# Exploring critical driving parameters affecting speeding using data from smartphones

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## Extended Abstract

Speeding is one of the most important human factors that influence road accident risk (WHO, 2020). Excess and inappropriate speed are responsible for a high proportion of the mortality and morbidity that result from road crashes. In high-income countries, speed contributes to about 30% of deaths on the road, while in some low-income and middle-income countries, speed is estimated to be the main contributory factor in about half of all road crashes. Controlling vehicle speed can prevent crashes happening and can reduce the impact when they do occur, lessening the severity of injuries sustained by the victims. However, it is of high importance to understand that the relationship between speed and road safety is a complex one; many physical and psychological factors play a role. In this paper, two such groups of studies are examined: studies aiming to define the factors that affect speeding and studies that have used in-vehicle recoding systems to investigate driving behavior.

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. 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. Additionally, recent works used a Driving Data Recorder (DDR) which can provide feedback on driver behavior for crashes analysis and other insurance issues (Ohta et al., 1994, Gu et al., 2019).

Moreover, a driving behavior and safety evaluation was conducted through a data recording system called Drive Diagnostics which is a dedicated In Vehicle Data Recorder (IVDR) system, customized inside the vehicle (Toledo et al., 2006). It is worth highlighting that in a survey which took place in young drivers during the first year after their licensure was found that drivers who knew that their driving behavior 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 behavior have been assessed and analyzed 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 aimed to detect road crashes and mechanical problems in vehicle that 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).

Based on the aforementioned, the aim of this study is to identify critical driving parameters affecting speeding using data obtained from smartphone sensors during naturalistic driving. Furthermore, the analyses are extended in order to determine the influence of road type (urban, rural and highway) in the percentage of speeding as well as any underlying correlations with other factors such as driving duration.

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According to the above information, the aim of this study is to identify critical driving parameters affecting speeding using data obtained from smartphone sensors during naturalistic driving. Furthermore, the analysis targets to determine the influence of road type (urban and rural) in the percentage of speeding as well as any underlying correlations with other factors such as distance and the mobile usage while driving.

The data, which was exploited to accomplish this research, was collected through OSeven Telematics Company's smartphone application (Figure 1). However, the distinctive of this study is that the data were extracted from two separated databases. The first dataset contains driving characteristics from a naturalistic driving experiment, which was carried out involving 100 drivers during a 6-months timeframe either in urban and rural area or in highway. The detection and the recording were conducted in real time using smartphone device sensors. Totally were collected data for 49,019 trips and for each one were measured traffic variables such as speed, acceleration, driving distance and more.

The second database included a detailed questionnaire, which was divided into four sections. The participants were requested to answer to all the questions before they start their first trip. The questions were referred to driver's driving habits and experience, driver's vehicle and demographic characteristics.


**Figure 1: Data chart flow**

With the combination of these two databases, some statistic charts were constructed so as to describe and comprehend better the collected data (Figure 2).

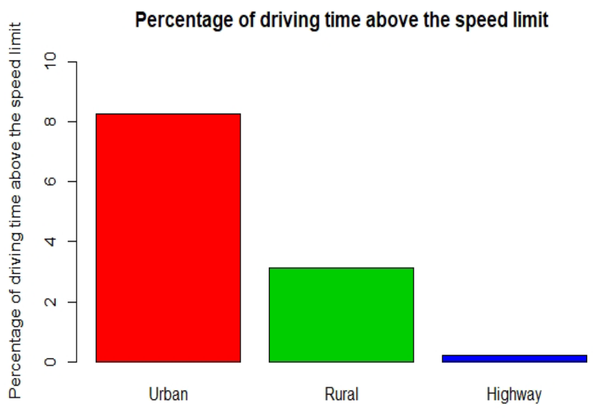


**Figure 2: Percentage of driving time over the speed limit examined per road type**

After appropriate data processing and a series of tests, three mathematical models were developed by transforming the speeding percentage per trip to an integer and Generalized Linear Models (GLMs) were implemented with a Poisson data distribution. The first one illustrates the critical factors influencing speeding regardless of the type of road while the other two present the critical factors influencing speeding for urban and rural road type respectively. Table 1 and 2 shows explicitly the critical driving parameters affecting speeding as well as the results of some acceptance criteria.

**Table 1: GLM model for speeding for all road types (overall model)**

| Trip Characteristic | βi | s.e | p-value | Relative Risk Ratio |
|---|---|---|---|---|
| Intercept | 3.694 | 0,656 | <0.001 | 40.205 |
| Mbu | 3.655 | 0,864 | <0.001 | 38.668 |
| harsh_acc | 0.485 | 0,126 | <0.001 | 1.624 |
| acc_avg | -1.244 | 0,39 | <0.001 | 0.288 |
| self-declared speeding never | -1.648 | 0,461 | <0.001 | 0.192 |
| self-declared speeding often | -1.148 | 0,350 | <0.001 | 0.317 |
| self-declared speeding rarely | -1.386 | 0,338 | <0.001 | 0.250 |
| self-declared speeding smt | -1.073 | 0,331 | 0.002 | 0.342 |
| AIC | | 406.96 | | |
| McFadden | | 0.209 | | |

**Table 2: GLM models for speeding for urban and rural roads separately**

| | Urban Model | | | | Rural Model | | | |
|---|---|---|---|---|---|---|---|---|
| Trip Characteristic | βi | s.e. | p-value | Relative Risk Ratio | βi | s.e. | p-value | Relative Risk Ratio |
| Intercept | 3.225 | 0.554 | <0.001 | 25.154 | 2.031 | 0.634 | 0.002 | 7.622 |
| distance | 0.163 | 0.035 | <0.001 | 1.177 | - | - | - | - |
| duration | - | - | - | - | 0.002 | 0.0004 | <0.001 | 1.002 |
| mbu | 3.355 | 0.726 | <0.001 | 28.646 | 5.842 | 1.236 | <0.001 | 344.468 |
| harsh_acc | - | - | - | - | 1.485 | 0.402 | <0.001 | 4.415 |
| self-declared speeding never | -1.59 | 0.372 | <0.001 | 0.204 | -2.758 | 0.828 | <0.001 | 0.063 |
| self-declared speeding often | - | - | - | - | -1.569 | 0.458 | <0.001 | 0.208 |
| self-declared speeding rarely | -1.118 | 0.281 | <0.001 | 0.327 | -1.804 | 0.446 | <0.001 | 0.165 |
| self-declared speeding smt | -0.804 | 0.276 | 0.003 | 0.448 | -1.949 | 0.441 | <0.001 | 0.142 |
| AIC | | 511.16 | | | | 352.72 | | |
| McFadden | | 0.203 | | | | 0.263 | | |

Modelling results reveal some intriguing findings:

Overall, the parameters of trip duration, trip distance, the number of harsh accelerations and mobile phone use while driving have all been determined as statistically significant and positively correlated with the percentage of speeding. On the other hand, the average acceleration and the low frequency of speeding according to the participant's answers on the questionnaire, are statistically significant and negatively correlated with speeding percentage.

Another significant result is that the drivers develop an aggressive behavior in longer distances exceeding the speed limits. The most likely explanation is that they want to reach their destination faster and the longer they travel, the more impatient they become, which results in exceeding the speed limits. As for the overall model, the exposure metrics have not been found statistically significant.

Furthermore, the number of harsh accelerations shows a probability that affects speeding while driving. To be more specific, the more the harsh accelerations per trip, the higher the probability of exceeding the speed limits. This may occur due to the fact that at high-speed driving, drivers are required to do more abrupt maneuvers.

Moreover, it is observed that between the two databases, naturalistic driving parameters are more significant in comparison with driver characteristics from the questionnaire. That led to the outcome that naturalistic driving data are superior to self-declared data.

Concluding, there are also some factors, which are not taken into consideration due to the lack of information, but they should be included in further research. More specifically, the influence of weather conditions or traffic conditions is a significant data because drivers react differently under different circumstances with respect to weather and traffic conditions. The presence of a passenger, alcohol consumption and the use of seat belt are also other factors that can affect driving and can lead to an extremely increase of speeding.

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