

# A New Perspective on Artificial Intelligence Applications in Analyzing Driver Behavior: Advances, Challenges, and Opportunities

Sami Shaffiee Haghshenas, *Student Member, IEEE*, Vittorio Astarita, Sina Shaffiee Haghshenas, *Student Member, IEEE*, Giuseppe Guido, *Member, IEEE*, Anastasios Kouvelas, *Senior Member, IEEE*,

**Abstract**— Recent developments in the discipline of transportation have spurred major scholarly attention to driver behavior. The most recent advancements in artificial intelligence have enabled the creation of an effective method using Internet-based technology to gather large-scale data for driver behavior assessment. This revolutionary development helps researchers access a wealth of data, facilitating in-depth studies and a better understanding of driver behavior patterns. Scholars have devoted significant time to comprehending the risk-taking habits, driving patterns, and decision-making procedures this demographic group displays. One of the most crucial criteria in order to reach the objectives of sustainable mobility is the increasing body of research in this field, which emphasizes the need to address the particular traits and challenges related to drivers, so striving to create safer driving environments for all road users. The main purpose of this article is to investigate the practical aspects of artificial intelligence in analyzing the driver's behavior. The document also highlights the challenges and opportunities in this field and calls for further research to address methodological limitations and explore new approaches in understanding and predicting drivers' behaviors using artificial intelligence.

## I. INTRODUCTION

Road accidents have increased in parallel with global population growth and the consequent surge in vehicular traffic. At the same time, advances in artificial intelligence (AI) have enabled deeper analyses of driver behavior and its impact on safety. Driving is an attention-intensive task: even minor distractions—such as mobile-phone use or roadside advertisements—significantly raise crash risk. Recent studies

confirm a strong correlation between distracted attention and accident incidence [1], [2]. Moreover, driver experience and personality traits both influence safety outcomes: while experience improves reactions under varied conditions, certain personality characteristics can predispose drivers to risky behaviors [3].

Considering the developments in AI and its use in driver behavior and road safety analysis, it makes a significant contribution to reaching the objectives of sustainable mobility. Consequently, researchers in general have extensively investigated the application of artificial intelligence, including simulators in assessing driver behavior, examining road safety, and optimizing its possibilities in their projects. This integrated effort aims to leverage artificial intelligence capabilities to raise general knowledge and application in several spheres of road safety [4], [5]. Contemporary researchers use various approaches to examine drivers' behavior and road safety; among them, the questionnaire approach is one of the most often used [6]. During the last decade, a lot of research has been done in the field of road safety. According to many advances in the field of artificial intelligence, researchers have found a great desire to use artificial intelligence algorithms that the random forest classifier is one of the famous ones [7]. Improving road safety and lowering accidents require a thorough awareness of the primary elements involved in this field, followed by the identification of suitable solutions. Investigating the use of artificial intelligence and driver behavior toward road safety is the aim of this paper. Another purpose of this study includes the study of the methods carried out on the driver's behavior to create appropriate solutions that comprehensively address the complexities of the road safety landscape and ultimately lead to the assistance of researchers in future studies. To summarize, the main contributions of this paper are:

**Comprehensive AI Literature Synthesis:** We review recent advances in deep learning, ensemble methods, and multi-modal data fusion for driver-behavior analysis, highlighting critical gaps in uncertainty quantification and external validation. We also discussed one of the most widely used machine learning methods, artificial neural networks and support vector machines.

**Mitigation Strategies for Real-World Data:** We propose practical guidelines to handle sensor noise, variable sampling rates, and missing values in OBD and smartphone streams, ensuring robust feature extraction and model stability.

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Sami. S. H. Department of Civil Engineering, University of Calabria, Via Bucci, 87036 Rende, Italy (Corresponding author; e-mail: Sami.Shaffieehaghshenas@unical.it).

V. A. Department of Civil Engineering, University of Calabria, Via Bucci, 87036 Rende, Italy (e-mail: Vittorio.astarita@unical.it).

Sina. S. H. Department of Civil Engineering, University of Calabria, Via Bucci, 87036 Rende, Italy (e-mail: Sina.Shaffieehaghshenas@unical.it).

G. G. Department of Civil Engineering, University of Calabria, Via Bucci, 87036 Rende, Italy (e-mail: Giuseppe.guido@unical.it).

A. K. Traffic Engineering Group, Institute for Transport Planning and Systems, ETH Zürich, Stefano-Francini-Platz 5, Zürich, 8093, Switzerland (e-mail: kouvelas@ethz.ch).

Road-Safety Research Roadmap: We identify three core challenges—noisy measurements, heterogeneous feature sets, and model uncertainty—and outline targeted research directions (e.g., Bayesian approaches, real-time ADAS integration) to address them.

The subsequent sections of this paper are organized as follows: Section 2 provides a brief overview of Driver behavior. Section 3 Challenging Problems of Driver Behavior Analysis. Section 4 outlines the methodologies pertaining to AI. In section 5, the discussion revolves around the challenges and opportunities associated with the utilization of artificial intelligence in driver behavior analysis. Lastly, Section 6 presents the concluding remarks.

## II. DRIVER BEHAVIOR ANALYSIS

Understanding and analyzing driving behavior helps one to get important insights that will help to create good tactics to reduce accidents and improve general road safety. One important contributing cause to accidents is driver behavior. As a result, many studies are focused on tackling this important issue by trying to create strategies and solutions meant to pinpoint actions that lead to mishaps. Understanding the seriousness of the problem, these scientists actively look for and analyze the particular actions that cause mishaps with the ultimate aim of preventing and reducing their frequency [8]. Regarding road safety, driver behavior is a pivotal and unpredictable factor. The Fuzzy Analytic Hierarchy Process (FAHP) presents a good way to solve the inherent uncertainty related to driver behavior. Using FAHP allows the detection and classification of driver behavior to adequately capture the uncertainty in driver thinking patterns, so offering a more complete knowledge of this important component of traffic safety [9]. Evaluating road traffic safety necessitates a comprehensive approach encompassing the entire life cycle of road development, operation, maintenance, and expansion. Conventional approaches depending on accident and conflict analysis have difficulty reflecting the complex influence of environmental elements. In order to meet this difficulty, a new road safety assessment technique emphasizing driving behavior has evolved. This driver-centric approach has become well-known as a study topic for evaluating road safety considering the contextual and personal differences in driving behavior [10]. Examining driver behavior starts with first-stage data collection from the driver. Questionnaire surveys, Global Positioning System (GPS) tracking, smartphones, and On-Board Diagnostics (OBD) devices are the most important of the several ways that one can gather driver behavior data. These techniques will be discussed in the next parts, so offering a comprehensive knowledge of their use and advantages in driver behavior analysis.

### A. Questionnaire surveys

Using several approaches, the delivery of questionnaires helps one to get information about driver behavior. The online technique has become one of the efficient ways to gather driver behavior data with technological developments and access to pertinent data [11]. Thanks to population increase and more inter-road travel, every year a considerable number of people suffer injuries or die in road accidents. Researchers have devoted great efforts to applying several

approaches, including the use of completed public questionnaires, in order to minimize this problem and improve safety. These surveys are very important in determining the elements causing accidents and developing plans to lower their frequency, thereby helping to achieve the goal of improving road safety in view of the increasing pressures on transportation networks [12].

### B. The Global Positioning System (GPS)

Better capabilities for real-time monitoring and control afforded by the instantaneous and accurate transmission of location data provided by onboard GPS devices come from improved efficiency and dependability in public transportation systems. Unsafe driver behavior plays a role in more than 90 percent of road accidents, making it crucial to identify drivers who engage in such practices. Driver Behavior Profiles (DBPs) as a novel method to assess driver behavior based on the likelihood of a casualty crash are introduced. DBPs assess and describe driving behavior patterns using data derived from GPS devices, enhanced with spatiotemporal features. Using this method helps one to reach a thorough awareness of dangerous driving behaviors, hence facilitating focused interventions to improve road safety [13]. Given the variances in driving skills and individual traits across different time periods, drivers exhibit distinct behaviors when encountering diverse driving environments, resulting in varying levels of driving safety injuries. It is crucial for drivers to acknowledge and rectify perilous behaviors in order to enhance their driving performance. For this reason, in their studies, researchers used several methods, including GPS. Using graphical modelling, they classified normal driving patterns depending on frequency, therefore creating a driving behavior graph that clearly shows the behavioral traits of every driver [14].

### C. Smartphones

In terms of technical development, smartphones can evaluate driving behavior. Researchers are thus looking at several techniques used in previous investigations, including sensing strategies, detecting algorithms, and the related degrees of precision and restrictions [15]. Understanding driving behavior is still rather important with the fast-increasing automation. Dissecting complex driving dynamics, enabling the development of user-friendly and generally accepted driverless vehicles, and ensuring the harmonic coexistence of autonomous and conventional vehicles on the streets depend on this knowledge. One useful method in understanding and predicting driving behavior has been mobile crowdsensing. This approach provides insights on the subtleties of driver behavior by using the combined power of mobile devices, therefore enabling improved safety and smooth integration of autonomous and conventional vehicles in the transportation system [16]. Drivers' behavior is intimately related to the safety of traffic and the energy efficiency of automobiles. Using cellphones and their built-in sensors, three-axis accelerometers, and GPS receivers helps road users access real-time data and feedback. This insightful information and direction help to improve driver awareness and support safety. By leveraging the capabilities of these modern mobile devices, drivers can be empowered with the tools necessary to make informed decisions, ultimately contributing to improved traffic safety and greater energy

efficiency on the roads [17]. Every year, a lot of car accidents happen at intersections mostly because of drivers doing "illegal maneuvers" or showing "unsafe behaviors." Researchers have presented several approaches to improve traffic safety, including a smartphone-based system called SafeCam. SafeCam uses real-time traffic control data, including traffic signals—along with vehicle dynamics—to recognize and examine dangerous driver behaviors at intersections. Safe Cam uses integrated sensors—inertial sensors—on the smartphone to create minute signals tracking several driving environments. It also uses vision-based algorithms to identify important driving events connected to crossings, such as running red lights, hazardous turns, and running stop signs. SafeCam is a creative way to encourage better driving habits and reduce hazards at junctures [18].

#### D. On-Board Diagnostics (OBD devices)

Focusing on how drivers operate the vehicle under various environmental and road situations, the Driver Behavior (DB) approach entails an all-encompassing study of driver patterns and styles. The database covers driver body dynamics. Major causes of mishaps that cause both large physical and financial harm are risky databases. Consequently, it is now essential to pinpoint dangerous databases and offer suitable remedies depending on driving behavior to handle the increasing traffic incidents. Fortunately, in this sense the integration of advanced sensors into embedded systems or OBD systems presents interesting support [19]. Not only for nations but also for major transportation corporations worldwide, the problem of traffic accidents originating from drivers' behavior causes great concern. Closely observing and regulating dangerous driving behaviors, including speeding, lane weaving, sudden braking, acceleration, and driving under the influence of alcohol, is absolutely vital. Researchers have looked at sensor-based approaches to spotting harmful driving behavior recently. This has prompted the creation of an OBD-II port-connected driver behavior monitoring gadget for the car. Using integrated management software, the gadget gathers data and sends it to a control center, thereby allowing thorough monitoring and control of driver behavior [20].

### III. CHALLENGING PROBLEMS OF DRIVER BEHAVIOR ANALYSIS

A number of challenges are created when applying survey questionnaires, GPS, smartphones, and OBD devices to driver behavior analysis.

One of the most conventional approaches to investigate driving behavior is by means of questionnaire surveys. Still, they run across some challenges:

- Drivers show the possibility of biases and subjectivity in the answers by responding either in line with what others expect or in a socially acceptable manner instead of their actual actions. This self-reporting tendency could cause the results to be distorted.

- Limitations on Recollection: Since drivers don't always remember or document their driving habits, drivers could not give completely accurate information.

Through the use of GPS, a more unbiased approach to evaluating driving behavior may be achieved. Difficulties encompass:

- Data Volume: Much of the data produced by GPS can be difficult to rapidly arrange and grasp.

- Signal Accuracy and Loss: Some areas, like urban canyons or areas with plenty of trees, where GPS signals could be absent or erroneous, can result in missing or incorrect data.

Although they have their own issues, smartphones can be used to gather driving behavior data on individuals:

- Battery Drain: Constant data collecting rapidly runs out the battery of a smartphone, thereby restricting its lifetime for usage for data collecting.

- Diverse ecosystem: Operating systems of smartphones vary, so the quality and capacity to acquire data vary as well.

OBD devices come with certain issues even if they provide immediate access to information on the operation of your vehicle:

- Installation and Maintenance: OBD devices must be installed and maintained correctly, so many different kinds of users may find it difficult to acquire them.

- Limited Behavioral Insight: Although OBD devices can provide a lot of information about the condition of your car, they do not offer much on drivers' opinions or feelings.

### IV. ARTIFICIAL INTELLIGENCE (AI)

By using AI in transport and on the roads for safety, the benefits accrue towards a pursuit of much smarter, safer, and more efficient transportation systems to the benefit of all road users. Current research work goes on to focus on how to avoid or mitigate accidents. Conventionally, most of the approaches have focused on passive accident response by identifying high-risk sections of roads using historical data. Some researchers, however, have proposed proactive accident prevention based on risk assessment supported by simulation data and actual vehicle driving route data, such as digital tachograph (DTG) data. This approach evaluates accident risks in advance of the occurrence and hence can support preventive measures in time [21]. The future road networks would consist of autonomous, automated, and human-operated vehicles. This would demand increasing the capability of ADAS in existing lower-class vehicles so that everyone can be kept safe in the mixed network of road users. Real-time prediction of the risk of safety during driving plays an important role in an efficient ADAS. Lured by recent progress in artificial intelligence, the authors were able to model and run their study with deep and diversified AI techniques—from elastic net regularized multinomial logistic regression to the best of their abilities using the data available [22]. There are multiple applications of artificial intelligence in analyzing driver behavior. However, probably the most significant application is that of the pattern recognition approach. Pattern recognition is a technique of data analysis that uses machine learning algorithms to automatically detect and identify patterns and regularities within various types of data, such as text, images, sounds, and much more. Such

systems are particularly adept at rapidly and accurately recognizing familiar patterns, which can contribute to efficient data analysis and decision-making processes. The following sections explain a range of techniques used in pattern recognition. In the following, two of the most widely used artificial intelligence methods, namely artificial neural networks and support vector machines, will be examined.

#### A. Artificial neural networks (ANNs)

Artificial neural networks (ANNs) have become an invaluable resource for AI researchers and problem solvers due to their remarkable capacity to learn from data and provide intelligent predictions. One of the main causes of the high accident rates is the way drivers behave. Nevertheless, if they can recognize their actions, it might be feasible to learn to avoid accidents caused by drivers' quirks [23]. A multitude of cognitive operations across different levels of abstraction are required for the complicated activity of driving. A significant number of agents, each behaving in a unique way, interact to produce traffic patterns. The enormous number of agents involved has, however, made it historically very difficult to simulate these interactions with micro-simulators. Thanks to improvements in processing capacity, it is now feasible to simulate a greater number of different vehicles according to their distinct characteristics. The car-following and lane-change sub-models are the usual components of such models. A few lane-change models provide individualized solutions that take individual granularity into consideration, and even fewer use computational intelligence (CI) methods. Researchers investigate the lane-change acceptance aspect, which focuses on whether a driver performs a lane change based on their intention and the surrounding vehicle environment. They demonstrate how the specific driver's lane-change acceptance can be learned in an urban setting using computational intelligence (CI) techniques like feed-forward ANNs, including multilayer perceptrons (MLPs) and convolutional neural networks (CNNs) [24].

#### B. Support vector machine (SVM)

Support vector machines provide a practical method for analyzing driving behavior data via pattern-based classification of events. Once we identify divides, we can design models that offer personalized feedback to guide drivers towards optimal efficiency. This input seeks to inform drivers on how changing aspects of their performance might help to save more fuel. One can understand the elements of driving behavior by using driving simulators and naturalistic driving research. Traffic safety depends on an evaluation of real-time driving behavior, which also helps Advanced Driver Assistance Systems (ADAS) to act and ensure safe driving. The research on this single issue of modeling conduct at junctions using support vector machines can bring about a solution improvement in such decision-making mechanisms. The approach with SVM allows classification and identification of trends, thereby helping the designer of the technology provide an opportunity to pass through a busy area more safely [25]. Eq 1 presents part of the sample set used in the classification of the learning data. [26], [27].

$$S = \left\{ (x_i, y_i)_{i=1}^n \mid x_i \in R^N, y_i \in \{-1, 1\}, i = 1, 2, \dots, l \right\} \quad (1)$$

Target variable of the i-th sample is observed. The i-th sample data should be represented as also. Construct hyperplanes after which the ideal hyperplane is selected because it possesses maximum margin. The ideal hyperplane will be decided based on the existing support vectors and constraints. Constraints in Eqs 2 and 3 [28].

$$\text{Min} \frac{1}{2} \|w\|^2 \quad (2)$$

$$\text{s.t. } y_i (wx_i + b) \geq 1 \quad (3)$$

Where 'w' is the weight vector and 'b' is the bias vector. Subsequently, after error coefficient has been brought into consideration, constraints are remade and corrected using Eqs 4 and 5. This error coefficient refines the accuracy of the categorization process. The variable c is the punishment coefficient. According to Eq 6, the SVM classification problems can be expressed as a dual optimization problem by using the Lagrange technique [28], [29].

$$\text{Min} \frac{1}{2} \|w\|^2 + c \sum_{i=1}^n \varepsilon_i \quad (\varepsilon_i \geq 0) \quad (4)$$

$$\text{s.t. } \begin{cases} y_i (wx_i + b) \geq 1 - \varepsilon_i \\ c \geq 0 \end{cases} \quad (i = 1, 2, 3, \dots, n) \quad (5)$$

$$\begin{cases} W(a) = \sum_{i=1}^n a_i - \frac{1}{2} \sum_{i,j=1}^n a_i a_j y_i y_j K(x_i, x_j) \\ \text{s.t. } \sum_{i=1}^n a_i y_i \quad (0 \leq a_i \leq c; i = 1, 2, 3, \dots, n) \end{cases} \quad (6)$$

K represents the kernel function in mathematics. Eqs 7 to 9 displays a range of kernel functions, such as linear, radial basis function (RBF), and polynomial. The classification of kernel types is determined by the values of gamma ( $\gamma$ ) and d. Both RBF and POL kernels use the gamma parameter, whereas the "d" parameter is only necessary for the POL kernel to specify the degree of the polynomial term. Crucially, the kernel function receives the dataset and converts it into the suitable format. An individual's comprehension of how separate kernel functions are used in related situations might impact the quality of a category [30], [31].

$$G(x_i, x_j) = x_i^t x_j \quad (7)$$

$$G(x_i, x_j) = \exp(-\gamma \|x_i - x_j\|^2) \quad (8)$$

$$G(x_i, x_j) = (-\gamma x_i^t x_j + 1)^d \quad (9)$$

## V. OBSERVATION AND DISCUSSION

Advanced AI and ML technologies have made driver behavior analysis more efficient, improving road safety.

Technology development has led to a decrease in the use of the former evaluation methods. Systems that accurately calculate driving habits based on real-time data replaced them instead. Despite these improvements, the complex issue of driver behavior analysis still requires further investigation and innovative solutions. The research conducted highlights some of the most critical observations and inferences [31].

One of the most critical observations is how technological advancements have transformed driver behavior analysis. In the past, accident reports and field observations were the primary methods for identifying hazardous driving habits, but modern technology now provides more accurate and real-time insights. Today, AI systems are able to analyze driver decisions in real-time using information from vehicle sensors, GPS, and connected tech. The integration of these systems has greatly improved the precision of recognizing risky driving movements such as sudden lane changes, speeding, and slow responses to critical situations. The ability to analyze such conduct in real time has improved predictive safety models, allowing them to intervene timely [32].

Another important observation is the role of multi-source data fusion in driver behavior research. Data from GPS, in-vehicle sensors, video cameras, and smartphones all have their respective strengths and limitations. GPS data, for instance, can effectively track movement patterns but cannot analyze micro-level driver behavior. On the other hand, vehicle onboard sensors provide data on vehicle activity (e.g., speed, acceleration, braking) but not cognitive information on decision-making by drivers. Merging these disparate sources of information and linking them in AI systems can develop a more complete and accurate understanding of driver behavior [14], [15], [32].

Aside from technology, behavioral accident analysis has identified hidden driving habits that are not visible but are the causes of accidents under some circumstances. For instance, drivers who frequently use high levels of sudden braking may do so on a regular basis in stressful conditions or dense traffic environments. Such a discovery makes it feasible to design intelligent warning systems that inform drivers about incoming threats so that they have sufficient time before it becomes risky [32]–[34].

Studies have shown that psychological factors significantly influence driving habits. Studies indicate that stress, drowsiness, and distraction heavily degrade a driver's ability to make quick and rational decisions, increasing the risk of accidents. AI-driven driver monitoring technology can detect such mental states and warn in time to prevent hazards. Putting together ADAS and AI-driven behavior analysis can also make cars safer by changing how they react based on how the driver is feeling at that moment [32]–[34].

Additionally, to conduct better analysis of driver behavior, more sophisticated AI models must be utilized. An effective means of doing this is through the optimization of machine learning algorithms for the parallel processing of multi-source data. Utilizing deep neural networks and hybrid learning models would enhance behavioral prediction accuracy and reduce false positives. Furthermore, the incorporation of real-time feedback systems that advise drivers about their risky behavior and suggest corrections

could be highly beneficial for reducing accidents. Moreover, personalized AI models grounded on unique driving patterns and suggesting recommendations accordingly also support road safety measures [32], [35].

While our methodological framework establishes a clear pathway for applying SVMs and other AI techniques to driver-behavior analysis, several limitations remain. First, all input and target variables derive from OBD-computed values or smartphone sensors, which are subject to measurement uncertainty due to noise, sampling irregularities, and underlying stoichiometric assumptions. We recommend that future studies incorporate formal uncertainty quantification methods—such as Monte Carlo simulations or Bayesian neural networks—to propagate and assess these errors. Finally, translating this framework into real-time, in-vehicle applications will require optimizing computational efficiency and exploring hybrid AI architectures that combine interpretable models with high-capacity deep networks. Addressing these areas will be crucial for advancing AI-driven road-safety solutions.

Finally, by employing cutting-edge technologies to inspect and analyze drivers' behavior, road safety can be revolutionized in terms of being able to prevent accidents proactively rather than reacting to them. Multi-source data fusion, psychological behavior modeling, and machine learning optimization are some challenges. With more sophisticated AI algorithms, real-time monitoring systems, and personalized feedback mechanisms, overcoming such challenges will lead to an enhanced transportation safety environment.

## VI. CONCLUSION

This paper investigates driver behavior and the application of artificial intelligence to identify key factors contributing to road accidents and their impacts on overall traffic safety. By exploring the intersection of these domains, our study highlights how advanced AI techniques—including ANNs and SVMs—can be combined with data from surveys, GPS, smartphones, and OBD devices to enhance safety analysis. Our findings demonstrate AI's powerful ability to model and predict driver behaviors that lead to accidents, revealing, for example, the significant roles of distraction, mobile-phone use, and individual personality traits. A review of prior research confirms these factors' substantial influence on crash risk, underscoring the importance of integrating diverse data sources and machine-learning methods. Finally, we emphasize the critical need to reduce accident rates within the broader framework of road-safety management and suggest that future work should extend AI applications into additional civil-engineering domains. By clarifying these interconnections, this paper advances our understanding of how intelligent systems can contribute to safer road networks.

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