framework of GIDAS (German In-Depth Accident Study) investigated the injury protection and accident causation parameters for motorcyclists, among groups of vulnerable road users, alongside pedestrians and bicyclists. It was found that in the majority of the cases, motorcycle riders failed to correctly evaluate the information received from the traffic environment or the situation of their own vehicle (Otte et al., 2012).

The accurate monitoring of motorcyclist riding behavior is therefore of high importance. Although motorcycle accidents have been widely investigated by researchers, the lack of detailed naturalistic riding data remains a persistent obstacle for the scientific community. Several existing studies have shown promising results on the analysis of motorcyclist riding behavior by means of naturalistic experiments (Espié et al., 2013). Williams et al. (2016) examined the contributing factors that influence motorcyclist accident risk, exploiting data from the MSF 100 Motorcyclists Naturalistic Study (31,000 trips from 100 riders). Their results can be utilized for further investigation of road safety levels during daily riding. Other recent studies have attempted to develop methodological techniques to allow either for rider profile detection (Will et al., 2020) or for measuring the lean angles of motorcycles on a large scale (Stanglmayr et al., 2020). Furthermore, the validity of approaches based on smartphone applications has been demonstrated in past studies. Using applications solely, stopping and dangerous riding events have been detected with a reported accuracy of 90.1% for scooters (Hsieh et al., 2014) and 86.8% for bicycles (Gu et al., 2017).

However, to the best of the authors' knowledge, this is the first attempt to understand behaviors and risks related to rider speeding on the basis of data collected from smartphone sensors. Additionally, since several studies have correlated speeding with rider aggressiveness (Lin & Kraus, 2009; Vlahogianni et al., 2012) and with environmental/exposure metrics, as expressed, for instance, by night-time riding (de Rome et al., 2016), the authors' aim is to investigate the respective influence factors and come to conclusions regarding their impact on speeding. More precisely, rider speeding is expected to increase due to:

- rider aggressiveness
- travelled distance
- nighttime riding

In light of the aforementioned, the objective of the present study is twofold: (i) to explore the riding behavior of motorcyclists while speeding, based on detailed riding analytics collected by smartphone sensors, and (ii) to investigate whether personalized feedback can improve rider behavior.

METHODS

The BeSmart Application

In order to achieve the research objective, an innovative smartphone application developed by OSeven (www.oseven.io) was exploited aiming to record rider behavior using the hardware sensors smartphone devices. OSeven has also developed a seamless integration platform for collecting and transferring raw data and recognizing the riding behavior metrics via Machine Learning (ML) algorithms. These steps of data pre-processing are exclusively performed by OSeven and do not constitute part of this study; only the main features of the system are outlined below. The standard procedure that is followed every time a new trip is recorded by the application is showcased in Figure A1.

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. Once stored in the backend cloud server, they are converted into meaningful riding behavior and safety indicators such as harsh accelerations, harsh brakings and percentage of driving duration with speeding, using signal processing, ML algorithms, Data fusion and Big Data algorithms. This is achieved by using state-of-the-art technologies and procedures, which are protected Intellectual Property of OSeven and operate in compliance with standing Greek and European personal data protection legislation (GDPR).

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 riding. Moreover, the riding indicators associated with riding behavior consist of the following: speeding (distance and time of riding over the speed limit and the exceedance of the speed limit) and riding aggressiveness, measured in the present approach by the number and severity of harsh events (harsh brakings/accelerations).

It should be noted that harsh events are calculated via data fusion and machine learning algorithms and not a rule-based approach using as input the values of the accelerometer as well as values from additional sensors (e.g. orientation, magnetometer, GPS, gyroscope). Therefore, the determination of the harsh events is not based on specific thresholds. Yet, some indicative examples of speed and acceleration data related with specific harsh events from the available dataset are illustrated, so that harsh events can be better comprehended. Indicative harsh accelerations: (i) speed increase from 31km/h to 40km/h within one second and (ii) longitudinal acceleration 0.28g; Indicative harsh brakes: (i) speed decrease from 51km/h to 40km/h within one second and (ii) longitudinal deceleration 0.30g. It is stressed out that these are four indicative cases of harsh events and the respective values cannot be considered as thresholds, as the determination of the events is based on the coevaluation of several time series. In addition, the reliability of the OSeven algorithms has been extensively evaluated against literature data, OBD data, on-road experiments by certified experts on the assessment of driving behavior, and experiments on driving simulators (Tselentis et al., 2019; Petraki et al., 2020). Taking into consideration that the cited studies deal with car drivers, the authors clarify that the mentioned algorithms have been calibrated based on (i) on-road annotated experiments, and (ii) the comparison between the car and motorcycle data that quantify the vehicle dynamics.

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 vulnerable road user group of motorcyclists is analyzed. The experiment consisted of two different phases differing in the type of feedback provided to riders.

The conceptual framework of the developed application features during the feedback phase was based on previous studies investigating the effect of driver feedback in regards with safety, namely speeding and aggressive driving style (Soriguera & Miralles, 2016) as well as eco-driving (Dahlinger et al., 2018) or both (Toledo & Shiftan, 2016). In Tselentis et al. (2020) an extensive literature review regarding the type and time of provided feedback was conducted; the authors conclude that feedback should be granted to drivers in a training and motivational context in order to ease their learning process.

The first phase of the experiment lasted for 12 weeks; participants were asked to ride in the way they usually did, without receiving any feedback on their riding behavior from the smartphone application. At this phase, only the trip list and the vehicle characterization were accessible to the application user (Figure 1). The purpose of this phase was to learn the participants' naturalistic riding characteristics which provide a baseline for comparison. The second phase lasted for 10 weeks; participants were provided with personalized feedback; namely a trip list and a scorecard regarding their riding behavior, allowing them to identify their critical deficits or unsafe behaviors (Figure 2). The respective feedback was provided to participant smartphones through the application, each time a trip was completed. More specifically, Figure 2 (right) demonstrates the Trip List which now enables the per trip score on a 0-100 rating scale. With respect to the left site of the Figure 2, the Scorecard is introduced, allowing for additional feedback score on the three driving behaviour indicators (from the left to the right); speeding, harsh breaking, harsh acceleration. As a note, the BeSmart Project is conducted in Greece; therefore, the application has an exclusively Greek interface. However, for the purpose of this paper, the application interface has been translated in English so that the reader can easily understand it.

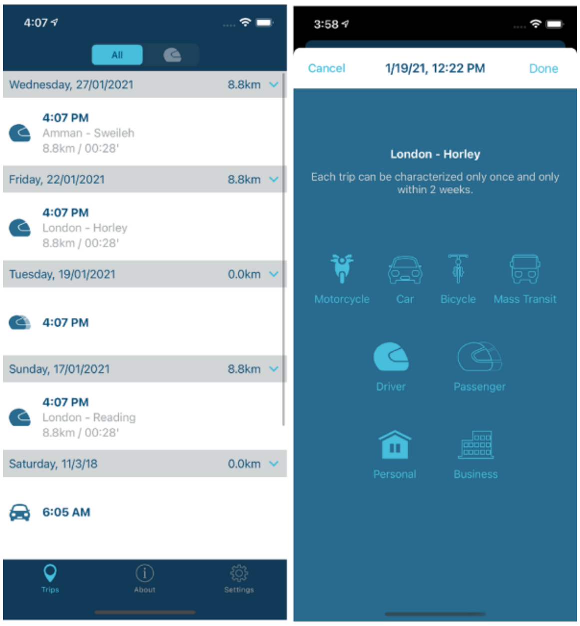

Figure 1 – Example screenshots from the application features in Phase 1 (Baseline)

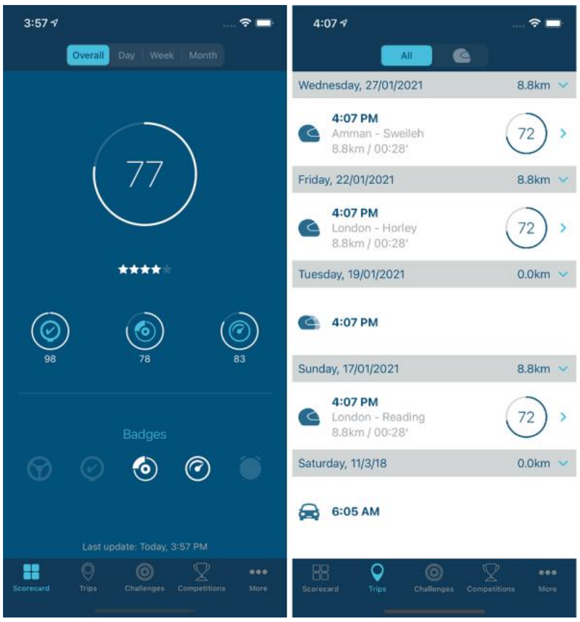

Figure 2 – Example screenshots from the application features in Phase 2 (Feedback)

Rider Panel

Originally, 20 motorcyclist riders volunteered to participate in the experiment and to allow for monitoring their riding behavior through the respective smartphone application. However, for the present analysis it was decided that the final sample should consist only of riders who have participated equally in both phases on terms of trips. An additional criterion was set; all riders selected for the analysis were required to have ridden for at least 40 trips. This number approximately equals the typical monthly number of working trips, assuming that each rider drives 2 trips a day for 5 working days a week. This number is reasonable to filter out riders for which there are not enough observations, and it is also the 'industrial' criterion set by OSeven to start providing rider evaluation to clients. As a result, from the 20 motorcyclists, 13 riders (4 female, 9 male) were ultimately selected. All participants possessed a valid driving license while the 11 out of 13 rode their own motorcycle (the other two rode the motorcycle of a family member). The participants were aged between 25-34 (n=9) and between 35-45 (n=4). Detailed sample information is presented in Table 1.

Table 1. Participant panel description regarding riding and vehicle data (N=13)

Riding parameter	**Distribution of participants**			
Riding experience (number of years)	<5	5-10	11-20	>20
	7.7%	30.8%	53.8%	7.7%
Driven distance per year (km)	<5000	5001-10000	10001-15000	>15000
	15.4%	7.7%	61.5%	15.4%
Motorcycle engine size (cc)	<251	251-500	501-1000	>1000
	46.1%	7.7%	23.1%	23.1%

Methodology

The variable of interest in the present analysis is the fraction of speeding while riding. Speeding refers to instances when riders are exceeding the speed limits in the respective type of road network, after comparison the treated speed value (after outlier detection and smoothening) as measured by the BeSmart application with the speed limits derived by the map provider, i.e. OpenStreetMaps. In addition, it should be mentioned that a tolerance value is added to the speed limit to accommodate any deviations of the speed value derived by the GPS.

The aforementioned quantity was originally available either as a portion of trip time during which the speed limit was exceeded, or as a binary variable for the entire trip (yes/no). The first approach was selected for modelling in the present research. After transforming the speeding percentage per trip to an integer, Generalized Linear Models (GLMs) were implemented with a Poisson data distribution. GLMs are known to be better used when dealing with frequency (count) data. However, in this particular study, and 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 rider speeding.

The general form of the GLM models the log-odds via a linear predictor. More precisely, if y is the observed speeding percentage per trip i, and λ is the expected speeding percentage to be predicted, then the model is specified as:

$$y_i \sim Poisson(\lambda_i) \quad (1)$$

And the linear predictor is:

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

Where β are the fixed-effect parameters (constant and coefficients) for n independent variables, and ε is the error term. Additional reference with respect to the methodology used in the paper can be found in the bibliography in the Appendix.

However, one may also consider that in the present dataset there are repeated measurements (trips) over the same units (riders). Therefore, in order to capture personal rider traits, such as personality and experience, which affects their riding style, and thus the speeding percentage 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:

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

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

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

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

RESULTS

Descriptive Statistics

Overall, during the two phases of the experiment a large dataset of 3,537 trips from a sample of 13 motorcyclists were recorded. Before presenting the model development, exploratory descriptive analysis of the data is implemented, allowing for an overview of the percentage of speeding while riding, as well as the other three riding indicators that are presented via the application in the feedback phase. 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 riders receive feedback about their riding behavior, which constitutes an incentive for modelling the impact of feedback. Additionally, this finding is observed in all different road types, indicating a smoother performance of the respective riding metrics when riders are receiving feedback. However, in the case of highways, it is remarkable that the reduction of the examined riding indicators is much slighter compared to the urban and rural road network. This seems logical, taking into consideration the riding pattern in highways, as longer distances are covered and high speeds are developed.

Table 2. Descriptive statistics of the per trip values of the variables and the respective standard errors (in parenthesis) recorded for Phase 1 (Baseline) and Phase 2 (Feedback)

Variable	Road type					
	Urban		Rural		Highway	
	Baseline	Feedback	Baseline	Feedback	Baseline	Feedback
Average speed [km/h]	35.82 (0.30)	33.66 (0.29)	50.08 (0.66)	38.28 (0.48)	97.01 (0.58)	77.62 (0.66)
Speeding percentage [%]	13.41 (0.41)	9.84 (0.33)	10.33 (0.62)	3.07 (0.34)	5.60 (0.96)	5.35 (0.90)
Harsh accelerations [count]	2.54 (0.08)	1.70 (0.06)	2.02 (0.09)	1.38 (0.06)	0.81 (0.11)	0.22 (0.04)
Harsh brakings [count]	1.59 (0.05)	1.14 (0.04)	1.27 (0.07)	0.81 (0.04)	0.45 (0.08)	0.16 (0.03)

Generalized Linear Mixed-Effects Models

In order to model the expected percentage of speeding per trip for the participant riders, mixed-effect models in a GLM framework (GLMMs) were calibrated. Specifically, 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. Furthermore, it is important to note that the sample consists of driver trips, as opposed to drivers directly, thus allowing the training of statistically robust models.

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. After conducting log-likelihood test ANOVA comparisons, the most informative configuration of random effects was included both random intercepts and random slopes in the GLMMs to capture unique rider traits. Table 3 provides a description of the parameters of the models.

Table 3. Description of the parameters used in the models

Independent Variable	**Description**
Rider Feedback (binary dummy variable)	Provision of rider feedback through the application (yes/no)
Trip Duration (continuous numerical variable)	Total trip duration (sec)
Harsh Accelerations (discrete numerical variable)	Number of harsh accelerations per trip
Risky hours (binary dummy variable)	Hours with high risk rate 00:00-05:00 (yes/no)
Morning Rush (binary dummy variable)	Morning rush hour 06:00-10:00 (yes/no)
Afternoon Rush (binary dummy variable)	Afternoon rush hour 16:00-20:00 (yes/no)

The final models are presented in Table 4. Modelling results reveal some interesting findings: The parameters of trip duration, the distance driven during risky hours, morning peak hours and the number of harsh accelerations have all been determined as statistically significant and positively correlated with the percentage of speeding. In the same context, riding during the feedback phase of the experiment, as well as afternoon peak hours are statistically significant and negatively correlated with speeding percentage.

Table 4. GLMM models for speeding models for all road types, and separately for urban roads and rural roads

Trip Parameter	**Overall model**		**Urban roads**		**Rural roads**	
	B	*p*-value	B	*p*-value	B	p-value
Intercept	1.898	<0.001	1.810	<0.001	-	-
Rider Feedback	-0.145	<0.001	-0.031	0.005	-0.420	<0.001
Trip duration	0.194	0.042	0.001	<0.001	0.003	0.004
Harsh accelerations	0.248	<0.001	-	-	0.056	<0.001
Risky hours	0.018	<0.001	0.006	0.001	0.019	<0.001
Morning Rush	0.067	<0.001	0.093	<0.001	0.130	<0.001
Afternoon Rush	-0.286	<0.001	-0.303	<0.001	-0.436	<0.001
AIC	37114.1		54460.9		34576.3	

The aforementioned results could be further interpreted, calculating the relative risk ratio of every variable and thus measuring the increase in probability of speeding while riding. The exposure metrics of trip duration, trip distance during risky hours and morning peak hours seem to increase speeding percentage by a factor of exp(B=0.194) = 1.214, exp(B=0.018) = 1.018 and exp(B=0.067) = 1.069 respectively for the overall model. The variables are found to have similar significant effects both in urban and in rural areas. In other words, motorcyclists seem prone to speeding while riding under circumstances that increase their impatience and/or stress such as long trip durations, riding during hours of increased traffic conflicts, lane splitting, hurrying while commuting, etc.

Additionally, the riding behavioral parameter of harsh accelerations increases speeding percentage by a factor of 1.281 in the overall model, indicating the pattern of a stressful riding style. The variable is not found statistically significant for the urban road model, but regarding rural riding, the number of harsh accelerations seem to increase the speeding percentage by a factor of 1.060.

Providing motorcyclists with feedback about their riding performance during experiment Phase 2 led to a remarkable decrease of speeding percentage by 14.5%. Particularly, in the developed models rider feedback seems to decrease speeding percentage, having a risk ratio of exp(B=-0.145) = 0.865 for the overall model, and exp(B=-0.031) = 0.970 and exp(B=-0.420) = 0.657 for urban and rural road types respectively. As explained above, during the feedback phase, riders received personalized feedback regarding their weak points, namely speeding and aggressive riding (harsh accelerations and harsh breakings) by means of a scorecard through the smartphone application. Therefore, the quantification of the positive effect of rider feedback on riding performance indicates new ways of improving road safety.

DISCUSSION

This paper aimed: (i) to explore the riding behavior of motorcyclists while speeding based on detailed riding analytics collected by smartphone sensors, and (ii) to investigate whether personalized feedback can improve riding behavior. For that purpose, high-resolution smartphone data collected from a naturalistic riding experiment with a sample of 13 motorcyclists were utilized. Using risk exposure and riding behavior indicators calculated from smartphone sensor data, a statistical analysis was carried out for correlating the percentage of riding time over the speed limit with other riding behavior indicators, namely by means of Generalized Linear Mixed-Effects Models. In particular, an overall model was developed for all trips, and additional separate models were developed for riding on urban and rural roads.

The results from the interpretation of the estimated parameters of the models can be summarized as follows: Trip length and riding during the morning rush and night-time risky hours are exposure metrics significantly associated with the odds of speeding while riding. Harsh accelerations are also associated with the odds of someone exceeding the speed limits, outlining a pattern of an overall unsafe riding behavior.

Furthermore, the outcomes of this study entail both scientific and social impacts. The present research contributes a preliminary example of the quantitative documentation of the impact of personalized rider feedback on one of the most important human risk factors; speeding. The ultimate objective when providing feedback to riders is to: (i) trigger their learning and self-assessment process, thus enabling them to gradually improve their performance and (ii) monitor the shift of riding behavior as the application provides feedback. The present results capture and quantify the positive effects of rider feedback, thus providing needed impetus for larger-scale applications as well as relevant policy interventions. State-of-the-art interventions can include approaches for driver or rider training and support through innovative rider behavior monitoring and feedback tools for different types of riders, such as cyclists or motorcyclists.

The current lack of motorcycle instrumentation certainly limits the potential of detailed multifaceted analysis. Nevertheless, the proposed methodology reaches noteworthy findings, even though the riding exposure and behavior metrics are solely based on smartphone sensors and no other methods, e.g. optical sensors. It is important to highlight that there is little or no previous experience on analyzing and predicting rider speeding behavior through microscopic riding behavior metrics collected from such a portable and low-cost device, and therefore the results of the present research cannot be directly compared to those of the existing literature.

Furthermore, as already discussed, the calculation of the harsh events for motorcycles is based on ML and data fusion algorithms, utilizing data from several smartphone sensors, after the application of the appropriate filtering and data cleaning algorithms on the raw signals. These algorithms evaluate the processed time series from the smartphone sensors of the complete trip. Although the applied algorithms increase the accuracy of harsh events detection; by nature, they do not include specific threshold values or explicit explanations that could be presented in the existing paper for verification purposes – nonetheless, some practical examples were illustrated. Harsh events were treated as a given input of rider behavior for the investigation of their speeding behavior; the examination of their definition or detection falls outside the scope of this research.

The BeSmart project is still ongoing, and will include future research efforts which will focus on several different types of personalized feedback that will be communicated to motorcyclists in the next phases of the experiment, namely incentives within a social gamification scheme, with personalized target setting, benchmarking and comparison with peers, and comparative assessment of their performance. There will be examinations of the impact of feedback over time, the influence of its evolution on riders and its consistency. Moreover, microscopic data analysis of the collected database could also be conducted through machine learning techniques and other techniques such as structural equation models. Finally, future research could also include self-assessment strategies (e.g. DBQ - Driving Behavior Questionnaire, Driving Skill Inventory - DSI etc.) in order to further improve feedback processes, thus resulting in a better riding behavior.

Ethics approval

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

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Appendix

Figures

Figure A1 – The OSeven data flow system.

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