Investigating the impacts of COVID-19 pandemic on Eco-driving behavior

Eleni Mantouka[1]*, Panagiotis Fafoutellis[2], Eleni I. Vlahogianni[3], Petros Fortsakis[4]

[1]Department of Transportation Planning and Engineering, National Technical University of Athens, 5 Iroon Polytechniou Str, Zografou Campus, 157 73 Athens Greece, elmant@central.ntua.gr
[2]Department of Transportation Planning and Engineering, National Technical University of Athens, 5 Iroon Polytechniou Str, Zografou Campus, 157 73 Athens Greece, panfaf@mail.ntua.gr
[3]Department of Transportation Planning and Engineering, National Technical University of Athens, 5 Iroon Polytechniou Str, Zografou Campus, 157 73 Athens Greece, elenivl@central.ntua.gr
[4]OSeven Single Member Private Company, 27B Chaimanta Str., GR-15234, Athens, Greece, pfortsakis@oseven.io

Abstract

The outburst of the COVID-19 pandemic has significantly disrupted the operation of the existing transportation systems, decreasing the total number of trips, as well as the habits of the majority of the travelers. In this paper, the impact of the pandemic on driving behavior and, specifically, on ecological driving is investigated. First, a clustering approach is adopted to identify different driving profiles in a dataset of naturalistic driving data. It was found that there are three discrete profiles, each with its respective characteristics: aggressive, eco and typical. Furthermore, a statistical analysis and comparison of the distribution of the trips in the three profiles was conducted in four different time periods: before the lockdowns, during the first lockdown, between the two lockdowns and during the second lockdown. Interestingly, the results indicate that the new conditions that emerged have steered drivers towards smoother and, thus, safer and more ecological driving behavior.

Keywords: eco-driving; covid-19; driving profiles

1. Introduction

The spread of the coronavirus COVID-19 forced governments worldwide to take measures to contain the pandemic by completely changing everyday life and consequently, altering the mobility characteristics of citizens. During the year 2020, a series of unrivalled global measures were applied such as lockdowns and suspension of all retail. These global mobility restrictions imposed in light of COVID-19 and their impacts on mobility are an active subject of research, with an obvious consensus regarding the general reduction in both long distance trips and short distance daily trips and their strong correlation with infection rates and affected countries [1]. This reduction in mobility has been accelerated by the administrative orders for controlling the dispersion rate of the virus [2] and has seriously affected modal shift [3]. The aim of this research is to identify potential changes in the ecological behavior of drivers (while driving) emerged due to the exceptional conditions during the pandemic, namely due to reduced traffic flows, modal shift, less trips, etc.

Eco-driving is defined as the adoption of a driving behavior that leads to reduced fuel consumption and greenhouse gases emissions. In general, it refers to the adjustment of the vehicle's speed and acceleration, as well as the choice of routes and departure time that minimize fuel consumption [4]. For example, accelerating smoothly, maintaining a constant speed and avoiding driving in congested conditions play a very important role in fuel economy [5]. It is estimated that eco-driving is capable of reducing fuel consumption by 15% to 25% and GHG emissions by about 30% [6], [7].

Alleviating human-driven climate change and reducing pollution of the environment, as well as the high level of dependence on non-renewable resources for energy production are considered as some of the most important challenges targeted as priority by both the United Nations sustainability goals and the European Union Green Deal [5], [8]. In general, the transport sector is responsible for the production of the highest volume of greenhouse gases, estimated about 30% of the manmade emissions [9], having increased by 22% from 1990 [10]. The transport sector consumes about 20–25% of the total energy produced [5], [11], [12], the 65–75% of which is related with road transport [5], [12], [13].

Eco-driving is seen as a facilitator for raising drivers' awareness regarding their ecological footprint. Driving behavior, as any other human behavior, is affected by a variety of factors among which are individual's habits, personal characteristics, perceptions as well as road characteristics, the traffic environment, and other unexpected factors such as disruptions, pandemics etc. Recently, the pandemic of COVID-19 and its consequences, including the lockdown of March and April 2020, have created unprecedented conditions on the road network (decreased congestion, driver's psychology etc.), the effects of which on driving behavior are worth studying.
The rest of the paper is organized as follows: first, the proposed methodological approach is presented in detail. Following, the main results with the corresponding discussion is provided, and finally conclusions and future research directions are proposed.

2. Methodology

A comparative analysis is performed to identify potential changes in driving behavior of the entire traffic deploying well known statistical and data-driven approaches. More precisely, first, following a k-means clustering procedure, driving behavior is detected on a trip level, where each trip is characterized based on the emergence of aggressiveness or "econess" during driving. Subsequently, a comparative statistical analysis is performed to highlight differences in driving behavior during the lockdown of Spring 2020 and before it. The methodological approach followed includes three steps: first, k-means clustering is implemented for all the trips using a selection of driving parameters. Then, the dataset is divided into four distinct periods based on the lockdowns imposed due to COVID-19 pandemic, and finally, a comparative analysis between the emergence of each driving style in each of the four periods is conducted.

2.1 K-means clustering

The most widely used and studied algorithm is K-means clustering [14]. While using K-means clustering method, the goal is to partition the dataset into a predefined number K of clusters. A cluster can be thought as comprising a group of data points whose inter-point distances are small compared with the distances of points outside of the cluster. For each data point X_n, a corresponding set of binary indicator variables$r_{nk} \in \{0,1\}$ are introduced, where $k = 1, \dots, K$ describing which of K clusters the data point X_n is assigned to, so that if a data point is assigned to cluster k then $r_{nk} = 1$, and $r_{nj} = 0$ for $j \neq k$. Then, an objective function is defined, given by:

$$J = \sum_{n=1}^{N}\sum_{k=1}^{K} r_{nk}\|x_n - \mu_k\|^2 \qquad (1)$$

which represents the sum of squares of the distances of each data point to its assigned vector μ_k, where μ_k represents the center of the k^{th} cluster [15].

Clustering validation measures evaluate the goodness of clustering results, and are considered as key for the success of clustering applications. There is a variety of validation measures, such as silhouette index, Dunn's index, Davies-Bouldin index, R-square, Hubert's Γ statistic, Calinski-Harabasz criterion and many more. In this paper, the following three measures are used:

Silhouette index

For a given cluster, X_j (j =1,….,c), this method assigns to each sample of X_j a quality measure, *s(i)* (i=1,….,m), known as the Silhouette width, which is defined as:

$$s(i) = \frac{b(i)-a(i)}{max\{a(i),b(i)\}} \qquad (2)$$

where *a(i)* is the average distance between the i^{th} sample and all of the samples included in X_j; 'max' is the maximum operator, and *b(i)* is the minimum average distance between the i^{th} sample and all of the samples clustered in X_k (k =1,….,c; k ≠ j). From this formula, it follows that $-1 \leq s(i) \leq 1$. When a *s(i)* is close to 1, one may infer that the i^{th} sample has been assigned to an appropriate cluster. When a *s(i)* is close to 0, it suggests that the i^{th} sample could also be assigned to the nearest neighboring cluster. If *s(i)* is close to −1, one may argue that such a sample has been assigned to a wrong cluster. Thus, for a given cluster it is possible to calculate a cluster Silhouette index S_j, which characterizes the heterogeneity and isolation properties of such a cluster:

$$Sj = \frac{1}{m}\sum_{i=1}^{m} s(i) \qquad (3)$$

where *m* is the number of samples in S_j.

2.2 Time periods studied

The analysis is performed in the basis of four periods based on COVID-19 regulations and lockdowns as seen in Table 1.

Table 1: COVID-19 regulations and lockdown periods.

Period reference	Duration	Description
1st period: Normal conditions	January- February 2020	Until the end of February only three cases have been confirmed in Greece.
2nd period: 1st lockdown	March, April, May 2020	On the early days of March, local guidelines and regulations started to take effect, such as closure of schools and suspension of cultural events. Shortly afterwards cafes, bars, restaurants and more facilities were also closed. On 22 of March the country was put on full lockdown, which suspended all non-essential activities outside people's homes.
3rd period: between lockdowns	June- October 2020	On May 4, the restrictions were gradually lifted, with local or not as strict regulations occurring in the summer months, for example people should be seated at all times at bars.
4th period: 2nd lockdown	November, December 2020	On the 7th of November the country was in lockdown again, with some differences than the previous one, for example primary schools remained opened and a month later some facilities, shops, hairdressers and others, were allowed to operate under strict safety measures.

2.3 Data collection

Data is collected from an already developed smartphone application for both iPhone and Android devices. The application is always running in the background of the smartphone's operating system so that no user action is required while commuting. Using several criteria the application starts to collect raw data from smartphone using accelerometer, gyroscope and GPS sensors. The accelerometer can record a smartphone's acceleration in m/s^2 in respect to gravity acceleration while the gyroscope records smartphone's angular velocity in rad/sec. Finally, GPS data are collected to record the speed of the vehicle and the coordinates of the vehicle. Since the application is using cloud-based services, after the automatic detection of the end of the trip, data are uploaded to the server for storage in an anonymized way for further process.

For each trip, numerous variables are extracted to be included as input features in the clustering. Statistical measurements of acceleration and deceleration during a trip are included that describe how smoothly the driver changes his/her longitudinal position. In addition, speeding measurements are collected that describe smoothly and with speed excess driving, as well as mobile usage indicators are estimated that describe how cautious the driver is. Finally, several other driving environment aspects are detected and recorded, such as the type of road, the day of the week, etc. Table 2 illustrates the driving parameters used in the specific approach.
The harsh events per minute (acceleration and breaking) are defined as the times the driver's acceleration or deceleration exceeded a specific threshold and, therefore, they can be considered as an indication of aggressive and even unsafe behavior, as well as a non-ecological one. The smoothness indicator is an estimation of the total kinetic energy the vehicle consumed (via consuming fuel) during a trip and is related to whether the driver maintained a constant speed or not during the specific trip. Finally, the non-eco acceleration duration is the percentage of the trip where the vehicle was moving with a high acceleration, thus consuming more fuel.

Table 2: Description of Variables Used in Clustering

Variable	Description
Harsh acceleration per min	The number of harsh accelerations per minute.
Harsh brakes per min	The number of harsh brakes per minute.
Smoothness indicator	The sum of differences of squares of final and initial speed, divided by trip distance.
Non-eco acceleration duration	The duration of the trip where the drive adopts a non-eco acceleration.

3. Analysis and Results

In order to detect different driving profiles and consequently provide the relevant characterization for each trip, K-means clustering is performed. The number of clusters is set to k = 3 while clustering is implemented on Euclidean distance matrix. Table 3 presents the centers of each cluster for each variable respectively. One may observe that the three clusters are separated clearly based on each variable, as it is also indicated by the silhouette index, which was estimated at 0.62. Therefore, three driving behavior patterns are detected, with well-defined characteristics:

- Eco driving, which has the lowest values of all the variables investigated and can also be considered as the safest and smoothest driving style, due to the low number of harsh events per minute.
- Aggressive driving, with the highest values of all variables, which can also be considered as the less ecological behavior.
- Typical driving, that illustrates values of the four variables that fall in between the two previous clusters.

Table 3: Clustering results: cluster centers

	Clustering centers			
Cluster name	**Smoothness indicator**	**Harsh acceleration per min**	**Harsh brakes per min**	**Non-eco acceleration duration**
eco	0.285	0.030	0.035	0.004
typical	0.403	0.091	0.343	0.009
aggressive	0.529	0.573	0.351	0.021

To evaluate the effect of the lockdowns on driving behavior, the distributions of the trips of the four periods among the three profiles were examined. Interestingly, the percentage of the trips that belong to the eco profile is observed to be gradually increasing, as the time passes, to the detriment of the typical and, secondarily, the aggressive trips. More specifically, before the first lockdown, about 51.5% of the trips were characterized as "typical", 33% eco and almost 15.5% aggressive, while during the second lockdown the above percentages were 46%, 40% and 14% respectively. During the first lockdown, it can be observed that a first significant increase of the trips that belong to the eco profile (+4.3%) emerged, which also continued between the lockdowns, while the aggressive trips also had significantly decreased.
The above changes on driving behavior between the different periods are illustrated in Figure 1 below.

Figure 1. Distribution of clusters between the four time periods

A glimpse on the statistical characteristics of trip's average acceleration per cluster for each time period indicates that the range of aggressive accelerations is slightly impaired between the lockdowns. In contrast, as far as it concerns the eco accelerations, during the lockdowns lower accelerations are observed compared to the first period corresponding to normal conditions. The above results are nicely illustrated in Figure 2.

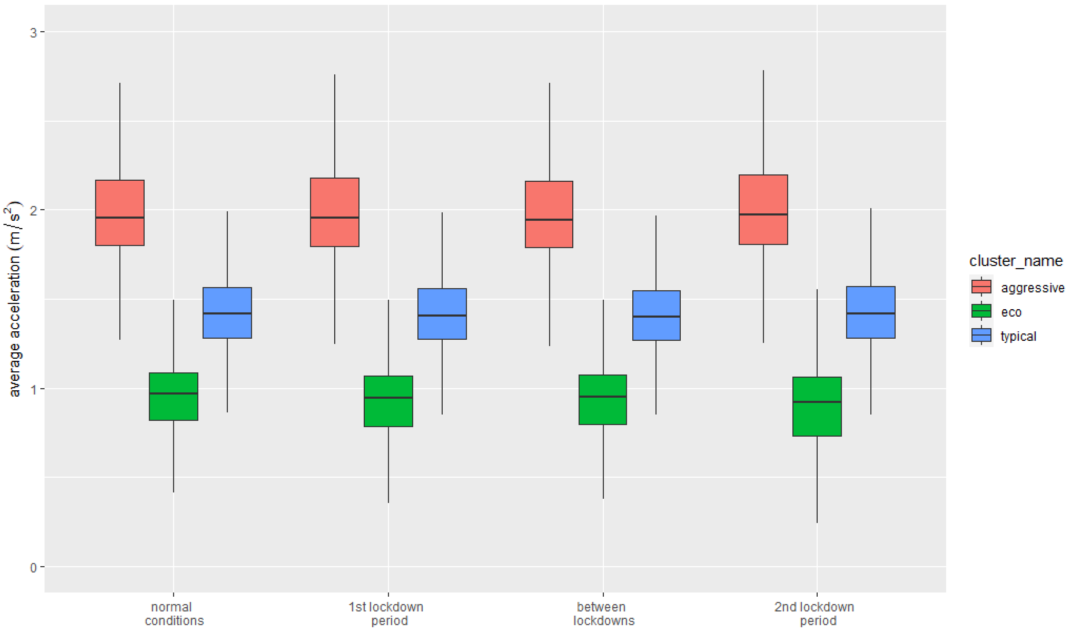

Figure 2. Boxplots of trip's average acceleration for each cluster per time period

4. Discussion and Conclusions

In this paper, the effect of the COVID-19 lockdowns on driving behavior and especially eco-driving was investigated. First, we were able to detect three different driving profiles (eco, aggressive and typical) in a dataset of naturalistic driving data, using an unsupervised learning framework. Then, the distribution of the trips during the four defined time periods (before the lockdowns, during the first lockdown, between the two lockdowns, during the second lockdown) was estimated, in order to detect differences between them.

While in the normal conditions, the typical trips were more than 50% of the total and 33% were eco, during the last year and because of the new conditions connected with the pandemic, the percentage of eco (and also safer) trips increased to about 40%, while the aggressive ones had also a significant decline, from 15.5% to 13.9%.

The above results indicate that the new normal that was introduced by the government measures and is characterized by lower traffic volumes and less trips per person, because of the high percentage of teleworking, the closure of retail shops, restaurants, etc., has led drivers to drive in a smoother way and, thus, safer and ecologically friendlier.

Our future research will definitely include the analysis of trips conducted later (in 2021), in order to investigate whether the trend that was witnessed in 2020 continues and whether similar conclusions can be reached. The conclusions of this research could also be exploited by policy makers and be translated into measures that would lead to similar outcomes, after the alleviation of all the pandemic-related measures and limitations.

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