Investigating the Temporal Evolution of Driving Safety Efficiency Using Data Collected from Smartphone Sensors

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INTRODUCTION

This paper attempts to shed light on the temporal evolution of driving safety efficiency with the aim to acquire useful insights for both drivers and road safety improvement. To this end, it presents a methodological framework to study the temporal evolution of measured driver's efficiency with the aim to provide valuable information on the different driving behavior profiles.

Many studies in driving behavior literature *(1, 2, 3, 4, 5)* have focused on measuring driving safety efficiency. Nonetheless, only a few of them have demonstrated that there is a potential in analyzing and evaluating driving behaviour using microscopic driving data (e.g. driving over the speed limits, mobile phone usage and the number of harsh acceleration and braking events occurred while driving) collected from naturalistic driving experiments *(1)*. As for data collection, literature review revealed that the methodologies most commonly used include driving simulators *(6, 7)*, questionnaires *(3)* combined with simulators and naturalistic driving experiments *(8, 9)*. Naturalistic experiments though provide a wide perspective of understanding typical microscopic travel and driving behaviour *(10)*.

Driving efficiency assessment using microscopic driving parameters is thoroughly studied *(1)* but the evolution of the driving performance in time is not yet investigated. The temporal characteristics of driving efficiency and especially stationarity, trend and volatility, are of outmost importance when driving efficiency is measured. This is because the average driving efficiency might be representative of the total driving risk only in those cases when driving behavior is not fluctuating in time.

In this study, several statistical, econometric, optimization and machine learning techniques are exploited and applied on data collected from a sophisticated platform that uses smartphone device sensors during a naturalistic driving experiment. The driving groups arising are the a) typical drivers, b) unstable drivers and c) cautious drivers. This methodology could be exploited as a platform's service in order to provide recommendations to drivers on how to improve their driving efficiency and become less risky.

METHODOLOGY

Previous research has shown that data envelopment analysis (DEA) is an effective methodology to measure efficiency *(14, 15)*. In this work, the driver is considered a DMU with an aggregate performance and his driving behavior is equivalent to the sum of the driving characteristics for the entire period examined. For instance, the total distance travelled in rural road is equivalent to the sum of the distance travelled in rural network in each $trip_{ij}$ (where i is the index of $driver_i$ and j the index of $trip_j$ of $driver_i$) by the specific $driver_i$ (DMU_i).

When studying driving behavior, efficiency is defined by the number of driving metrics recorded for a specific period or distance that a driver is being monitored *(1)*. Literature review revealed that distance travelled, the number of harsh acceleration/ braking events, speeding and mobile usage are the most influencing accident risk factors, among those that can be recorded from the smartphone sensors, and therefore they should be included in the models implemented. These are used as DEA inputs and outputs in order to estimate a driving safety efficiency index.

The temporal features of driving efficiency used in the analysis performed are driver's behaviour volatility measure, stationarity and trend, which are components of the driving efficiency time series. All these features are exploited using a k-means clustering algorithm to evaluate the different driving profiles arising.

OSeven Telematics has developed an integrated platform for the recording, transmission, storage, evaluation and visualization of driving behaviour data using a smartphone application, statistical and advanced machine learning (ML) algorithms. Recorded data come from various smartphone sensors and data fusion algorithms provided by Android and iOS. A significant amount of data is recorded using this platform and data are anonymized before provided by OSeven so that driving behavior of each participant cannot be connected with any personal information. This is a data exploitation approach that is user-agnostic and therefore not user intrusive.

To achieve the goals of this research, large-scale driving data of 38,000 trips are randomly selected from the OSeven database of which 23,000 trips are performed in urban road by one hundred (100) drivers and 15,000 trips are performed in rural road by one hundred (100) drivers. In order to create time series of the same length for all participants, 230 urban and 150 rural trips are collected for each driver. In order to acquire a reliable measure for analyzing driving patterns and changes in drivers' behavior over time, driver's sample size is specified based on *(11)*.

FINDINGS

Components of the Efficiency Time Series

Driver's efficiency is estimated for each time step of a sliding time window, following the same procedure described above for the estimation of total driving efficiency. The length of the time window is empirically estimated using specific statistical tests that identify the convergence of the driving analytics of each driver to a certain behavior. Results on the specific dataset indicate that this time window is 75 and 82 trips for urban and rural road types respectively.

Figures 1 and 2 illustrate the driving efficiency time series of seven drivers in the urban and rural sample respectively. The observed time series fluctuation is indicative to the existence of different driving patterns. It is observed in both figures that drivers who are least efficient in total, also appear to be least volatile among the rest. The most efficient drivers also appear to be less volatile but not as much as the latter. On the other hand, medium efficiency drivers are the most volatile among the drivers sample.

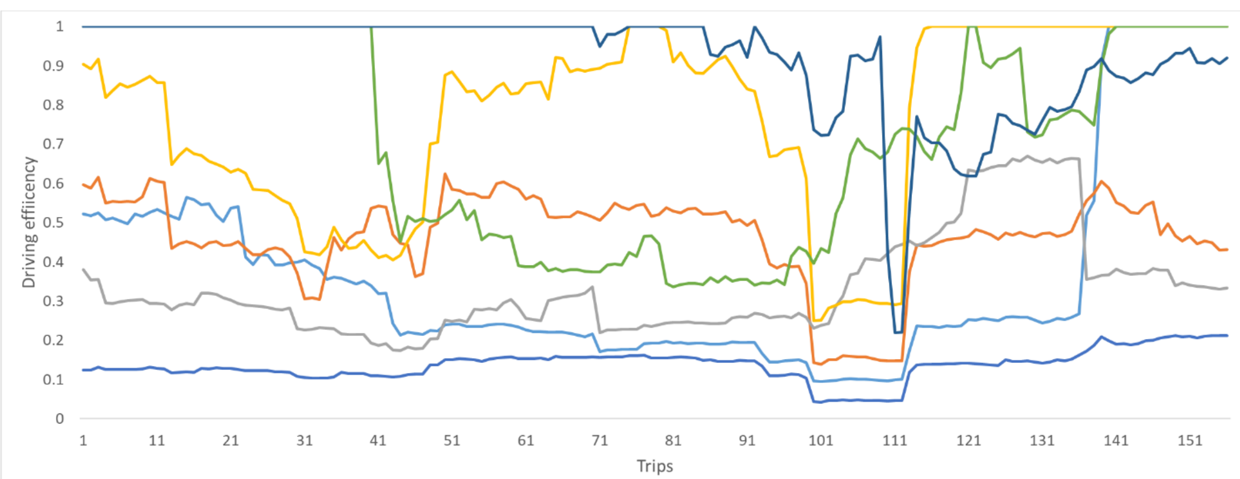

FIGURE 1: Efficiency time series of the anonymous urban sample.

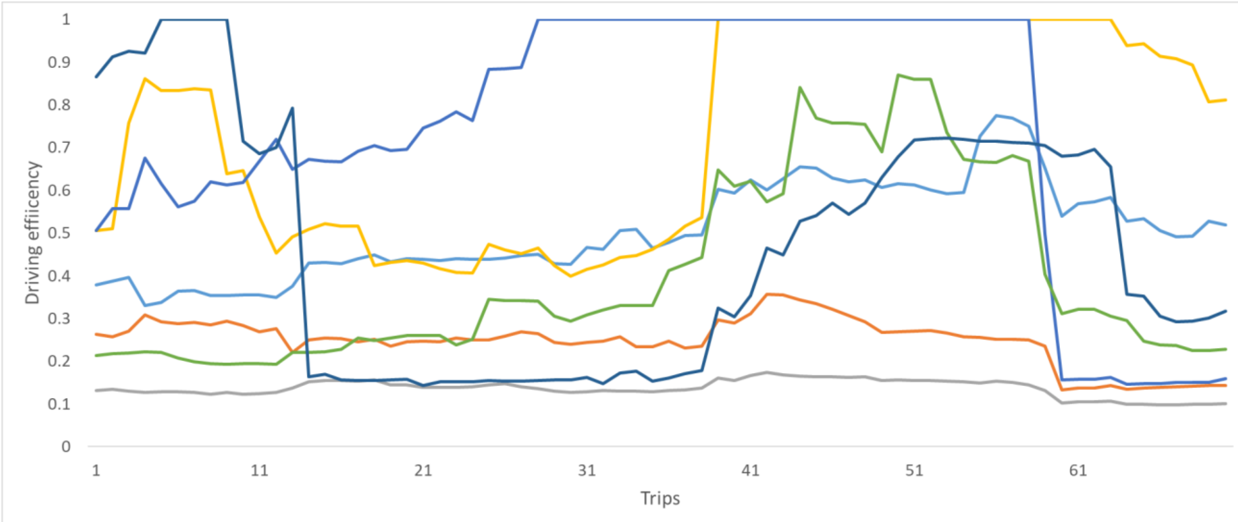

FIGURE 2: Efficiency time series of the rural sample.

Table 1 illustrates the results of the volatility analysis performed, which indicate that although there is a higher range of volatility in rural road type, the average is approximately the same in both road and sample types. Based on driving volatility's definition, it is inferred that when it is equal to zero, a driver demonstrates a solid performance throughout monitoring. As a result, drivers with steady unit efficiency exist only in rural road since the minimum value of volatility is found to be higher than zero in urban road.

TABLE 1: Descriptive Statistics of the Driving Efficiency Volatility and Trend of the Drivers' Sample

Sample type	Volatility		Trend (*10-3)	
Road type	**Urban**	**Rural**	**Urban**	**Rural**
Min	0.022	0.000	-4.56	-8.79
Max	0.152	0.379	4.09	8.46
Average	0.119	0.111	0.68	0.66
Standard Deviation	0.021	0.055	1.25	2.69
Median	0.123	0.095	0.51	0.80
Kurtosis	7.245	6.393	3.820	3.696
Skewness	-2.388	2.102	-0.222	-0.550

Time series is afterwards decomposed to acquire trend and stationarity using the methodological approach described above. It is observed in Table 1 that the average trend is approximately the same between the two road types despite the fact that median trend is diverged. This indicates the existence of high outlier trend values in urban road and low outlier trend values in rural road that influence the average trend value. Regarding the number of differences required for a time series to become stationary, zero urban road users and five rural road users with a stationary driving behaviour were found. The number of required differences for a time series of become stationary is equal to one for the vast majority of users and therefore, this variable is not illustrated in Table 1 and not used in the clustering procedure.

Clusters' Driving Characteristics

The k-means algorithm is applied to cluster drivers based on the total driving efficiency, volatility, and the trend of the time series. The optimal number of clusters is determined using the elbow method and is found to be 3. Driving characteristics of all clusters are presented in Table 2.

TABLE 2: Macroscopic Characteristics of the Drivers' Clusters

Road type	Cluster	Statistical character	Trend (*10-3)	Volatility	Rating	Number of drivers
Urban	Cluster 1 (typical drivers)	Min	-1.045	0.066	0.122	79
		Max	1.686	0.152	0.725	
		Average	0.516	0.123	0.340	
		Standard Deviation	0.534	0.013	0.108	
		Median	0.486	0.124	0.328	
		Kurtosis	0.303	4.969	0.944	
		Skewness	-0.123	-1.438	0.713	
	Cluster 2 (unstable drivers)	Min	2.032	0.066	0.448	13
		Max	4.085	0.141	1.000	
		Average	3.006	0.119	0.673	
		Standard Deviation	0.628	0.022	0.206	
		Median	3.067	0.125	0.608	
		Kurtosis	0.334	-1.815	-2.281	
		Skewness	0.209	-1.278	0.732	
	Cluster 3 (cautious drivers)	Min	-4.557	0.022	0.367	8
		Max	0.322	0.122	1.000	
		Average	-1.512	0.080	0.746	
		Standard Deviation	1.530	0.038	0.263	
		Median	-0.937	0.090	0.813	
		Kurtosis	-1.027	0.925	-1.154	
		Skewness	-1.053	-0.385	-0.237	
Rural	Cluster 1 (typical drivers)	Min	-1.987	0.048	0.127	72
		Max	3.375	0.228	0.664	
		Average	0.764	0.099	0.363	
		Standard Deviation	1.040	0.035	0.120	
		Median	0.778	0.091	0.356	
		Kurtosis	-0.639	2.144	-1.806	
		Skewness	-0.252	1.437	0.410	
	Cluster 2 (unstable drivers)	Min	-8.785	0.072	0.323	12
		Max	-1.545	0.379	1.000	
		Average	-4.288	0.155	0.716	
		Standard Deviation	2.530	0.088	0.246	
		Median	-3.811	0.125	0.685	
		Kurtosis	0.412	2.323	-0.250	
		Skewness	-0.824	1.490	-0.042	
	Cluster 3 (cautious drivers)	Min	0.000	0.000	0.483	16
		Max	8.455	0.306	1.000	
		Average	3.904	0.133	0.847	
		Standard Deviation	2.573	0.072	0.160	
		Median	4.295	0.115	0.880	
		Kurtosis	-0.712	1.167	-0.268	
		Skewness	0.398	0.789	-0.802	

The macroscopic characteristics of the urban sample's clusters that resulted from the clustering analysis revealed in Table 2. Cluster 1 presents a very low positive trend, a medium to high volatility and an average low total efficiency value. All the above along with the high number of drivers included in the specific cluster, lead to the conclusion that this cluster mainly represent the typical driver. As for cluster 2, it features a medium positive efficiency trend, a medium to high volatility and a medium average rating which all demonstrate that this cluster is comprised from unstable drivers with less risky behaviour and a constant trend of improvement. Drivers of cluster 3 present a medium negative trend, a low to medium behavioural volatility and a medium to very high average driving efficiency confirmed by the low accident frequency. Consequently, this cluster includes the most cautious drivers of the sample. It is highlighted that the results arising for the rural sample are similar to those in urban and their main difference is between drivers of cluster 2, who present a high negative trend instead of a medium positive.

CONCLUSION

All the above lead to the conclusion that when driving efficiency is benchmarked using DEA, the sample should be assessed on a regular basis to identify any alterations made in the efficiency frontier, which will result in a change in the ranking of the drivers. As a result, drivers should be continuously monitored and re-evaluated to capture these shifts and provide personalized advice on how their behaviour could be improved in the future.

A potential is identified in this study for classifying drivers' sample based on macroscopic temporal driving characteristics. In a real case scenario, drivers could be monitored for a certain period to analyze and evaluate their driving behavior. Thus, the most risky driving traits that significantly influence accident probability would be recognized. Those results can potentially feed a platform's service and provide feedback and recommendations to drivers on their driving characteristics that need further improvement to become less risky. To this end, gamification policies based on this approach such as competitions, learning goals and awards could contribute to this scope. The results of this research could also be exploited in order to create innovative insurance pricing schemes that will be based on driving characteristics (e.g. Pay-How-You-Drive driving insurance schemes) and not mainly on demographics.

The main driving characteristics of the clusters that result from the analysis such as mobile usage, speed limit violation and number of harsh events should be further analyzed in the future to acquire a clearer picture on the dominant driving patterns that exist. Future research should also focus on larger drivers' samples with a representative sample collected from the entire population or from many countries so that more generalized conclusions can be drawn. It is a fact that models become more representative of the average characteristics of each cluster as more trips and drivers are aggregated. On the top of that, it would be beneficial to collect the accident record of the participants and include it in the clustering procedure in order to check if results arising are also representative of the individual driving risk. Finally, more driving metrics influencing accident risk should be used and test whether or not driving behavior models are improved.

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