Driver Behavior Analysis Methods: Applications oriented study

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Abstract

The main objective of this paper is to provide a study on driver behavior analysis methods. Firstly we define the classes of applications interested in studying driver behavior which are vehicle-oriented, management-oriented and driver-oriented. In this paper we choose to focus on the latter category, then we present its three main sub-applications (i) Accident prevention (ii) Driving styles assessment, and (iii) Driver intent prediction. The studies we are reviewing in this paper are classified according to two criteria. The first criterion is the final objective (that coincides with one of the sub-applications), the second criterion is the nature of input factors taken into account during the analysis phase, they can be either quantitative or qualitative factors. We present the final result on the form of a trinomial expressions; for each analysis method we present the maximum number of quantitative and qualitative factors considered as well as the rate of appearance relatively to the total number of papers in each sub-applications. The results show that Descriptive statistics and Bayesian classifiers are the methods that were adopted in all of three sub-applications and operated on both quantitative and qualitative factors. As for the most employed methods we find Hidden Markov Model, Support Vector Machine and Image processing.

Key Words

Driver behavior applications, analysis methods, accident prevention, driving styles assessment, driver intent prediction, quantitative/qualitative factors.

1. Introduction

Many studies have focused on modeling driver behavior, either for commercial purposes, management functions or awareness campaigns. Their main goal is to explain the correlation between driver behavior and other factors through their model. It is a complex system characterized by a wide variety of variables and it has been proven than the majority of accident are caused by human errors such as conscious law violations, distraction, inattention, fatigue, etc. The evolution of this area of studies is made possible thanks to the progress of data analysis methods over the years. The development of these approaches improved the quality of driver behavior analysis and opened the door for new fields of applications.

However, there hasn't been any standard model proposed in literature, and given the lack of a unified framework for analyzing driver behavior, we presented in a previous work [73, 74] a first attempt to gather in one model the set of variables controlling driving actions. We captured a set of quantitative and qualitative factors that are essential in the evaluation of driver behavior. They are either driving-related or driver related. These

factors are the result of a literature review that brings together different models and derives the factors taken into account relatively to driver behavior. These factors are then classified according to their priority in studies they were cited in, as well as their rate of appearance. Table 1 assembles these factors according to their types.
In this paper, we are going to present a literature review for driver behavior analysis methods used in literature, then classify them according to their objective and the nature input factors.
The remaining of this paper is organized as the following; we firstly define the research method we followed in section II, then we present the different driver behavior-based applications in section III. Later in Section IV, we introduce the set of different analysis methods we encountered during the literature review. Section V includes the results of our study.

2. Research Method

In this paper, we present a literature review found on driver behavior-based applications, we sum up the state of the art of analysis methods adopted in studies that focused on analyzing driver behavior. Our study depends on three main segments (i) we consider the final objective of the reviewed study as the first selection criterion; we are going to define the major fields involved in studying and modeling driver behavior and then select the papers interested in the driver as the fundamental subject (ii) we also consider the factors taken into account in the reviewed papers as main classification criteria; the type of input factors determine the class to which we assign the given method. The factors are presented in table 1.

Table 1 : The set of quantitative and qualitative factors we were based on in our method

Quantitative factors	Qualitative factors	
	Driving-related	Driver-related
• Speed - Acceleration • Braking • Orientation • Position • Time range • Mileage • Road type	• Distraction • Attention • Law violation • Maneuvers prediction	• Sensation seeking • Impulsivity • Anger/Vengeance • Narcissism

For bibliographic research, we use the Google Scholar, Science Direct, ACM Digital Library and IEEExplorer scientific databases with combinations of the following keywords:

- Driver behavior – Review – Survey
- Analysis method – Algorithms
- Vehicle – Data – Collecting – Telematics
- IoV – Driving assistance – Automobile insurance - safety awareness
- Driving style - Attention – Distraction – Risk – Intention

We apply a temporal filter (year greater than 2012) and we select studies that focus on understanding and simulating driver behavior.

3. Driver Behavior Analysis Applications

Driver behavior modeling is an important research topic for the automotive and intelligent transportation industry, automobile insurance, and the government organizations controlling infrastructure and public transportation. These areas are interested in understanding such behavior in order to innovate optimal solutions that improve the performance of their missions. Several techniques are employed in this sense, including monitoring the driver's physical condition (facial recognition, physical features monitoring etc.), collecting navigation data using on-board telematics, driving styles assessment etc.

All of these applications are classified in this paper according to their final objective. We define three categories of research presented in figure 1.

(i). Vehicle-Oriented Applications: These practices focus primarily on the vehicle as an end point. They aim to improve the driving experience by producing intelligent systems that assist drivers during their journey, and provide solutions that interact with them in real time to facilitate the driving task. These applications vary according to their degree of autonomy, they vary from basic driving assistance (parking assistance, lane keeping systems) to the maximum degree of autonomy which is self-driving cars (Autopilot).

(ii). Management-oriented applications: This type includes applications that aim to optimize the use of the vehicle, such as fleet management and traffic modeling.

(iii). Driver-Oriented Applications: This type of applications considers the driver as the entry point for all functions. Parameters collected on the drivers include physical and mental state, operations on the vehicle, driving styles and so on.

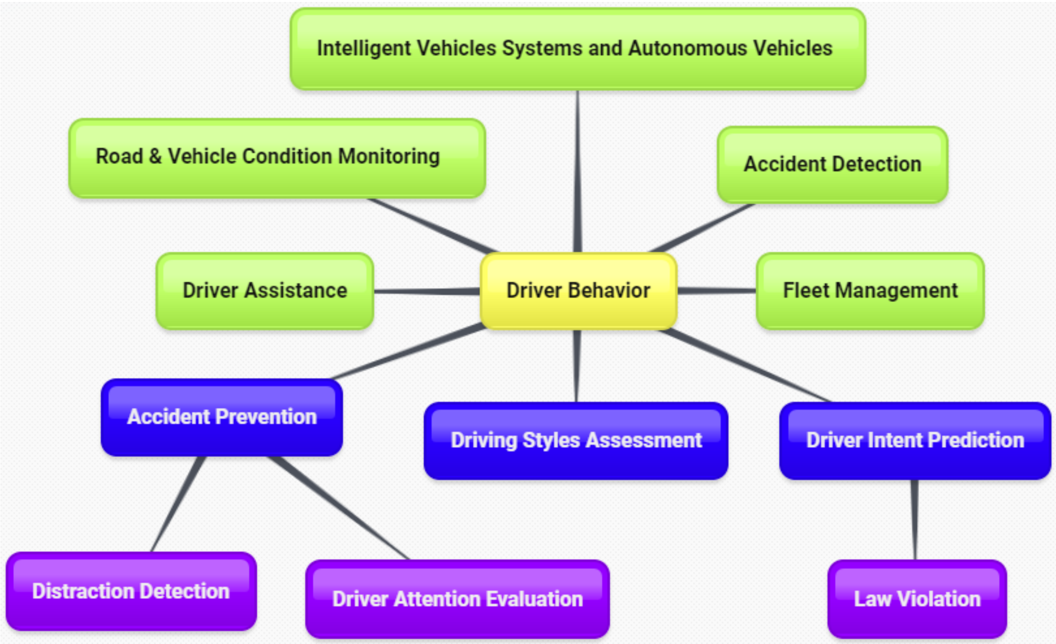

Figure 1: Application fields of driver behavior analysis. The elements presented in blue are associated with driver-oriented applications.

3.1. Vehicle-Oriented applications

According to (Meiring, GA M et al., 2015) and (Mittal et al., 2016), the major application areas that fall into this category are "Intelligent Vehicles Systems and Autonomous Vehicles", "Driver Assistance" and "Accidents detection".

Intelligent vehicles systems and autonomous vehicles are recent fields of research that aim to automate the functions of cars by exploiting new technologies in communications and data analysis [39, 56, 57]. Google has developed its first fully autonomous car prototype [38], followed by automotive manufacturers Tesla, Mercedes and Volkswagen. This type of research uses advanced vehicular control and environmental detection technologies [37] based on real-time data flow (traffic data, nearby vehicles, etc.). In addition, the connected objects integrated in the vehicle allow continuous communication with various components of the vehicular system.

Regarding the automatic detection of accidents, several studies have been carried out in this direction [30, 35, 36]. The major function of this field is the immediate dispatch of emergency and assistance services to the injured driver who may be unconscious and unable to report the accident himself. The techniques used include real-time evaluation of the vehicle's properties (speed, acceleration, sudden stop, etc.), they enables the identification of abnormal events that are likely to indicate that the vehicle in question has just had an accident.

As for the driving assistance, it is an application that aims to facilitate the driving task for the driver (parking assistance, video blind spot etc.). There are nowadays more developed assistance systems introduced by car manufacturers that try to minimize driver error rates due to inattention, distraction and carelessness, such as lane keeping assistance systems [60, 61] and emergency braking systems [58, 59].

3.2. Management-Oriented Applications

This type of studies focuses on the management of infrastructure and material resources, specifically the monitoring of the road state and the vehicle. These applications enable effective planning of road maintenance and traffic management. They integrate road condition recognition systems based on the maneuvers applied by the driver (accelerations, braking, etc.) and triaxial acceleration signals [62, 63].

This category also has commercial applications by transport companies; the main objective of fleet management is to control the maintenance of vehicles, monitor their speeds as well as fuel consumption, health and safety inspection. With effective fleet management, companies can minimize the risks to which vehicles and drivers are subjected, improve the efficiency of their services and reduce overhead costs [64, 65].

3.3. Driver-Oriented Applications

This category constitutes the general context of our study. It includes all the research that consider the driver as the main focus, they are represented in color blue in Figure1.

Driver attention evaluation is one of the main areas of behavioral research, the level of attention is often analyzed by acquisition platforms of the driver’s physiological data. These sensors provide information such as eye activity, driver's face tilt, heart rate, and many other information in order to monitor the somnolence of drivers and their degree of consciousness [68, 69]. As for distraction detection, secondary task recognition systems are developed to identify the degree of driver concentration on the road. They are able to identify distraction from the driver's reactions [66, 67].

Other research area that we classify in this category is the driving style assessment and driver intent prediction. The first application consists of classifying the driving mode according to several criteria applied to the driver's actions (acceleration, speed, braking, steering, etc.) [70, 71]. The most common styles in the scientific literature are Aggressive style and Risky style. These techniques are very useful for automobile insurers who adopt

Usage Based Insurance [72], this technique calculates the insurance costs of each customer according to their driving score and performance. Regarding driver intent prediction, this application consists in predicting the future actions of the driver using the techniques of automatic recognition of maneuvers.

4. Review of Driver Behavior Analysis Methods

The main work that we present in this paper is the capture of driver behavior analysis methods proposed in the literature. To do this, we have grouped together a set of studies that meet the criteria of our method (see section II) from which we extracted the factors taken into account as well as the analytical systems mentioned in each study. In this section, we will present the methods considered in the literature for driver-oriented applications.

4.1. Index Systems

The principle of this method is to define new parameters from other primary factors captured during the study. These new relevant parameters respond to specific needs in a given context and serve to express a phenomenon more clearly. As an example, [34] developed a driving style evaluation system for Usage Based Insurance. In their article, the authors define their own index system dedicated to this application; they translate the concept of '' risk '', which is a subjective notion, into indexes defined from the quantitative factors collected directly from the vehicle. Their work includes several sets of indexes, among which are '' Acceleration Energy Efficiency Index Ee ''. This index reflects the relationship between the energy consumed by the vehicle and the energy consumed in the ideal case where the vehicle rolls perfectly smooth. According to the formula presented by [34] , the calculation of this index makes it possible to conclude the degree of risk of the driver on a given path from the mass of the vehicle, its speed and the length of the path.
In the same context, [8] have also developed an index system to measure the driver's degree of consciousness. They defined the TTC (Time To Collision) index which expresses the time the vehicle will spend before hitting an object in its environment. This index is then used to calculate an environmental risk score at a given time that the authors have named '' yi (t) ''.
With regard to [4] , the aim of their research is to predict the behavior of drivers at red lights, to be able to detect vehicles likely to not respect the traffic light. To do this, they adopt a system of indices composed of two parameters which are "Time to intersection TTI" and "Distance to intersection DTI" which include several data including speed, acceleration and direction.
From these examples, we conclude that the definition of new indices allows for more appropriate and relevant modeling for the system studied. This operation exploits the data resources already available and takes the opportunity to develop new concepts and methods of analysis.

4.2. Image processing

Image processing is one of the most considered methods for the analysis of Driver behavior in the scientific literature. Several applications are in this category; [40] are based on this method to assess the driver's sleepiness and degree of concentration on the road. The input data they consider are the images of the road that are processed in order to estimate the position of the vehicle in relation to the lines drawn on the track, and subsequently conclude whether the driver manages to maintain a correct position on the road. [11, 29] also used image processing in their research, they focused on the driver's face to determine his vision area during the ride. They use a driver's eye tracking and detection system to estimate whether it is focused on the road or distracted by secondary actions. As for [15, 26, 27] , their research is aimed at measuring driver fatigue, they have developed a system that follows the driver's mouth and eyes to detect eye conditions and yawning.

4.3. Statistical methods and Machine learning

This category includes all models based on supervised learning methods such as regression [46, 47, 45, 48, 52, 53, 19, 49, 50, 54] , PCA (Principal Component Analysis) [24, 22] , ANOVA [23, 44, 22, 51, 49] , HMM (Hidden Markov Models) [1, 5, 9] .
As for example, [1] employed Hidden Markov Model in order to represent the temporal nature of driving maneuvers, [5] were based on HMM in order to identify the type of maneuvers performed by the driver. The authors defined two type of maneuvers which are lane keeping and lane changing. The parameters that their contribution was based on are learned from training data. They presented two applications of this method in their paper which are a lane keeping assistance system and an adaptive cruise control system.
As for the Principal Component Analysis (PCA), [22, 24] were based on it in order to minimize the dimensionality of their datasets, using a combination of various quantitative parameters.
Regression is also widely used in the context of driver behavior analysis, [45, 46] were based on linear regression to investigate the correlation between gender and personality traits, [47] performed a multiple linear regression to determine the impact of some personality traits on reported actions of risky driving behavior.
Classifiers are machine learning algorithms used to classify input data into categories according to defined criteria. Several types of classifiers have been adopted by driver behavior analysis studies, these types are presented in Table 2.

Table 2 : Different types of classifiers and the references they were employed in

Classifiers	References
Random forest classifier	[6, 4]
Naive Bayes classifier/Bayesian network	[42, 2, 28]
Decision tree	[7]
K-means	[13]
AdaBoost classifier	[3, 25]

Random forest classifier is used in [4] and [6] ; the goal of [4] is to classify drivers into two categories "violation & compliance", the evaluation of this classifier has shown a precision rate reaching 93.6%. As for | 6] , their goal is to develop a system that monitors the driver to gauge his level of distraction. Their method of analysis was based on the Random Forest classifier to estimate the driver's vision area, they justified their choice of method by its efficiency and ease of implementation, their results demonstrated a precision rate of 94%.
The Naive Bayes classifier is a probabilistic technique in the category of classifiers, it has been used in several studies including [42] . Their goal is to build a platform that detects aggressive driving style based on data collected from the vehicle. The data analysis phase was based on this technique to assess the correlation between driving style and input

data. According to their results, its accuracy rate is 90.5%. [28] were also based on this technique for the classification of the driver's condition (distraction / neutral), it demonstrated a precision rate greater than 70%.
SVM (Support Vector Machine) is a widely used technique in the context of driving data analysis; [16] evaluated driver's eye state using an SVM classifier , [3, 13] were based on it in order to build a system able to detect and track driver's hands, [4] employed it to predict law violations behavior namely red light running. Their results demonstrated a high prediction accuracy of 97%. [12] adopted SVM during the activity recognition phase; the authors aimed to classify the driver's activities based on his head and hand positions.

5. Research results

As we mentioned before, our main objective is to classify these techniques according to their applications in the driver-oriented category as well as the nature of their input factors. In the following we present the result of our study for each type of sub-applications.
In tables 3,4 and 5, we present a sample of the factors considered in each reference; due to the limited space of our paper, we are only presenting an example of the classifications we performed. The references that are not shown in the tables are cited in the last line of each table. However the results and the percentages of each sub-application are based on the entirety of papers reviewed.

5.1. Driver Intent Prediction

For this first sub-application, the results are presented in figure 2. For each method, we mention the maximum number of quantitative and qualitative factors, as well as the rate of appearance relatively to the total number of papers.
The syntax "Method(max_quan,max_qual,rate)" denotes that the give method has been employed with a maximum number of qualitative factors equal to "max_quan", a maximum number of qualitative factors equal to "max_qual". "rate" refers to the percentage of papers the method was used.

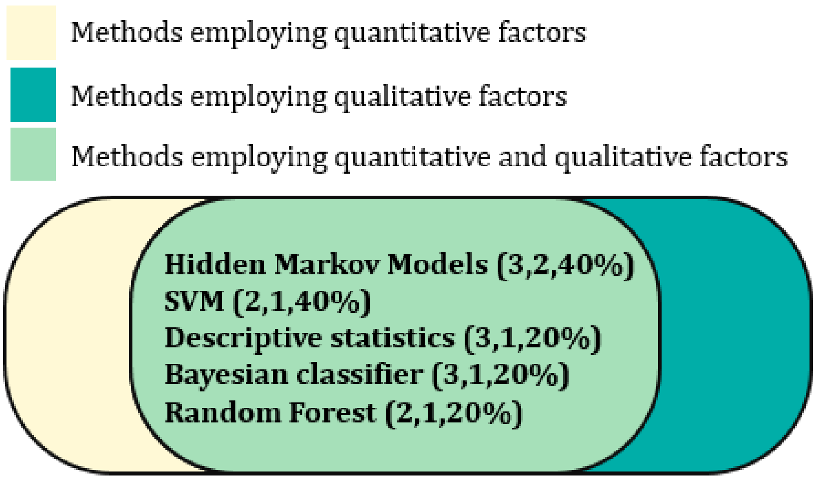

Figure 2 : The set of analysis methods adopted in papers focused on driver intent prediction.

The total of papers that were classified in the "Driver Intent Prediction" sub-application is about 5 papers. As shown in figure2, the main analytic techniques employed for this category are Hidden Markov Models and Support Vector Machine with a rate of 40% of appearance.

We notice that all the methods are based on a combination of quantitative and qualitative factors, with a slight tendency towards the quantitative side.

5.2. Accident Prevention

In the same context, we present the results for the sub-application "Accident Prevention" in figure3. The total number of papers in this category is 26. The notation in the figure3 shows the maximum number of quantitative and qualitative factors as well as the rate of appearance for each method.

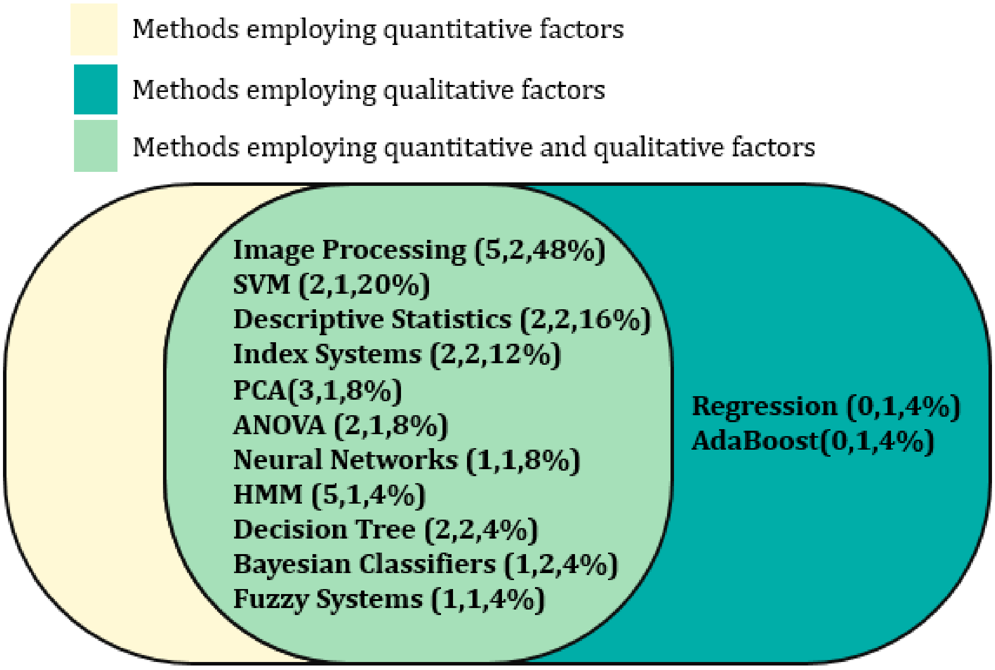

Figure 3 : The set of analysis methods used in papers working on Accident Prevention.

The results above show more analytical methods than the previous category, with new algorithms such as PCA, ANOVA, HMM and Neural Networks. The most employed method are Image Processing, SVM and Descriptive statics. They're all based on a combination of quantitative and qualitative factors. On the other hand, Regression and AdaBoost classifier are located on the qualitative side with a 4% rate of appearance; this means that they were used with only qualitative factors in this category

5.3. Driving Style Assessment

The last sub-application is "Driving Style Assessment". Following the same approach as the previous ones, figure4 includes the results of the analysis methods.

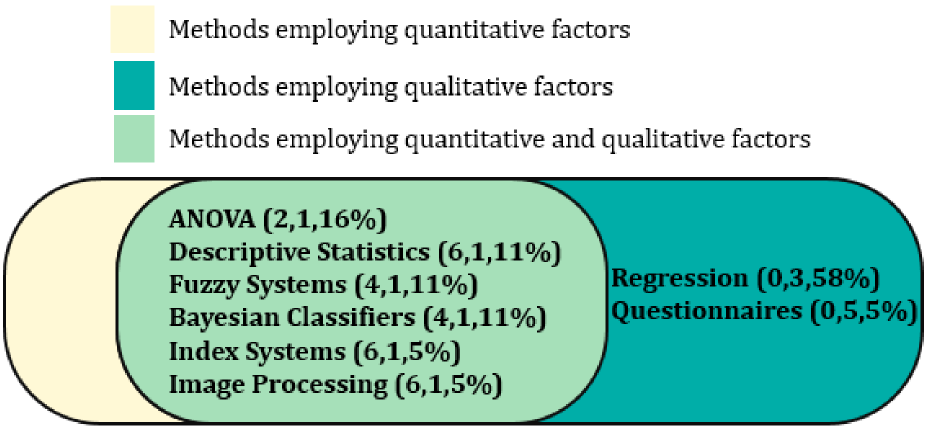

Figure 4 : The set of analysis methods adopted in Driving Style Assessment studies and their rate of appearance.

The results show that ANOVA is the most adopted algorithm with a rate of 16% of appearance, followed by Descriptive statistics, Fuzzy systems and Bayesian classifiers with 11% of appearance. Similarly to the previous category, Regression appears again in the qualitative side, with a rate of 58%, followed by behavioral questionnaires with 5%. This high percentage reflects the high applicability of regression in the context of driving styles assessment. It can be explained by the nature of its application; the majority of studies classified in this category depend upon some kind of self-report measurement, their analysis generally requires a linear modeling, which is precisely where regression performs the best.

6. Conclusion

In this paper, we present a literature review for analysis method adopted in studies that were aimed to analyze driver behavior from a driver-oriented approach. We began by defining the three types of applications interested in investigating this behavior, which are vehicle-oriented, management-oriented and driver-oriented. Then we detailed the latter into three sub-applications; driver intent prediction, accident prevention and driving style assessment.

The starting point of our study was the set of quantitative and qualitative factors that we managed to capture in a previous paper. From each reviewed paper, we selected the factors taken into account as well as the analysis method adopted by the authors.

The classification of these papers was conducted through two phases; the first one is according to the main objective, which falls into one of the three sub-applications. The second one depends on the nature of the input factors; quantitative vs. qualitative.

The results show that for the majority of sub-applications, the analytical methods use a combination of both quantitative and qualitative factors, which reflects the importance of these two types of inputs. However, regression, AdaBoost classifier and questionnaire are situated in the qualitative factors, which means they were adopted for only analyzing one type of factors. We remind that our findings do not reflect on the quality of the mentioned algorithms, nor on their performance.

As for the rate of appearance, the most employed methods in the conjunction of all sub-applications are the Hidden Markov Models, SVM, Descriptive statistics, Image processing, ANOVA and Index systems. Regarding the methods that appear in the intersection of all three sub-applications, we find Descriptive statistics and Bayesian Classifiers. There two techniques can be found in any driver-oriented applications and they have been both validated by quantitative and qualitative factors.

This paper has two main outcomes: (i) the classification we accomplished gives a general idea about the most employed analytical methods in the area of driver behavior research. These techniques have surely proved their performance as well as their efficiency in evaluating driving data. However, for the next generation of studies, researchers could experiment with new data mining tools and develop new procedures that combine between new types of input factors (ii) as shown in the results previously, the majority of factors taken into account in this type of studies are classified as quantitative. This tendency shows the focus on objective measures (speed, acceleration, position, mileage etc.) more than human factors such as personality traits (sensation seeking, impulsivity, anger, narcissism etc.). This finding should motivate future applications to be more inclusive and focus equally on the quantitative factors as on the qualitative ones.

Appendix

Table 3 : A sample of the extraction of quantitative factors from the reviewed papers.

Reference	Quantitative factors							
	Speed	Acceleration	Braking	Orientation	Position	Time range	Mileage	Road type
[1] 2015	x			x	x			
[2] 2016	**x**			x	x			
[3] 2015			x	x				
[4] 2015	x	x						
[5] 2015		x		x	x			
[6] 2014		x		x	x			
[7] 2013	x			x				
[8] 2012	x			x				
[9] 2014	x	x	x	x	x			
Other references : [20, 21, 22, 23, 24, 28, 32, 33, 34, 40, 41, 42, 44]								

Table 4 A sample of the extraction of qualitative factors from the reviewed papers (driver-related)

Reference	Qualitative factors – Driver related			
	Sensation seeking	Impulsivity	Anger/ vengeance	Narcissism
[43] 2016	x			
[44] 2014	x			
[45] 2016			x	x
[46] 2015		x	x	x
[47] 2013	x	x	x	
Other references : [48, 49, 50, 51, 52, 53, 54, 55]				

Table 5 A sample The extraction of qualitative factors from the reviewed papers.(Driving related). We remind that many factors are not presented in the table due to the limited space of the table's width

Reference	Qualitative factors – Driving related					
	Distraction		Attention		Maneuvers prediction (Overtaking, turning)	Law violation
	Secondary tasks	Poor perception & vision	Sleep/ alcohol detection	Pedestrian/ Policemen awareness		
[1] 2015					X	
[2] 2016					x	
[3] 2015					x	
[4] 2015					x	x
[5] 2015					x	
[6] 2014		x		x		
[7] 2013		x		x		
[8] 2012		x		x		
Other references : [9, 10 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 31, 32, 33, 34, 40, 41, 42, 46, 51, 52, 55]						

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