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Correlation of driver behaviour and fuel consumption using data from smartphones

Evanthia Michelaraki[a], Armira Kontaxi[a]*,
Panagiotis Papantoniou[a], George Yannis[a]

[a]*National Technical University of Athens, Department of Transportation Planning and Engineering, 5 Heroon Polytechniou str., GR-15773, Athens, Greece*

Abstract

This research aims to investigate the correlation of driver behaviour and fuel consumption using data from smartphones. To achieve this objective, data collected from 17 drivers who participated in a naturalistic driving experiment for four months in Greece, are analyzed. During the first two months, participants drove in the way they usually did and over the following two months they were asked to improve their driving style. Statistical analyses were carried out using linear and lognormal regression models, which examined whether driving characteristics such as speed, harsh accelerations, harsh braking, smartphone usage affect and can therefore predict fuel consumption. The results substantiate that there is a remarkable reduction in fuel consumption, as the participants improved their driving behaviour. A stronger correlation has emerged between harsh accelerations and fuel consumption, but also speed and braking had a direct impact on fuel consumption.

Keywords: driver behaviour; fuel consumption; before-after; eco-driving; naturalistic driving experiment; lognormal regression

* Corresponding author. Tel.: +30-210-772-1575;
E-mail address: akontaxi@mail.ntua.gr

1. Introduction

Across the globe, temperatures are rising rapidly and experts claim that the environment is under threat by toxic emissions caused by man-made Carbon Dioxide (CO_2). Exhaust gases from motorized vehicles are one of the biggest contributors to this problem. In recent decades, a number of new technologies have been introduced into vehicle manufacturers with the aim of reducing fuel consumption and CO_2 and other greenhouse gas emissions. In addition to external circumstances, such as travel-related factors, weather, road conditions, tire pressure, vehicle characteristics, weight or air resistance and traffic congestion (Ahn et al., 2002, Zhou et al., 2016), one method of reducing gas emissions and saving fuel with potentially untapped potential is to improve driver behaviour. Undoubtedly, a more environmental friendly manner of driving, called as eco-driving, refers to an ecologically sensitive driving style, which not only reduces fuel costsand maintenance costs of the vehicle, but also has long-term benefits for the society. .Being the operator of a vehicle, the driver is able to handle the speed, harsh events (braking, acceleration, cornering), engine rotations, gear engaged, even or his driving aggression (Chan et al., 1994, Reiter, 1991). Therefore, it's suggested that a driver can save a significant amount of fuel through eco-driving and at the same time increase road safety. A literature review from recently published studies around the globe suggests that it can get accomplished up to 10% or more fuel savings by changing driving behaviour (Waters et al., 1980, Landuyt et al., 2007, SenterNovem, 2007).

In a very short amount of time, with the evolution of technology, the automotive telematics market is growing steadily and a few innovative telematics and driver monitoring systems are introduced in our life. Nowadays, most drivers look for new services providing more options in order to identify their weak points in driving, adjust their driving style and techniques, reward their progress and promote maximum road safety for everyone and minimum motor vehicle emissions. Automotive telematics technology receive information from vehicles, including GPS coordinates, engine diagnostics, sensors, wireless internet connections, radar, touch screens as well as cameras inside and outside the vehicle and send it to a centralized server where it is then analyzed and managed using fleet management software. In this paper, studies that refer to the driver behaviour through technological devices adapted to the car's brain are presented. Many surveys were conducted to analyse driving behaviour characteristics using data from smartphones with focus on key risk indicators, namely the number of harsh driving events.

More specifically, in many studies that have taken place internationally, a device agnostic platform has been developed with the ability to collect data from different sources such as smartphones, OBDs and 4G/5G connected cars. Additionally, recent works used a Driving Data Recorder (DDR) which can provide feedback on driver behaviour for accident analysis and other insurance issues (Ohta et al., 1994, Gu et al., 2019). Also, a driving behaviour and safety evaluation was conducted through a data recording system called Drive Diagnostics which is a dedicated In-Vehicle Data Recorder (IVDR) system with dimensions of 11x6x3cm, customized inside the vehicle (Toledo et al., 2006). The IVDR system collects data such as vehicle's speed, harsh events (acceleration and braking), position estimated through GPS, frequency of lane change, fuel consumption, etc. It is worth highlighting that in a research which recruited young drivers during the first year after their licensure, was found that drivers who knew that their driving behaviour was being monitored by this device, managed to be less aggressive and drove more ecologically (Prato et al., 2010). Moreover, real driving parameters of driver behaviour have been assessed and analysed through an On Board Diagnostics (OBD-II) device (Yannis et al., 2016). This recording system was developed in the United States of America and is designed to detect road accidents and mechanical problems in vehicle that are caused by high emissions above the acceptable limit values. An android smartphone connects via Bluetooth to the OBD-II and receives information about the vehicle status, such as speed, fuel, temperature, accelerometer values as well as accurate location with a specific latitude and longitude, via GPS updates (Zaldivar et al., 2011).

Particular emphasis is put on research that focus on the correlation of driver behaviour and fuel consumption. At first, Karl Dunkle Werner estimated that if every driver behaved more effectively and ecologically friendly, the fuel savings would be 17% for highway driving and 26% for urban driving. In addition, an experiment conducted by 108 drivers for a 6-week period has shown that participants who drove more carefully managed to reduce fuel costs and therefore CO_2 emissions by 12-19% (Dunkle Werner, 2013). A trucking industry study proposes that the use of an OBD device inside the vehicle and the environmental education of drivers can save on average 7.6% of fuel consumption (Hari et al., 2012). Specifically, an experiment was carried out involving 15 van owners who were asked to drive for a period of 4 months. During this trial, both visual feedbacks and audio warnings were communicated to drivers in order to improve their driving behaviour and in case of non-compliance with them, significant sanctions were imposed. As a result, participants drove in a calmer manner characterized by lower engine speeds and less harsh accelerations when compared to their normal driving behaviour. Supplementary, an experiment was accomplished before and after the course and a remarkable reduction in fuel economy of 29% was observed (Madureira, 2007). A similar survey, using an on-board vehicle device for the collection of data regarding driving behaviour, was conducted in order to estimate the long-term impact of eco-driving education on fuel consumption (Beusen et al., 2008). For 7 of the 8 drivers who took part in this research, fuel consumption diminished in the range of 1.7 to 7.3 percent but unfortunately, as it turned out, by the end of the trial most of the drivers tended to return to their original habits and fell back to their bad driving style, increasing fuel consumption again. This finding is in agreement with the international literature that have proven the short-term effect of fuel efficient driving (Wilbers, 1997, Johansson, 1999, Hornung, 2001).

Furthermore, 1,041 drivers from a fleet of Lisbon's public transportation buses participated for 3 years in a research that showed that adopting appropriate driving styles can reduce fuel consumption on an average from 3 to 5 lt/100 km, which practically means saving 15 to 30 liters per bus in just a working day (Ferreira et al., 2015). The huge data generated automatically from the vehicle's Controller Area Network (CAN) and the application of Online Analytical Processing (OLAP) and Knowledge Discovery (KD) techniques (Gray et al., 1997, Fayyad et al., 1996) were conducted to determine the main factors affecting average fuel consumption, such as engine speed, ignition, acceleration and harsh use of brakes and clutch. At the same time, another research demonstrated fuel savings of 4.35% on buses, during a monitoring driving experience for a period of 2 months (Zarkadoula et al., 2007). Focusing on the influence of gear changing behaviour on vehicular exhaust emissions and fuel consumption using the simulation tool VeTESS (Vehicle Transient Emissions Simulation Software), a first very interesting finding of this study was that eco-driving can save up to 30% of fuel consumption per trip and prevent additional emissions of pollutants due to engine operation (Beckx et al., 2007). Besides, it was observed that high engine speeds, harsh acceleration and driver aggressiveness increased the emissions of NOx by 15% and the change in PM and HC emissions was also significant with a 41% and 38% increase respectively. Previous research investigated the impact of providing real time eco-driving advice to the drivers based on real-time traffic speed, density and flow and the result was up to a 20-30% decrease in fuel economy, without a significant increase in travel time (Codd et al., 1993). Subsequently, an eco-driving study based on driving simulation was developed and achieved about 5% reduction in CO_2 emissions and fuel consumption (Zhao et al., 2015).

Based on the above, the objective of this paper is to investigate the impact of driver behaviour on fuel consumption through the exploitation of data from smartphone sensors. To that end, a naturalistic driving experiment was carried out in order to examine whether driving characteristics recorded by smartphone sensors affect and can therefore predict fuel consumption.

2. Data collection

2.1. Experimental process

For the purpose of this research, a naturalistic driving experiment was carried out involving 17 drivers aged 20-35 during a 4-months timeframe from June to September 2018 and a large database of thousands trips was created. The designed experiment included two different driving scenarios. During the first two months, participants drove in the way they usually did and over the following two months they were asked to improve their driving style, following strictly the Road Traffic Code. To clarify, the regulations of the Traffic Code are considered to lead towards less aggressive driving behaviour overall, and towards greener driving. Driving behaviour analytics were recorded in real time, using smartphone device sensors. More specifically, an innovative data collection system using a Smartphone Application that has been developed by OSeven Telematics was exploited. A set of sophisticated and personalised interactive tools is applied by OSeven Telematics, powered by breakthrough technology, smart algorithms and reliable metrics. The most advanced Machine Learning techniques have been implemented to detect harsh events and speeding, identify the trip transport mode, recognize whether the user is a driver or a passenger. Consequently, the OSeven platform helps drivers understand their weak points and motivates them to improve their driving behaviour and also reduce their fuel costs. The standard procedure that is followed every time a new trip is recorded by the App, is clearly presented in Figure 1.

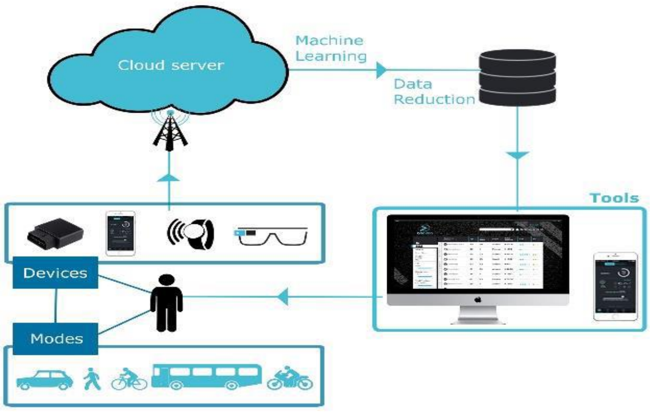

Figure 1. OSeven data handling chart

For every trip a driver completes, a large amount of data is recorded, transmitted through WiFi or cellular network and valuable critical information such as metrics, features, highlights and driving score is produced in order to evaluate driving profile and performance. The exposure indicators that are available include indicatively 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) time of the day driving (rush hours, risky hours) and weather conditions. Moreover, the driving indicators which can reliably quantify the risk associated with a specific driving behaviour are the following: speeding (distance and time of driving over the speed limit and the exceedance of the speed limit), driver distraction (caused by smartphone use during driving), number and severity of harsh events number and severity of harsh events (braking and acceleration), harsh cornerings, driving aggressiveness (e.g. braking, acceleration), and eco-driving (smooth use of the accelerator, steering, transmission and brakes).

It must be noted that since privacy and security consist two of the main principles, in the field of telematics, the OSeven platform has very clear privacy policy statements for the end users covering the type of data collected, the reason data is collected for, the time that data is stored and the procedures for data security based on encryption standards for data in transit and at rest. All this is done using state-of-the-art technologies and procedures in compliance with GDPR. In this framework all data has been provided by OSeven Telematics in an anonymized format.

2.2. Questionnaire

Before the driving experiment, each participant was requested to fill in a questionnaire which was divided into three distinct sections: a) overall driving data, b) attitude and behaviour toward road safety, and c) demographic characteristics. Specifically, drivers have provided valuable information such as age, gender, educational level, history of accidents, self–assessment, driving experience, vehicle type (cubism, fuel, etc.). They have also provided information on their driving behaviour, namely speed limits, traffic violations, harsh events (braking or/and acceleration) and mobile phone usage during driving.

2.3. Fuel consumption log template

During all stages of the experiment, drivers had to fill in the fuel consumption log sheet template. In particular, on each filling of the automobile's fuel tank, users were required to complete information such as the date, the litters of fuel used and the covered distance. Through this record, participants were able to evaluate the fuel economy of their vehicle and it also proved to be useful for making comparisons between the two different ways of driving. As a result, owners used this information to figure out how they can save money by understanding the fuel consumption of their car. In addition, new variables which were considered necessary for the correlation of driver behaviour and fuel consumption were formed. Firstly, a binary categorical variable called «before-after» that assigned numerical values e.g., 0 = before; 1 = after was created. In detail, the term before refers to «normal driving», that is the initial driving behaviour of participants during the first two months of the experiment (June-July). Regarding the term after, it refers to «eco-driving», that is the improved driving behaviour during the two other months (August-September). Subsequently, based on the fuel consumption log template completed by drivers throughout the experiment, a continuous variable named fuel consumption was calculated individually for each participant. Thus the variable fuel consumption, expressed in lt/100km, was created for each filling of the vehicle's tank, which was found by dividing litters of fuel tanked to kilometers or mileage made. Figure 2 illustrates the difference in mean driving speed between the first two months when participants drove in the way they usually did and over the following two months when they were asked to improve their driving style.

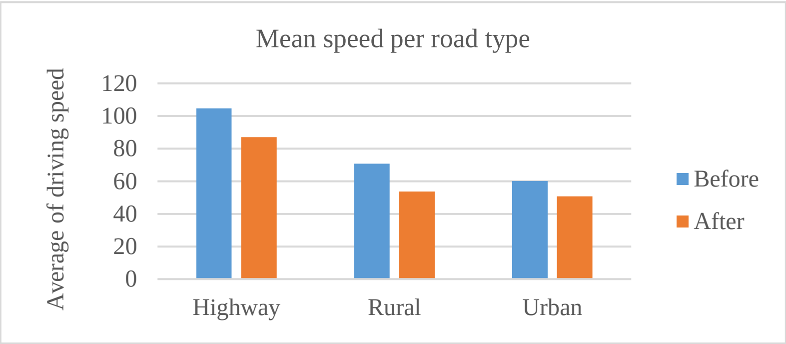

Figure 2. Mean driving speed per road type between the first two months and the two following ones

3. Methodology

As previously reported, data from the driving measures collected by OSeven backend office, the fuel consumption log template and the questionnaire were analysed using Microsoft Excel and SPSS. Afterwards, statistical analyses were carried out using multiple linear and lognormal regression models. This type of analysis was developed to examine whether driving characteristics such as speed, harsh acceleration, harsh braking, smartphone usage (dialing, talking, texting etc.) and driving at night affect and can therefore predict fuel consumption. The basic equation of the multiple lognormal regression model is the following:

$$y_i^* = \log(y_i) = b_0 + b_1{*}x_{1i} + b_2{*}x_{2i} + \ldots + b_v{*}x_{vi} + e_i \qquad (1)$$

In this case, four statistical regression models forecasting fuel consumption were developed: one overall model and three models for each different road type (highway, rural, urban), as shown below:

- Model 1: Predicting fuel consumption – overall model
- Model 2: Predicting fuel consumption driving on highway
- Model 3: Predicting fuel consumption driving on rural road
- Model 4: Predicting fuel consumption driving on urban road

Specifically, all models were designed to have exactly the same variables in order to make it easier to compare models with each other. Then, it was examined for all models separately whether the numerical results quantifying relationships between variables, did satisfy the models' quality. Within the present research, the scope of this analysis was to determine which observed independent variables are highly correlated with the dependent variable and at the same time which of them are inconsistent with each other. For this reason, the correlation coefficient R^2, which indicates the percentage of the dependent variable that is explained by the independent variables, needs to be as high as possible.

It is important to mention that the values and signs of the multiple lognormal regression coefficients b_i must be reasonably explainable. Also, the value of the t-statistic control and the statistical significance level should be acceptable and satisfactory for the confidence level commonly used. The constant coefficient of the equation, which considers all the parameters that have not been taken into account, must be the lowest possible, as well. Lastly, the elasticity (ei) that shows how responsive one variable is to a change in another but also the relevant influence elasticity (ei*) used for quantifying the influence of each individual variable should be examined, which allows for the comparison between the influence of different variables in a single model.

4. Analysis and Discussion

The final dataset obtained from this study consisted of several types of variables regarding driver characteristics, parameters extracted from the naturalistic driving experiment as well as parameters extracted from the fuel consumption log template and questionnaire and included driving performance nominal and ordinal variables such as average speed, harsh acceleration and harsh braking, mobile phone use while driving, totaldist, duration, riskyhoursdistance, smooth eco, gender, age etc. that were analysed in the current research. For each model, the dependent variable was the logarithm of the fuel consumption and the independent variables were the following: before-after, average speed, harsh acceleration, average deceleration, smartphone usage, risky hours distance, gender and educational level. Table 1 provides a description of the independent variables that were found to be significant in the multiple lognormal regression models.

Table 1. Description of the parameters used in the models

Independent Variables	Description
Before-After	Before: normal driving , After: eco-driving
Avgspeed	Average of driving speed (km/h)
Ha	Number of harsh acceleration events occurred (absolute value)
Avdecel	Average number of deceleration events (km/h/s)
MobileUsage	Percentage of mobile phone use while driving
Riskyhoursdist	Risky hours distance from 22:00 pm to 05:00 am
Duration	Total driving duration (s)
Gender	Gender
Educ_level	Educational level
Years_drv	Years of driving experience

In Table 2, the parameters of the driving experiment and the multiple lognormal regression results are presented. The developing models have given a more clear understanding of the relation of driver behaviour and fuel consumption, which can be directly translated into realistic coaching targets for drivers and realistic fuel savings expectations for different fleet owners.

Table 2. Summary table of the four mathematical models developed for fuel consumption

Independent Variables	**Model 1 (overall model)**				**Model 2 (highway road)**				**Model 3 (rural road)**				**Model 4 (urban road)**			
	b_i	t	e_i	e_i*	b_i	t	e_i	e_i*	b_i	t	e_i	e_i*	b_i	t	e_i	e_i*
Constant	1,335	16,182			1,413	15,990			1,371	21,930			1,365	22,210		
Before-After	-0,056	-2,971	-0,016	1,000	-0,042	-2,271	-0,012	1,696	-0,057	-2,764	-0,008	1,000	-0,056	-2,868	-0,007	1,000
Avgspeed	0,001	1,787	0,054	3,404	0,001	2,033	0,105	14,756	0,001	2,496	0,046	5,510	0,002	3,267	0,030	4,596
Ha	0,001	2,613	0,096	6,125	0,007	2,072	0,028	3,900	0,002	2,776	0,050	6,095	0,002	5,398	0,116	17,736
Avdecel	0,029	1,986	0,070	4,440	0,021	2,037	0,024	3,313	0,020	1,910	0,042	5,126	0,043	2,907	0,106	16,286
MobileUsage	-0,158	-2,056	-0,038	2,424	-0,047	-1,829	-0,007	1,000	-0,149	-2,630	-0,038	4,646	-0,079	-1,736	-0,026	3,983
Riskyhoursdist	0,003	2,581	0,041	2,592	0,002	2,036	0,029	4,074	0,003	2,465	0,030	3,660	0,003	2,498	0,035	5,371
Duration					0,000	-3,371	-0,082	11,432								
Gender	-0,087	-4,996	-0,023	1,479	-0,114	-5,607	-0,031	4,299	-0,087	-5,121	-0,026	3,181	-0,091	-5,995	-0,024	3,733
Educ_level	-0,101	-7,386	-0,023	1,456	-0,113	-6,880	-0,026	3,585	-0,107	-7,500	-0,026	3,108	-0,102	-8,495	-0,023	3,550
Years_drv									-0,016	-2,330	-0,017	2,000	-0,024	-3,634	-0,016	2,411
R^2	0,620				0,637				0,656				0,704			

The results indicate that there is a remarkable reduction, namely 15% in fuel consumption. In addition, by improving the way participants were considering the task of driving, a smoother and greener driver behaviour was achieved. Driving at a steady pace, keeping speed limits, avoiding harsh acceleration and deceleration has contributed to fuel efficiency and to pollutant emissions reduction in the atmosphere. Moreover, a strong correlation between harsh accelerations and fuel consumption was found. Furthermore, it was observed that speed, deceleration, smartphone usage while driving, night-time driving and demographic features had a direct impact on fuel consumption as well. Table 3 figures the comparison of the mathematical developing models for fuel consumption. It becomes easily perceived which of the independent variable has the greatest impact on each model and can affect fuel consumption to a significant extent.

Table 3. Relevant influence of the independent models' variables

Independent Variables	Model 1 (overall model)	Model 2 (highway)	Model 3 (rural road)	Model 4 (urban road)
Before-after	1,000	1,696	1,000	1,000
Average speed	3,404	14,756	5,510	4,596
Harsh acceleration	6,125	3,900	6,095	17,736
Average deceleration	4,440	3,313	5,126	16,286
Mobile usage	2,424	1,000	4,646	3,983
Risky hours distance	2,592	4,074	3,660	5,371
Gender	1,479	4,299	3,181	3,733
Educational level	1,456	3,585	3,108	3,550

In urban driving, acceleration has the greatest impact on fuel consumption, namely 4,5 and 3 times higher than its impact on highways and rural road respectively. In the same context, deceleration was identified as the second most influential variable in the model. These results can be probably explained by the fact that dense signalling and crossings in urban network force drivers to reduce the speed and drive more nervously, pushing the accelerator gas pedal intensively, resulting in fuel consumption increase. Additionally, it was observed that in motorways where speed limits are high enough, fuel consumption elevated considerably as the speed increased. It is a fact that excessive speed is the biggest fuel-guzzling factor in highways so drivers who respected the speed limits for all road types, ensured a gentler acceleration behaviour and achieved a fuel efficient driving. Particularly, the speed variable in the highway model seems to have 2,7 and 3,2 greater impact regarding the rural and urban model, respectively. In rural areas, driver behaviour seemed to be similar to that of urban roads, but it is important the fact that the majority of the variables have a smaller impact on fuel consumption.

What's more, mobile phone usage affect fuel consumption but not as much as other variables. Specifically, mobile usage had the slightest influence on the highway model, where drivers did not used their phone while driving, probably because high speeds required more concentration on the driving task. All models results indicate that night-time driving is positively correlated with fuel consumption. Participants who were driving at risky hours from 22:00 pm to 05:00 am, showed a more dangerous driving behaviour, performing more harsh accelerations and steep brakes, exceeding the speed limit which is probably caused by low traffic load. As a consequence, the largest fuel waste was occurred with their aggressive driving during night hours.

Furthermore, both genders improved their driving style, with the majority of women driving more carefully and ecologically than men. This research reveals that the vast majority of male drivers displayed less cautious behaviour during their trips and consumed more fuel than female drivers. The negative value of the gender coefficient in all 4 models implies that as the value of the variable increases (males coded as 1, females as 2), the fuel consumption gets lower.

Sensitivity analysis conducted is presented in figure 3.It shows to what extent the increase in the average driving speed influences fuel consumptions for males and females during the two different phases of the experiment(males: before-after, females: before-after). For this purpose, the values of all independent variables except from the average speed remained fixed and the average speed is plotted for these four circumstances.

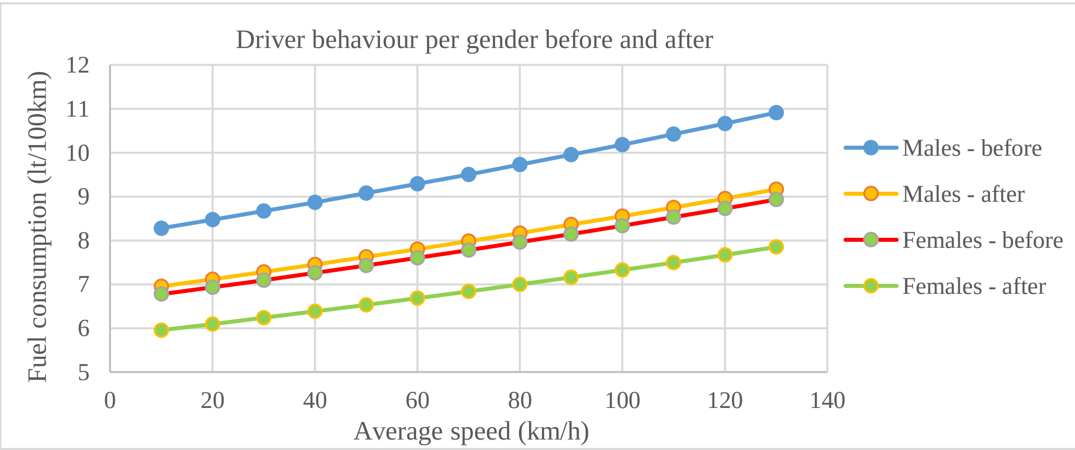

Figure 3. Driver behaviour per gender before and after

Additionally, sensitivity analysis displayed in Figure 4 shows to what extent the increase in the number of harsh accelerations occurred while driving, influences fuel consumption for males and females through the whole time of experiment. It is found that the higher the number of harsh accelerations occurred while driving, the higher the fuel consumption.

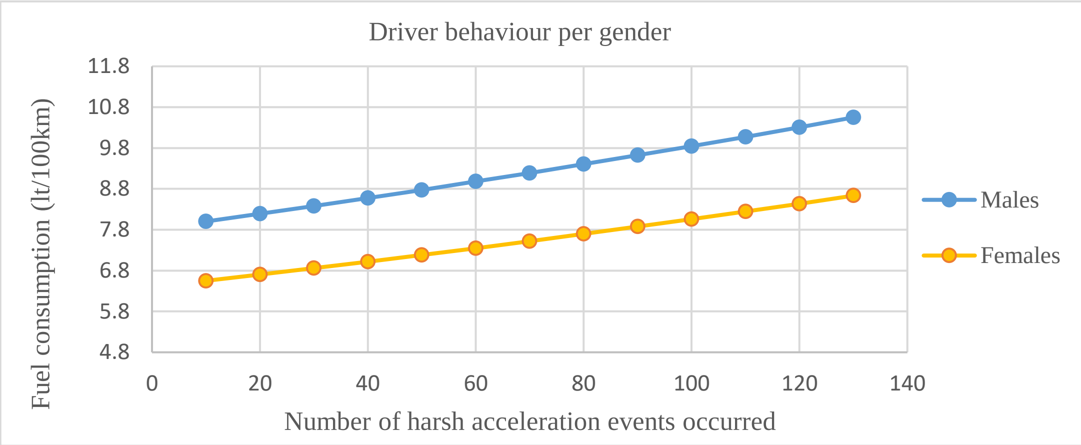

Figure 4. Driver behaviour per gender

It is also remarkable that experienced drivers and most educated road users adopted a more conservative and ecological driving behaviour and saved fuel probably due to their driving skills and driving experience. The negative value of the "Education level" coefficient in all 4 models implies that as the value of the variable increases (higher value means higher education level), the fuel consumption gets lower. With respect to driving experience, results indicate that this variable was found statistical important only to Model 3 and Model 4, having a negative effect on the fuel consumption, meaning that the more the years of participant's experience, the lower the fuel consumption. Nevertheless, both experienced and young drivers managed to improve significantly their driving style and reduce their vehicle's fuel consumption in the two last months of the experiment.

5. Conclusions and Future Reaserch

Nowadays, in a traffic environment where fuel is getting more expensive, a critical influencing factor on fuel consumption was found to be driver behaviour. Improving driving behaviour by keeping speed limits, reducing harsh accelerations and harsh braking and avoiding mobile phone use while driving, has been shown to contribute to a significant reduction in fuel use, thus resulting in air pollutant emissions reduction. Importantly, results of this paper substantiate that responsible driving style by slowing down, limiting acceleration and keeping long distance from the car ahead provides safety and fuel saving. Consequently, eco driving is a prerequisite but also promotes a safe driving which increases road safety, by reducing the likelihood of a road accident occurrence or its severity and by lowering the associated societal cost and state expenditure. The safer the driving behaviour becomes, the more ecological and environmental friendly the driving is.

At the same time, few innovative telematics systems are designed to specifically address these issues by working with the driver. It is expected that the technological devices will be the dominant player for the following years in the transport field as a fully scalable hardware-free solution. With the connected vehicles having been identified as the fastest-growing technological device after the smartphone and tablet, it gets easier to imagine the range of capabilities drivers can come to expect over the coming decade. The insights from the massive and ultra-accurate driving behaviour data can play a crucial role to road safety by providing driver feedback; drivers can receive the latest reports on potentially dangerous behaviour, improve their weak points and reduce the fuel consumption. Moreover, the use of modern mobile devices like smartphones or tablets and their internal sensors such as GPS receivers and three-axes accelerometers, allows road users to receive real time information on their behaviour that can be useful to increase awareness of drivers and promote safety.

Focusing on driver behaviour, drivers should understand that their style of driving significantly affects their vehicle fuel efficiency and can bring benefits not only to themselves but also to the environment. One of the most fundamental tools to achieve a better and smoother driver behaviour is a change in traditional ideas, mentality and way of thinking. Undoubtedly, mindset is all about attitude which is also depicted through driving style of each one. Saving fuel and therefore money must be a strong behavioural change motivator that will help drivers to adopt a culture that puts eco-driving and safety as the first priority and takes it seriously. Drivers have to embrace driving habits that unlock their full potential as safe and eco drivers, become more focused on the road, be more eager to drive safer and use clutch, brake and acceleration with the softer way. That is the most comprehensive approach to creating a safe and ecological driving culture.

Dozens of surveys reveal that recognizing risky driving behaviour can be a strong motivator for drivers to change their bad driving habits and improve their behaviour. It is self-evident that driving education is one of the most important aspects of the role of training. In particular, male drivers, who are over-represented in severe crashes compared to young female drivers, when also controlling for exposure (annual mileage), should be subjected in order to understand all these essential elements that can lead to a better and more safe driving behaviour. Also, driving training programs should enrich drivers with the proper driving skills and knowledge of the benefits of eco-driving, laws and rules of the roads and responsibilities of the driver so they can acquire a more prudent and safe behaviour and minimize their personal risks. Fully-educated drivers are more adept at handling their vehicle and learn to drive wisely even if they encounter in an unfamiliar traffic environment. Training results in 7-11% less crashes for novice drivers compared to untrained ones (SafetyCube, 2017).

Apart from the above, insurance companies could reward cautious drivers with lower insurance rates and costs over time and this can contribute to the reduction of road accidents, unnecessary fuel consumption and air pollutant gases. More specifically, according to Tselentis et al. (2017), usage-based motor insurance (UBI) schemes will play a key role in motor insurance market in the future and as a result it will strongly influence traffic safety in total. It is very essential to introduce economic incentives in form of a flexible discount on traffic charges depending on the driver's ecological and safe driving behaviour. Lastly, stricter police enforcement and more frequent harsher sanctions must be used to eliminate aggressive driving behaviour and reduce fuel consumption and emissions. Summarizing, driver training, in-vehicle technologies and innovative telematics systems constitute a key role by providing drivers information on fuel efficient driving techniques, while the technologies provide ongoing reminders encouraging drivers to use and further develop their fuel efficient driving skills.

The next steps of the present study include the organization of a following naturalistic driving experiment where the same 17 participants will be recruited in order to investigate if the improved driving behaviour did last over the long term and if so, in what extent. Furthermore, the experiment could be carried out in a larger sample of drivers with different age groups. The more drivers are participated at a naturalistic driving experiment, the more reliable the variables and results are. With regard to research methodologies, there are many different statistical data analysis methods, such as cluster analysis, factor analysis or time series analysis that can be used in order to icily exhibit different driving style at any types of road. Furthermore, it would be quite impressive to be achieved a similar experiment involving the worst-performing drivers of all ages.

Future research should also focus on the analysis of the separate impact of each noticed behaviour on fuel consumption which would be based on even more data like psychological status of participants or driving under the influence of alcohol. In addition, of particular interest would be the investigation of fuel economy performance according to tire pressure of the car and other vehicle body styles and structural characteristics such as driving force, horse power, cubic capacity, weight, age etc. Because of the fact that fuel prices are rising on an almost daily basis, it would be useful to find which type of fuel (gasoline, diesel, liquid petrol or compressed natural gas) is more environmentally friendly and affects fuel consumption in a lower degree.Finally, in a subsequent study participants would not complete fuel consumption log sheet template but fuel consumption could be recorded automatically via an On-Board Diagnostic device (OBD-II) connected inside the vehicle for more precise data.

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