Driving behaviour analysis using smartphone fusion sensors and machine learning techniques.

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Abstract*— An important area of interest in the solution to the road safety problem is the analysis of driving behaviour (DB) concerning traffic accidents, over 90% of traffic accidents are the result of human errors and infringements. Using smartphone sensors offers interesting ways to read real-time DB. According to Statista, 83.37% of the world's population possesses a smartphone. This indicates that a smartphone can be a key factor to support road safety. Understanding driver behaviour is crucial for Intelligent transportation systems (ITS) and applications for educational purposes. Processing and analysing the gathered data enable providing exceptional insights and solutions for Driving Behaviour Analysis (DBA), a bibliographic citation program, allowing references and footnotes to be translated into various fuel management, automated vehicle development, traffic safety, and driving identification to name a few. Then, it is important to identify the types of driving behaviours to provide a driver profile. This investigation study aims to explore the recent literature and summarize the key trends and challenges in the domain of DBA, especially around using Smartphone sensors and metric tactics to capture driver behaviours. This study also synthesizes the terminology and summarized the methodologies used in this domain that can also guide future work. Finally, it is identified the most used algorithms machine learning (ML) and deep learning techniques used for the different DBA tasks, and methods to evaluate the ML model performance used to find the patterns to categorize the type of driver's behaviour.

Keywords: Machine learning, driving behaviour, smartphone, intelligent transport system, road safety.

I. Introduction

Current issues with driving and road safety are gaining global significance. The World Health Organization (WHO) reported on the global condition of road safety in 2018; it found that there are 1.35 million traffic-related deaths globally each year, making it the leading cause of death for those between the ages of 5-29 years (Organization, 2019). Since the beginning of the twenty-first century, when the supporting data for road safety measures were established, WHO has been pursuing a systematic approach to the issue of road safety. Additionally, this research advocated for the adoption and enforcement of laws addressing significant risk factors, including speed, drunk driving, motorcycle helmet use, seat belt use, and kid restraints, which have been proven to reduce road traffic injuries in several developed nations. Since the WHO launched its "Decade of Action in Road Safety (2011-2021)" programme, a notable improvement in road safety has been apparent. Driver assistance and safety awareness programmes have been focused to reduce road safety incidents. The new decade programme 2021-2030, promises to cut down on traffic-related fatalities & injuries by at least 50%. Implementing competency-based testing for driver licencing and the use of graduated driver licencing for novice drivers are two of the actions that are advised to ensure the safe use of the roads (Organization, 2022). This has prompted a request for more research on the various levels of measures taken to ensure safe road use and who is involved in obtaining a license.

According to Statista, there are currently 6.648 billion smartphone users worldwide, which corresponds to 83.37% of the world's population and future growth is anticipated (O'Dea, 2022). The vehicle and navigation industries now have new ways to collect data, which benefits drivers, vehicle owners, and society at large. This is made possible by the continually increasing smartphone penetration around the world. The enormous amount of recently completed projects, both in academia and in business, demonstrate the enormous potential of smartphone-based data capabilities and have established a solid foundation for upcoming mass-market applications. Smartphone-based solutions are typically scalable, upgradeable, and affordable as a result of the unprecedented increase in smartphone demand. (Wahlström et al., 2017).

The evaluation of driving behaviour (DB) concerning road safety is a key area of interest in the solution to the problem of reducing traffic accidents. For intelligent transportation systems, which are built on significant data and insights obtained from related data, understanding the behaviour pattern of the driver is essential. The data collected can be processed and analysed to produce excellent insights and Driving Behaviour Analysis solutions. Machine learning (ML) plays an essential role in decision-support mechanisms by finding the DB patterns. exemplifies how a DBA using smartphones scenario may be used as an integrated part of ITSs.

Figure 1 shows three layers where everyone interacts with each other.

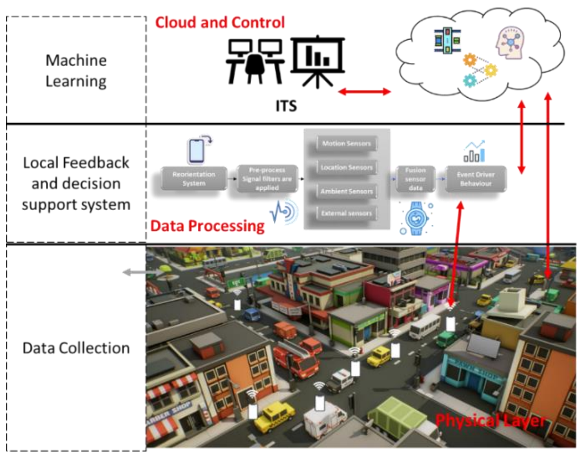

Figure 1. ITS environment with Integrated DBA smartphone integration.

The first layer is the physical layer where all the elements that circulate the streets and ITS interact. The next layer shows a common process for data processing for local feedback and a decision support system. This system flow shows the most common methodology that most of the current works in this area, which consists of a reorientation system, signal calibration, fusion data extraction, and analysis. Finally, the last layer captures the semi-analyse data to proceed to ITS tasks.

The study's objective is to review the relevant literature on Driving Behaviour Analysis (DBA) using Machine learning (ML) algorithms using a smartphone as an integrated part of Intelligent Transportation Systems. The goal of DBA and gathering real-time data is to offer feedback and support to raise awareness and encourage safe driving. However, the offline analysis also is done for more complex methodologies and used in other areas. The study is distributed in four main sections, First, identify trends of works related to the use of mobile phones for driver behaviour analysis, and machine learning (ML) algorithms in this area. Second, it is explored and analyses the systems to investigate the potential applications around ITS and individuals. A distinctive "driver behaviour pattern" is created by combining driving style data from numerous events and phases of driving into a "risk profile" or "safety scale". Then, it is investigated which metrics tactics and sensors have been used to define those systems. Some challenges and solutions also were identified, Finally, the last section identifies the most common algorithms, machine learning (ML) and deep learning (DL) used in these systems and their performance according to the literature review. The identification of these key factors will help support decision-making to determine which methodology to use and what is expected, in terms of ML algorithm use, metric tactics, sensors, and systems of DB, for Driving Behaviour Analysis (DBA) tasks using smartphones to individual drivers, or as part of integrated systems for private companies, or integrated for intelligent transportation system ITS. to prove the findings, a prototype was developed that fit in the category of event event-driving driving behaviour using thresholds to identify the events based on the methodologies such as driving style detection. The investigation's findings are intended to help reveal safe driving practices for automated transportation systems. Expand the potential for applications and develop new standards for DBA to benefit drivers and ITS to predict, control and support roads in terms of safety and traffic management.

II. Literature Review

A literature review was conducted addressing the historical and current use of machine learning algorithms, applications, sensors, and methods for driving behaviour analysis to gather information from relevant sources. As a result, relevant literature was selected and briefly discussed. A particular focus was placed on the employed machine learning methodologies, and the data extracted for the machine learning algorithms to address the stated research questions.

(Meiring & Myburgh, 2015) examines different driving styles and analyses solutions through machine learning algorithms. The author's research focuses on gathering the different applications for Driving Behaviour analysis, and the possible machine learning and artificial intelligence algorithms that were analysed for every application. Numerous types of DB were identified along with applications for driving style profiling, those were studied, and highlighted the key concepts. Consequently, the applications were classified for the machine learning algorithms that were used. The author suggested that Real-time ML applications in this area can be a remedial solution to reduce accidents, especially in developing countries. Finally, the article concluded that the Fuzzy Logic algorithm has a specific interest, and it was universally used in smartphone applications for driving behaviour performance but requires future investigation.

(Kanarachos et al., 2018) investigates the use of smartphone sensor data for monitoring driver behaviour, especially as an essential part of intelligent transportation systems, numerous articles were collected to focus on areas such as strategic, manoeuvring and reactive. Aggressiveness a type of DB and part of manoeuvring from driving behaviour was one of the important areas where the author found the key signals that can be helpful to read the driver's aggressiveness. Then, Acceleration, speed, speed variance, GPS position, map information, gyroscope and magnetometer are the most common metric tactics for this purpose. Furthermore, the machine learning algorithms to define the type of DB aggressiveness are Rule-based, Clustering, Fuzzy logic, Decision trees, Random Forest and Rough set theory where the last two archived the highest accuracy. Finally, the author suggested that machine learning algorithms were used to discover knowledge however deep learning methods are more suitable for this action.

The authors (Wahlström et al., 2017) have proposed an overview of smartphone sensors focusing on the role of a tool for user-interactive services Support for these claims is documented in an extensive review of smartphone sensors including GNSS, Bluetooth, Wi-Fi-based positioning, cellular positioning, magnetometers, cameras, microphones, accelerometers and gyroscopes. The author also mentions the smartphone's capabilities in terms of energy consumption. Furthermore, services and applications of smartphone-based telematics were presented, where Driver Behaviour Classification and Cooperative Intelligent Transportation Systems (C-ITS) stand out. Some metrics tactics were mentioned to assess driver safety for driver classification, a driving event such as harsh acceleration and harsh cornering was evaluated and concluded that drivers who produce those events tend to involve in more accidents. On the other hand, C-ITS is used for collision avoidance, emergency vehicle warning systems and traffic mitigation, this showed the importance of DBA for different levels. Finally, the article concluded by indicating that the new advances and smartphone use expansion is expected to catalyse new advances, currently, there are many articles with new idea waiting for implementation.

In (Chan et al., 2019) comprehensive literature review, the authors gathered extensive information to determine driving behaviour using smartphones with numerous methodologies to analyse the patterns. In particular, the authors focused on several factors of behaviours, such as fatigue, distraction, and drunkenness were the most frequent causes of abnormal driving. Moreover, this article analysed limitations, and challenges and bring viable solutions to manage the challenges in detail. However, it only went into machine learning algorithms such as Artificial Neural Networks (ANN), Support Vector Machine (SVM), Random Forest (RF), and Bayesian Networks (BN) where ANN showed high accuracy. Finally, the authors suggested that future works should focus on the issue of smartphone positioning inside the car as part of the main drawback of noise generated during the collection of data.

(Mantouka et al., 2021) proposes an inclusive methodological framework understand Driving behaviour sensed from a smartphone and recent literature was analysed to find the main challenges. The author's research focuses on finding the challenges to raising awareness among those who want to develop an application in this area. the author identified critical issues such as energy efficiency, data quality, low sensor quality, privacy, and security. Moreover, it was also highlighting the noise which makes to do more steps to process the data. Then, the author reviews several methods and classified them by driving indicators, software and driving behaviour. Finally, the article concluded by suggesting that mobile phones are becoming a reliable alternative for gathering data, it also indicated that there's a big demand for precise detection models. The framework purposed was organized in four stages: data collection, data preparation, data mining, and driving behaviour modelling.

(Abou Elassad et al., 2020) presented a theoretical framework to conceptualise driving behaviour, as well as a summary of the evidence concerning the use of ML techniques to build models. As a result, the authors identified and compared accuracy performance among different Machine learning models and condense the advantages and disadvantages. Furthermore, About Elassad investigated, identified, and compared the performance metrics across driving behaviour analysis. Then, they also mentioned and declared that there are two ways to define the diver state that are related to environmental factors: psychologically or physiologically, which were explored and modelled to be measured. For instance, vehicle-based Measures are related to driving events. Interestedly, the author found that Machine learning algorithms such as Bayesian Learner (BL), Neural Network (NN), Ensemble Learners (EL) and Support vector (SVM) were more frequently adopted for DBA. Finally, the author concluded that for a given ML technique to reach its full potential, ML models must be used early on in support of current conventional models.

(Aghayari et al., 2021) uses qualitative content analysis to examine all mobile apps associated with road traffic health/safety. The author categorizes applications into three main groups Blocking apps, apps that change interfaces to reduce interaction with the phone, driving feedback and coaching apps. In particular, the apps were categorised into groups according to their features Road Traffic Health & Safety (RTHS), Road Traffic Training (RTT), Road Traffic Navigation (RTN), and Road Traffic Apps (ORT). Road Traffic Training (RTT) is an interesting group where the author found 97 apps that are used for educational purposes focus on driving performance, and another important app feature is associated with traffic rules and road signs. Moreover, it is shown that 41% of the apps are found to use the mobile sensor, which is a high percentage across the other applications in this field. Finally, the author advised mobile application developers to carefully consider the comprehensive features for traffic health and safety.

(Vlahogianni & Barmpounakis, 2017) the capabilities of smartphone sensors to generate data for driving behaviour analysis, this paper compared methods of data extraction considering fixed and free smartphone positioning to eventually compare regular and irregular driving behaviour. In particular, the author analysed the collection of data using sensors such as GPS, accelerometers, gyroscopes, and magnetometers to establish the thresholds. In addition, dynamic reorientation, and smartphone positioning, are techniques that play an important role in data quality and collection. The author also mentioned the calibration of the sensors for the event detection algorithms which determined the target event to trigger actions such as notifications or warnings. Finally, the author drives two different experiments, first a driving behaviour induced by the expectations to calibrate the models and the second aims to compare the accuracy of the model for the events produced by the driver such as harsh acceleration or harsh braking, those experiments lead the author to experiment the two positioning techniques and compare them against the machine learning models.

(Saiprasert et al., 2017) proposes three algorithms that are compared and tested to find which has better performance, these algorithms detect and classify driving events for different applications. The author suggested three algorithms Rule-based (RB), Pattern Matching (PM), and Self Triggered Pattern Matching (STPM), which analysed raw data collected from a 3-axis accelerometer and GPS. Moreover, these algorithms were defined to indicate if the driver's behaviour is aggressive or not, this is helpful to make easy the process to classify the event. The article compared the algorithms and concluded that the PM algorithm overperformed RB, and STPM can be adjusted for different applications. Finally, the author suggested that the PM algorithm potentially become an unsupervised pattern machine algorithm to represent the 12 types of driving events.

(Khodairy & Abosamra, 2021) examines a Long Short-Term Memory (LSTM) classification deep learning technique for driving behaviour using smartphone sensors. In particular, the author focused on building two different classification models for different application tasks, classification models such as Fuzzy logic, K-nearest Neighbour, random forest, and support vector machine were analysed, however, the author found that LSTM experimentally proven is a computational model most suitable for driving behaviour analysis compared to the other models. Moreover, the paper showed the necessity to choose the best input features from the raw data and extracted features as part of the initial process, and the dataset was used where its main features are the outcomes task such as aggressive, drowsy, and normal driving behaviour based in, raw inertial measurements signals, GPS signals and pre-processed vehicle detection data. Then, the author performs their classification technique obtaining a highly accurate model, this is done by separating the process into different stages with different tasks to accurate the results moving through data collection, filtering and training and testing phase. Finally, the authors provided experiments where different road conditions were identified helping them to optimize their LSTM model and improving their outcomes in terms of accuracy model.

(Azadani & Boukerche, 2021) presents methodologies for DBA, main current and future trends, analyses different data resources, and discusses applications along with challenges and future directions in this field. The authors' research focused to gather all the methodologies related to driving behaviour analysis DBA that currently exists and claimed that there is no exits guideline to properly approached this field. In particular, the author categorized every aspect of DBA which is subdivided into data Sources, tasks and models. They identified as data sources CAN-bus, GPS, Smartphones sensors, Lidar and radar, multimedia and driving simulators, tasks that are considered in DBA are Driving style detection, driver identification, driver inattention, drunk driver detection, driving events prediction, and the models are subdivided into Threshold-base and fussy logic, classical machine learning and deep learning. In addition, datasets that are used in this field to build the models were deeply analysed to determine the main features and uses depending on the application. Finally, the author highlights the challenges and future work focuses on four main areas as big driving data analytics, semi-supervised driving behaviour models, driving profiling and vehicular communications for DBA.

(Marafie et al., 2021) provides detailed information on the driving behaviour of personalised feedback compared to non-personalised feedback, proving its effectiveness in improving a better user experience. In particular, this study incorporates personalized feedback, which is embedded in a driving environment driving behaviour system that is based on an event scoring engine, a pattern scoring engine that provides feedback to the user. In addition, the user develops a system that combines machine learning algorithms to classify events, they found SVM and KNN ML algorithms are the most suitable for pattern recognition and regression, their methods increase the classification accuracy to 93.4% for SVM and 81.4 for KNN. Finally, the author classifies algorithm results into 4 main groups and in combination with a reward, the engine provides personal feedback. Therefore, the authors prove the effectiveness of driving behaviour profiling and conduct a systematic pilot study that can lead to future works, it also explored concepts and define metrics to demonstrate a quantitative and qualitative approach to assess their application system.

(Rachad et al., 2021) explored several mobile applications related to driving assistance based on ML techniques, where the author identifies their functionalities, gamification components, type of data collected, and ML techniques and algorithms. In particular, the authors investigated the applications that have gamification engagement which promotes the user's active interest to improve their driving behaviours, generally, Mobile applications that purpose to enhance user skills, engagement, or behaviour with incorporate gamification techniques into their design. Additionally, the author developed a template to capture app description, App functionalities, app context, app data collection, machine learning techniques and gamification properties, this lead the author to identify the apps evaluated in the study and support to conclude that neural networks (NNs), support vector machines (SVMs), decision tree (DT), K-means, Bayesian learners (BL) and binary logistic regression (BLR) are the algorithms more used in those apps, they also identify trends in the functionalities and purpose of the development of apps. Finally, the authors found that most of the apps gather data such as travel distance, the number of hashes breaking, driving speed, slowing down, and sudden acceleration, or driver profile data such as gender, age, and position, but they observed that few apps collect driver's health data such as detection of fatigue, mood, sobriety, heartbeat and stress. On the other hand, apps can collect data before, during and after a trip where during the trip represents 96%.

(Mantouka & Vlahogianni, 2022) developed a driving recommendation framework that targets to enhance individual driving behaviour by considering aggressive and risk behaviour using a data-driven methodological approach. In particular, the author used Deep Reinforcement Learning for the ability to learn how a user interacts with an environment, this takes as input discrete time, an action, and the previous environment changes that produce a corresponding reward output, this algorithm the author indicates that has a great potential in Intelligent transportation. Moreover, the author identified in this case the actions or tasks that influence the algorithm such as driving parameters per trip (harsh acceleration, percentage of mobile use, average speed etc...), this also determine if a trip was aggressive, or non-aggressive which indicate the level of risk and distractedness. Finally, the author faced challenges and limitations to build the model, which relates to an overestimation bias that occurs when is estimated the values to feed the algorithm, in general, it can be a greater value and reduced to optimize the results, also overestimate the expected rewards was considered.

III. METHODOLOGY

The study employs a research methodology to locate possible literature that could be used to address the research questions. The results of the search will be expanded by manual searching through related articles and automatic searching at reputable journals and search engine such as google scholar. The use of high-quality journals like IEEE Xplore, Science Direct, Hindawi, Springer Link, MDPI, and Emeral will be used. The articles gathered must include vital details about the machine learning algorithms used to analyse diving behaviour data obtained from a smartphone over the previous ten years.

A. Research questions

Understanding and modelling driving behaviour is a difficult study topic today. It is generally acknowledged that different drivers' driving behaviours vary depending on a range of factors, such as driving history, emotions, population, and environmental conditions. In addition, even the same driver's driving style can change from trip to trip or context to context. Understanding driving behaviour is crucial, particularly when attempting to identify the circumstances in which a driver demonstrates risky driving behaviour. Therefore, this study reviewed the most recent journals that trying to solve the challenges and difficulties in this domain trough machine learning using smartphones. Then, it proposed three questions that attempt to understand what is needed to apply driver behaviour analysis.

Q1: What are the trends of the purpose to use smartphones to capture driving behaviour using machine learning techniques?

Q2: What metrics tactics are used to define the types of driving behaviours predicted with the data collected from smartphone sensors?

Q3: What machine learning algorithms and metrics performance are used for driving behaviour analysis?

Q1 is to find trends in the use of smartphone sensor data to analyse driving behaviour, it was resolved using a methodological search in google scholar using keywords related to this specific area, and different queries and filtering papers over the last 10 years were counted to find the patterns correlated to the queries. The goal of **Q2** and **Q3** is to present an overview of the most recent techniques and methods used for driving behaviour analysis, where machine learning and metrics performance are used to identify the type of driving behaviour using as inputs metrics tactics.

B. Search Process

The selected journals were selected using the methodology that is illustrated in Figure 2. The **Q1**. Look to see the trends around this area, Therefore, it was critically formulating the queries to use in google scholar to collect the publication data between 2012 to 2022. The queries were divided into 2 categories, trends by specific area for example *Driving behaviour and machine learning and smartphone*, and by Sector like t*ransportation and Machine learning*. These categories were compared with similar queries to see trends around the same domain. Finally, these categories were plotted to see the results using a count query.

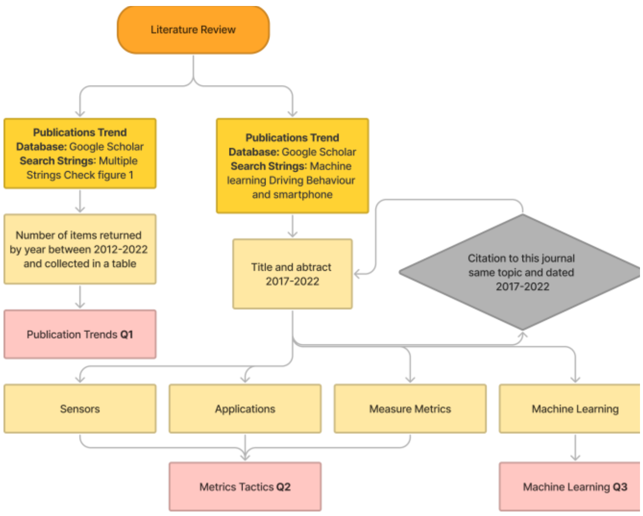

Figure 2. Research Methodology

Questions **Q2** and **Q3** were selected by reading titles, abstracts, and introductions and jumping to the conclusion to identify their usefulness. To find recent literature over the past 5 years, it was analysed the related work of some documents that guide authors to their research, this guided this research to resent citations associated with the question to resolve.

IV. Results

The study's findings are covered in this section. First, the literature trends over the last 10 years are presented **(Q1).** Next, the results of which measure metrics are used within the driving behaviour using smartphones **(Q2)** include applications, sensors, and driver metrics. Finally, machine learning algorithms and metrics performance are used for driving behaviour analysis **(Q3)**.

A. Publication Trends Q1

1) Trends by specific area

For every query was taken the number of publications for every year between 2012 – 2022, and the trends by specific area using the search query 1-7 were shown in Table 1. In return, several results were recorded and represented in Figure 3. These trends, in general, show an important increase from 2016, but Machine learning and Road safety have increased over the last 5 years and machine learning and driving behaviour follow the same trend. Another significant trend is machine learning and intelligent transportation system query tend to continue increasing, it has a slight curve indicating that research in this area is becoming crucial. While driving behaviour and smartphone has constantly increased over the last 10 years. I believe that intelligent transportation systems including smartphones as an integrated part will become an as important part of society.

N	Search Key Words - Google scholar 2012-2022	Results
1	"machine learning" AND ("driving behaviour" OR "driving behavior") AND (smartphone OR mobile phone)	5,828
2	"machine learning" AND ("driving behaviour" OR "driving behavior")	13,098
3	("driving behaviour" OR "driving behavior") and ("Intelligent Transportation System")	3,154
4	("smartphone" OR "mobile phone") AND ("Intelligent Transportation System")	5,921
5	"intelligent transportation system" AND "machine learning"	10,639
6	("driving behaviour" OR "driving behavior") AND ("smartphone" OR "mobile phone")	13,060
7	road safety AND "machine learning"	16,319
8	"transportation" AND "machine learning"	248,870
9	"Finance" AND "machine learning"	220,410
10	"Public health" AND "machine learning"	226,090

Table 1. Queries to research trends

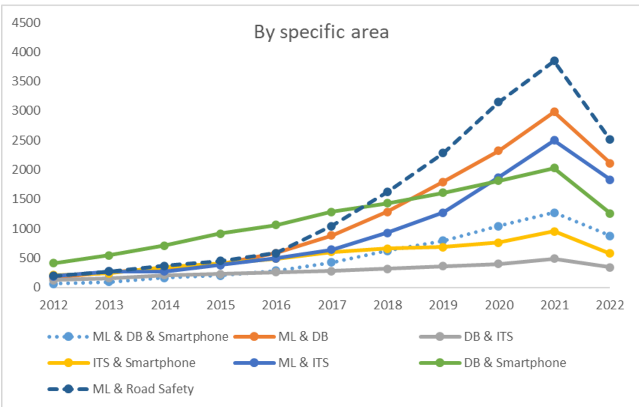

Figure 3. Result trends from queries by specific areas

2) *Trends by Sectors*

Important sectors such as finance and public health are around transport, therefore they were compared and shown in Figure 4. There was used the queries 8-10 shown in Table 1. Transportation has been increasing substantially since the world pandemic. This sector has similar trend behaviour to machine learning and road safety, which may suggest that Since the WHO launched its "Decade of Action in Road Safety (2011-2021)" programme, the research in this area increased to support this program. Now the new decade program to cut down on traffic-related fatalities & injuries by at least 50% will increase the research around Intelligent transportation systems looking for alternatives to integrate into this system such as driving behaviour analysis using smartphones. It also shows that transportation and Machine learning overlap Finance and public health between 2017 to 2020 which can suggest the importance that this sector is becoming relevant as technology advances and the use of ML becomes essential for systems that integrate a massive number of data collected.

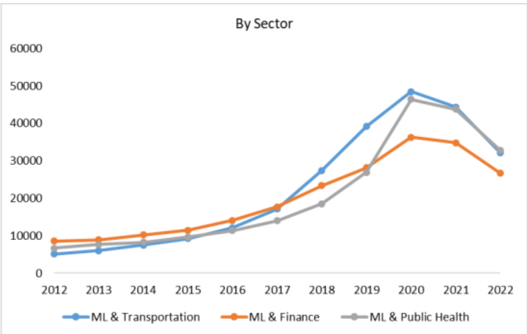

FIGURE 4. RESULT TRENDS FROM QUERIES BY SECTORS

B. *Metrics Tactics Q2*

In this section, the objective is to identify the metrics tactics that are considered to determine different types of behaviour for different applications. Therefore, it is important to identify the sensors and the data that a smartphone is capable to access, the challenges, and limitations of using these devices as integrated parts and the methodologies to analyse the parameters that can lead to a precise identification of the type driving behaviour DB. It can be taken in different levels such as strategic, tactical and reactive (Kanarachos et al., 2018). The strategic used is related to transportation modes, while tactics are around the driver's actions, and reactive solution to travel time, or route choice prediction. Common applications are identified and reviewed their functions, also. As indicated before DBA is an essential part of ITSs, therefore, to research this section has explored the anatomy of an ITS shown in Figure 6 and was compared against the application purposes that can be provided in an integrated DBA with a smartphone environment. The figure was adapted from (Guerrero-Ibáñez et al., 2018) which represents six categories based on the type of application for ITS.

The services expressed here is to indicate the purpose of DBA they were classified from several sources that refer to a different name with the same purpose which is represented in Figure 5, Then, they were reduced and classified this application name into a small group that can be represented across according to the application that is investigated and also can guide future research.

FIGURE 5. CLASSIFICATION EXTRACTION FOR APPLICATION PURPOSES

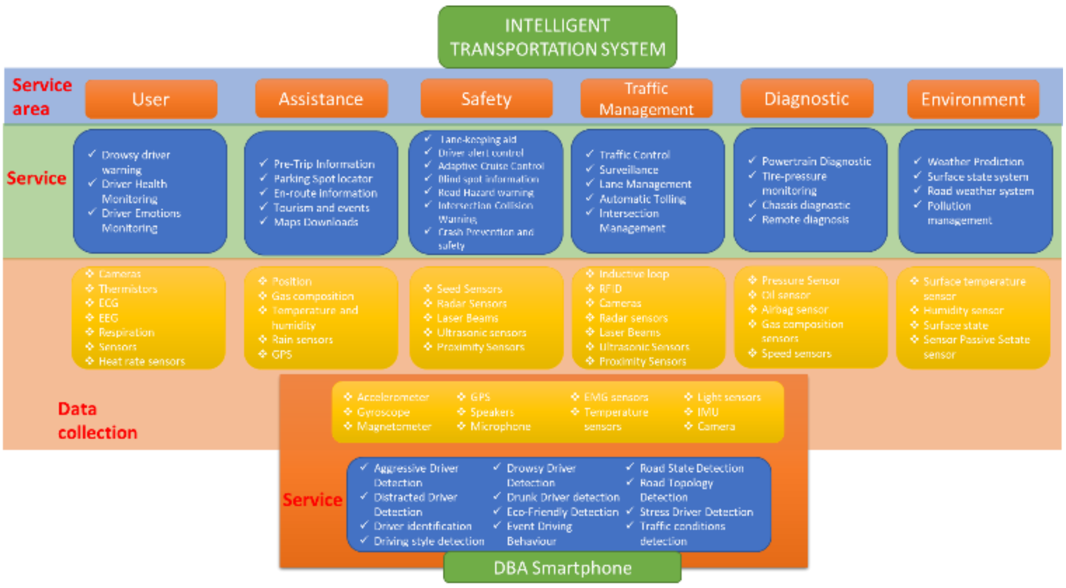

FIGURE 6. COMPARISON ITS ANATOMY AGAINST DBA SMARTPHONE BASIS

To compare the services that the DBA smartphone basis against ITS anatomy was required to define the purpose of every application extracted and the purpose of the service where those applications can fit into the ITS environment this is demonstrated in Table 2. This also serves as a dictionary to determine some terminology that literature use with the same purpose.

Classification name	Application purpose	ITS Service Area
Aggressive driver detection: a typical rating that shows the driver's risk level when driving becomes dangerous. Many different types of literature mention aggressive behaviour; however this does not necessarily imply that the driver is hostile or aggressive; rather, it just signifies that their actions are outside of the standard for safe driving.	Aggressive or safely, Aggressiveness detection, Classify driving behaviour on a gradient from smooth to aggressive behaviour with a special focus on the elderly drivers, Detect aggressive behaviour, Risk level of the driver	User, Assistance, Safety, Traffic Management
Distracted Driver Detection: demonstrate a driver's inattentive or distracted behaviour	Distractedness, Driver attention detection, Driver distraction, Driver distraction detection, Drivers distraction, Drivers inattention	User, Assistance, Safety, Traffic Management
Driver identification: search for the driver fingerprint base, as each driver has a unique driving style.	Driver identification, The person behind the wheel, Driver characteristics or performance	User, Assistance, Safety, Traffic Management
Driving style detection: refers to different driving styles that can detect, for example, and application of driving style can detect if the driver is driving normal, aggressive, drunk, drowsy or fatigue	Aggressive, distracted, drowsy, Driving style detection, Driving styles, Normal, Aggressive drowsy events, Recognition of driving styles normal, drunk, Drowsy, and fatigue, Risky events	User, Assistance, Safety, Traffic Management
Drowsy Driver detection: refers if the driver state is half asleep, it is similar to fatigue which share characteristics, but the reading are different between each other.	Drowsiness detection, Drowsiness recognition, Drowsy detection, fatigue detection	User, Assistance, Safety, Traffic Management
Drunk Driver detection: refers to the detection if the driver is driving under the influence of alcohol.	Drunk driver detection, Drunk drivers, Drunkenness,	User, Assistance, Safety, Traffic Management
Eco-Friendly Detection: It is comparable to aggressive driving detection. The application differs in that it is based on fuel consumption. According to various literature, hard accelerations, for instance, increase fuel consumption, which also means a rise in pollution. As a result, driving safely or normally can improve the environment.	Fuel consumption, Fuel in an energy-efficient manner	Diagnostic, Environment
Event Driving Behaviour: it is the methodology that detect the actions that the driver do with the car such as accelerate, change the lane, braking and cornering within the most common	Driving events, Abnormal behaviour, Abnormal driving events, Classify driving events as safe and aggressive events, Detect abnormal driving behaviour, Detect vehicle manoeuvres, Detecting driving events, Driving event, Driving event detection, Driving events, Manoeuvre detection, Recognizing different driving events, Safe or unsafe driver behaviour, Steering behaviour prediction and Unusual events detection	User, Assistance, Safety, Traffic Management
Road state Detection: a methodology to detect changes in the smoothest of the street, therefore, it is the methodology to detect pumps, and potholes	Identify road anomalies such as bumps and potholes, Road abnormalities	Diagnostic, Environment
Road Topology Detection: methodology to detect the type of road that the driver is driving such as rural, highway, city, hill etc.	Driving Condition, Route topology	Diagnostic, Environment
Stress Driver Detection: refers to the driver state	Drivers stress detection, Stress	User, Assistance, Safety, Traffic Management
Traffic conditions detection: methodology to detect if is congested or not congested	Congested or not congested	User, Assistance, Safety, Traffic Management
Transport mode detection: refers to the methodology where the system detect if the individual is walking, biking, in a bus, in train or driving	Transport mode	User, Assistance, Safety, Traffic Management

TABLE 2. APPLICATION DBA SMARTPHONE BASIS IN ITS ENVIRONMENT SERVICES BY AREA

1) Applications

Driving behaviour Analysis can be used in different areas depending on the application, most application use driver-style classification to determine the driver who is controlling the vehicle. In contrast, other application uses the benefits of smartphone sensors to determine different conditions on the road and events. A vary of methodologies are used and they were summarised in Figure 7. This figure was based on the methodologies shown by (Kashevnik et al., 2019). It is helpful to understand the application and how this is archived.

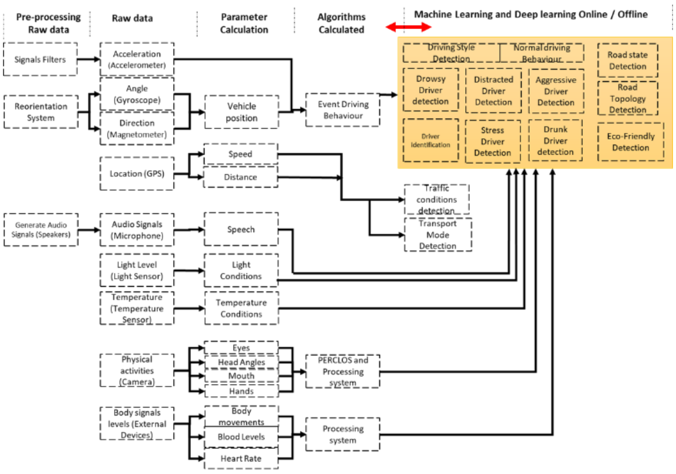

FIGURE 7. METHODOLOGIES AND MOBILE APPLICATION FOR DRIVER BEHAVIOUR ANALYSIS.

a) Strategic

The strategic approach is commonly used by ITS whose priority is to keep the road safety, then, DBA in these systems play an important role to characterize the driver and their intentions. The applications in this category vary depending on the purpose of the system. (Azadani & Boukerche, 2021) indicates that Driver identification can benefit from a DBA perspective. The possibility to identify drivers according to their driving behaviour can be employed for real-time monitoring and finding imposters. The outlined the benefits of incorporating smartphone sensing into intelligent transportation system applications, particularly for driving style recognition and vehicle and road monitoring systems.

Transportation mode classification is another important area of research where travel mode plays a crucial role in ITS to identify what is on the road, this classifies modes like bicycle, walk, bus, motor vehicle and train. This is done by collecting data with different sensors, the most common is the GPS and classifying with different machine learning algorithms (Kanarachos et al., 2018).

Accident Detection is carried out using techniques for monitoring traffic density, analysing critical changes in sensors that are incurred in accident events such as suddenly or critical braking through ITS based on real-time driving data (Meiring & Myburgh, 2015), applications around this area are included release immediate emergency services, and road-side assistance services.

b) Tactical

Driving behaviour at the most basic and tactical level refers to the actions that a driver takes to accelerate, press the brakes, change the line, or turn in a corner. This can have incidence in different aspects like road safety, traffic flow and fuel consumption. Consequently, improving tactical driving behaviour can lead to increase concern in those facets. The most important aspects found that are also interrelated are Driving aggressiveness and eco-friendliness. (Kanarachos et al., 2018) identified the most popular metrics to characterize tactical driving. These metrics are based on acceleration, braking, speeding, smoothness, swerving, cornering, eco-ness, elapsed time, elapsed distance, time of day and location. It is important to highlight that correcting driving behaviour also helps the global warming problem due to transport being one of the major contributors.

(Azadani & Boukerche, 2021) identify other classifications such as level of risk, drunk driving detection, aggressiveness index and more. They indicate that the competence of level is also important in other areas like insurance telematics, where the rate of payment by the driver is correlated to the driver's behaviour in a model called Pay-How-you drive. These tactical applications are based to score the driver in a real context while traditional insurance companies use questionaries correlated to driver history.

(Mantouka & Vlahogianni, 2022) on the other hand develop a model that personalizes driving recommendations to Mitigate Aggressiveness, riskiness, and level of distractedness. While (Meiring & Myburgh, 2015) identified tactical applications such as Driver assistance, Drowsiness and distraction Detection.

According to the literature, most of the tactical applications are based on levels or progress, feedback, points or scoring or scoring to the incentive to driver to behave better and make progress every time is driving. (Aghayari et al., 2021) categorized applications into three main groups Blocking apps, apps that change interfaces to reduce interaction with the phone, driving feedback and coaching apps and 97 smartphone apps that deliver Educational Content.

c) Reactive

Route choice and Travel time prediction are applications that benefit drivers and ITS. Many transportation solutions get this knowledge from GPS signals but the challenge is to get these signals accurate, Route choice can automatically change how traffic behaves according to reduce stress on main streets. (Kanarachos et al., 2018) indicates that sparsity can make predicting and identifying the best route more difficult. On the other hand, travel time prediction is influenced by Traffic, then capturing traffic data is crucial and is obtained by GPS position and speed.

Road Condition monitoring consists of monitoring road surface conditions and their capability to damage the vehicles, concern of road maintenance is also important for fuel consumption, driving comfort and the risk of an accident caused for road conditions (Wahlström et al., 2017). To obtain road data differ, the most comm is the use of GNSS, magnetometer, gyroscope, microphones and OBD suspension sensors.

Applications that fit in this area require standardization methods, and characterization of the signal and road conditions in terms of traffic, route choice, and road surface. The idea behind this is to reduce the tension on drivers and routes that constantly are affected by these parameters.

2) Sensors

Sensors embedded in smartphones are required for many applications across DBA. Understanding driving behaviour through the data collected from these sensors is a difficult task and it is crucial to understand what the sensors are challenges and limitations of using them for driving style recognition.

Smartphone sensors can be divided into three categories: motion sensors, such as the gyroscope, magnetometer, and accelerometer (compass), location sensors; like the Global Positioning System (GPS), which is frequently used in outdoor settings, and network-based location services, and ambient sensors, such as the light sensor, microphone, and proximity sensor.(Mantouka et al., 2021). A extra category is added External Sensors that contains sensors that can read heart rate, breathing rate and body temperature, It reviews the most common sensors and their role in driving behaviour analysis showed in the Figure 8.

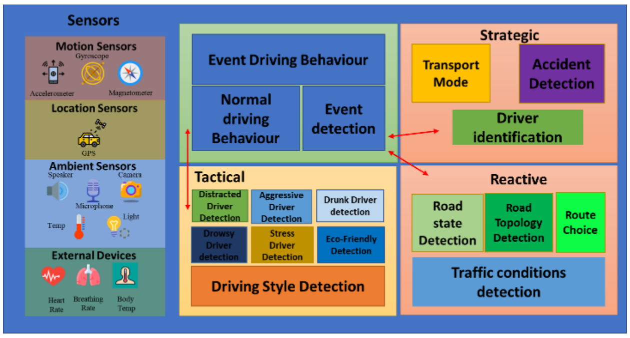

FIGURE 8. SENSOR STRATEGY FOR DRIVING BEHAVIOR ANALYSIS USING SMARTPHONES

a) Motion sensors

Motion sensors are the most used in this are for the capability to recognize mobile position, events changes, and location according to a compass. Therefore is an ideal tool to explore the event changes in relation that the driver and car involved, the challenge here incur that every sensor in its form leaves open to reduce the quality of data, for instance, the **accelerometer** is capable to indicate the acceleration of the phone in 3 axes, x, y and z, but, itself is not able to indicate a fix position of the car just the smartphone itself this is shown in Figure 9, although many research use just the accelerometer as a source of data to determine diving events. but (Vlahogianni & Barmpounakis, 2017) compared methods of data extraction considering fixed and free smartphone positioning to eventually compare regular and irregular driving behaviour. In particular, the author analysed the collection of data using sensors such as accelerometers, gyroscopes, and magnetometers to establish the thresholds.

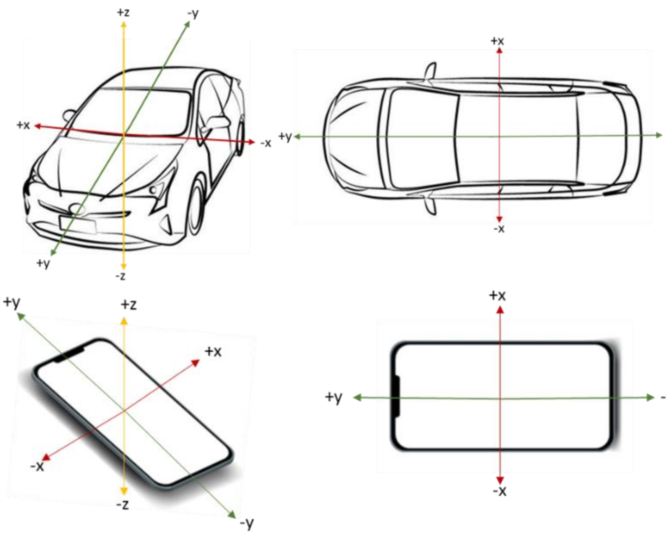

FIGURE 9. SENSOR COORDINATE SYSTEM EMBEDS INTO VEHICLE

Fused Sensor is a term to indicate the use of accelerometers, gyroscopes, and magnetometer sensors together. The use of fused sensors can determine the position and direction according to the car's fixed position. The gyroscope sensor reflects the rotation rates on three axes in term of rad/s and play the role to indicate when the car is turning and can change lane or turn in a corner, while the magnetometer estimates the magnetic field at the position of the device and earth. It is used to estimate the angle between the horizontal elements. The fused sensor can determine a fixed position dynamically, this mean that the position of the phone can vary but the x and y axis are fixed according to the car's position. Different techniques use dynamic reorientation are used but the most common is computing Euler Angles which is implemented by (Vlahogianni & Barmpounakis, 2017) for their literature.

As indicated before treating the signal and reducing the noise that can be from different sources such as gravity on the accelerometer measurements. Then, at this point is vital to calibrate the signal obtained, a solution proposed by (Vlahogianni & Barmpounakis, 2017) is using a rough set theory that differs from traditional machine learning approaches, this does not aggregate or adjust data to account for discrepancies. (Vavouranakis et al., 2017) used another technique that consists in filter the signals with a high and low pass filter during the sensing. Therefore, the data is processed to reach the level of measurement that is required.

b) Location sensors

Important sensors such as GPS and GNSS are used to determine the location, GPS and GNSS technologies work together to deliver accurate location positioning anywhere on earth. The use of more satellites results in increased receiver accuracy and reliability. GNSS/GPS is being used in a variety of fields where the use of precise, continuously available position and time information is required. The difference between GNSS and GPS is that GNSS is a term for all satellite position systems, whereas GPS refers to American satellites.

GNSS and GPS also provide speed or velocity, IMU and attitude (orientation). First, it is more common and used GPS for driving behaviour applications some data can be usefully obtained from this sensor but also required a complementary process, for instance, speed is obtained from this sensor and internally calculate the distance and the time used to travel between two locations, then the speed is given. However, the speed to be useful it is necessary to be compared with the speed of the road to determine if the driver is driving within the speed limit, this is where location plays an important role because it can be used to identify the exact place where the driver stands, APIs such google maps can offer the service with this information to determine the route and speed limit.

IMU can be used to determine three-dimensional estimates X, Y and Z to indicate the position of the smartphone, A navigation system will give estimations of the smartphone's dynamics and position rather than those of the car. When considering apps like driver navigation and speed compliance, the difference is often insignificant for the location and velocity predictions if the smartphone is fastened to the car. However, the smartphone's attitude and the car's attitude are completely different. One generally requires some understanding of the smartphone-to-vehicle orientation to create estimates of the vehicle's attitude based on estimations of the smartphone's attitude (Wahlström et al., 2017).

c) Ambient sensors

Ambient sensors are related to the environment, the environment can be outside of the vehicle or inside the cabin, temperature, noise level, road conditions and driver activity are the most common data collected, sensors such as temperature, light, camera, and microphones are also included in the smartphone and can be used to monitoring the environment to increase the level to detect driver behaviour. Therefore, these sensors can construct a context that determines which circumstances are dangerous. To prevent traffic accidents, recommendations are created based on the context and risky scenarios that have been assessed. Temperature sensors support the idea of an environmental situation and could influence a driver's physical and mental state for example drowsiness or fatigue (Halin et al., 2021). These states are also influenced by the light, then, monitoring lighting conditions inside the cabin with the light sensor supporting the idea to evaluate the driver state (Kashevnik et al., 2019), using the lights as an indicator can be used to warm the driver and keep ideal conditions for driving.

The microphone is useful in several ways, it can be used to determine if the driver user indicator lights before turning in a corner or changing the line (Chan et al., 2019), and monitoring this driver action supports the feedback system to keep the ideal a driver behavioural. On the other hand, noise levels have also influenced by the state of the driver, different sources of sound inside and outside the car might be broken down and localised using techniques for separating audio sources (Halin et al., 2021). Evaluating the auditory environment can determine a level of discreteness, some methods check the driver's behaviour with the passengers and how is affected by them.

An important sensor or feature that smartphones have today is a camera and it can be a front camera or back camera. Strategically positioning the smartphone could be useful for monitoring the driver or road, the disadvantage to using the camera is image process consumption and battery consumption, which have a high cost to the device functions. However, a camera is the most common solution to analyse driver behaviour according to the road direction or driver actions during driving, for instance, drowsiness, distractedness or even drunkenness can be detected using software to detect these states, track pictures of the driver's face from the front-facing camera using OpenCV and DLib extract visual attributes of the driver that normally describe it state (Kashevnik et al., 2019). Other methods are used to analyse the driver’s hands and common actions that the driver does when driving (Fan et al., 2021).

Cameras can bring information about the driving scene. Methods to determine drowsiness is using the camera to monitor the lanes, so, it can be determined the car state between lanes, this has been accomplished by tracking the lane-delimiting lines when cameras are placed internally, behind the windshield, or commonly incorporated beside the rear-view mirror. However, when a driver crosses the lines, rumble strips - also known as sleeper lines, audible lines, or alarm strips are also an indicator and can be also used. Another method with a low-cost feature is using microphones and/or vibration sensors and processing this signal to establish that event is occurring. These are designed to produce an audible, acoustic signal intended to be sensed directly by the driver (as an urgent warning or wake-up call) (Halin et al., 2021).

d) External sensors

Nowadays hundreds of devices are developed that can be connected to a smartphone to control or read data collected from them, (Sun et al., 2021) use the term wearable sensors an example of this is smartwatches which are capable of providing data such as heart rate (HR), skin temperature, and electrodermal activity (EDA). Then, the possibility to integrate other drivers’ states is open to be evaluated and developed in this field. For instance, states safety belt is worn, hands positions, and driver movements inside the car can determine driver behaviour such as distraction and abnormal behaviour.

(Halin et al., 2021) indicates the driver states are tracked using a variety of physiological indications, including heart rate, breathing rate, body temperature, and pupil size. Alcohol is known to speed up respiration and heart rate. Cannabis is known to make breathing more difficult and raise the heart rate. Alcohol makes arteries and other blood vessels more active, which raises the warmth of a drunk person's face.

(Fan et al., 2021) proposes and developed a solution that detects abnormal driving behaviour using wearable EMG sensors, EMG signals capture the unique patterns of five typical abnormal driving behaviours shown in Figure 10. Driver actions such as turning the wheel smoothly and slowly TSW, Driver intention to move to the front FF, picking up objects from the floor PU, open sunroof TS, turn back to reach objects TB were effectively detected.

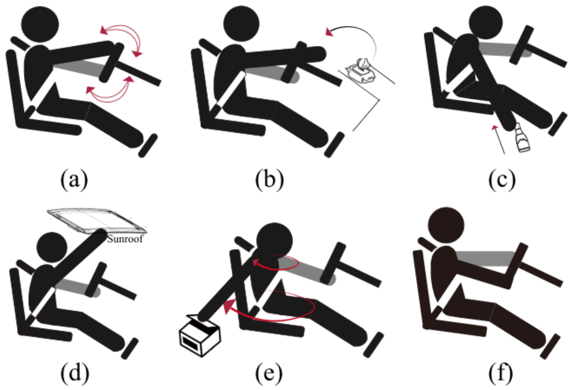

FIGURE 10. NORMAL AND ABNORMAL DRIVING BEHAVIOUR. (A)TSW. (B)FF. (C) PU. (D) TS. (E)TB. (F) NORMAL DRIVING. (FAN ET AL., 2021)

3) Driving styles

It is not a secret that every driver can have their own driving style, this is according to different aspects like psychological or physical. To drive is require having a combination of both including driving experience that brings alertness and responding to several events that can occur while driving. This section presents the most common driving styles that are evaluated to determine different states while driving.

a) Aggressive Driver Detection and eco-friendliness driving

Driving tactics have a significant impact on fuel efficiency, traffic flow, and road safety. Aggressive driving and eco-friendliness were the two primary tactical behaviour facets that are widely examined. According to studies, aggressiveness and eco-friendliness are correlated. However, there are so many different driving habits and smartphone sensor signals are noisy, it can be challenging to tell when an event is safe or not. For that reason, several methods use Machine learning, algorithms, and deep learning to process the data collected (Kanarachos et al., 2018). Some applications employ this technique to compute a safe and aggressive driving score for the manoeuvres. These results are used to categorize the driver's driving style. A driver is considered aggressive if their score for safe driving is lower than their score for aggressive driving(Chan et al., 2019). Since aggressiveness does not always imply the presence of other unsafe behaviours, such as exceeding the speed limit, speeding is much severe in the case of non-aggressive trips. Due to this, some studies have made a distinction between dangerous but potentially non-aggressive driving (Mantouka & Vlahogianni, 2022) which identifies the most common parameters to recognize the manoeuvres in Figure 11.

Driving parameters per trip.

Variable	Description	Unit
harsh_acc_per_min	Average number of harsh accelerations performed per minute	integer
acc_avg	Average acceleration	m/s^2
acc_std	Standard deviation of acceleration	m/s^2
acc_q90	90% percentile of acceleration	m/s^2
harsh_brk_per_min	Average number of harsh decelerations performed per minute	integer
dec_avg	Average deceleration	m/s^2
dec_std	Standard deviation of deceleration	m/s^2
dec_q90	90% percentile of deceleration	m/s^2
mbu	Percentage of driving with mobile usage	%
speeding_percentage	Percentage of driving with speed over the speed limit	%

FIGURE 11. DRIVING PARAMETERS PER TRIP. (MANTOUKA & VLAHOGIANNI, 2022)

Acceleration and jerk are characteristics utilised in driving behaviour categorisation as extremely effective indicators for evaluating aggression. The information is gathered using sensors built into smartphones (e.g., inertial measurement sensors, GPS). Most of the models included the vehicle speeding, speeding variation obtained from GPS, acceleration along the roll, pitch, and yaw axes, as well as acceleration along the x, y, and z axes(Khodairy & Abosamra, 2021). Another model recognizes road characteristics such as the number of detected vehicles and distance from the ahead vehicle at this tactical level it assesses the driver actions such as car following, lane change and overtaking.

The acceleration or deceleration exceeds a certain threshold, it is said to be "harsh" acceleration or deceleration. The precise value of this threshold is determined through cutting-edge machine learning analysis of thousands of actual driving data points gathered by the application and previous analysis to determine the model. The same occurs for changing the lane and cornering. The speeding parameter is considered comparing with the speed limit and the distance the driver travels from the limit.

b) Distracted Driver Detection - Inattentive Driver Detection

As mentioned before, the driver's level of expertise brings the control to avoid distractions and keep alert continuously during a trip. One of the most causes of road accidents is a distraction or inattentive driving, unexpected events that happen at random can lead to distracted driving. Such as a driver may unintentionally slow down or make abrupt longitudinal and transversal movements due to an increased response time to external stimuli(Chan et al., 2019). However, the key causes identified are eating, drinking, texting, or talking on the phone playing with the navigation, entertainment, or stereo system, but fewer can be monitored. These actions can be recognised by a smartphone's various sensors. For example, the accelerometer and gyroscope measurements will change slightly when drivers use their phones to perform any of the actions. The techniques differ for phone usage detection while driving and can depend on the application development such as texting, talking or removing background noise caused by jerky phone movements. It is important to clarify that applications that use another system for detection that include an accelerometer gyroscope can interfere between the system and other solutions must be found.

(Mantouka et al., 2021) found that to detect such events is used a filter-based strategy with a two-step method based on linear correlation and information gain for feature extraction. Another study has created a mixed effects model to determine whether driving behaviours like speeding, making sudden turns, accelerating quickly, and braking suddenly can serve as predictors of driver distraction, and more specifically, whether the driver uses a mobile phone while driving. The results showed that using a mobile phone while driving was negatively associated with exceeding the speed limit and the number of harsh driving incidents, showing that distracted driving can be identified even in the absence of other risky driving behaviour. Other capabilities are connected, including steering control, lane position control, and speed control measurements.

(Mantouka & Vlahogianni, 2022) observed that identifying drivers is challenging with a lack of appropriate data, and inattention continues to be difficult to manage. To do this, the measurement of distraction is related to the amount of time a driver uses a mobile phone while driving. Regardless of whether the user is talking or texting, the time spent using a mobile device while driving is equal to the amount of time the screen is on.

c) Drunk Driver Detection

Drunk driver detection is related to the driver using alcohol, this compromised the ability to control the vehicle in a normal way, the use of alcohol makes the blood alcohol content (BAC) of at least 0.08 grammes per decilitre (g/dL), affecting logical thinking, mental processes, and reaction times, all of which are essential for safety (Azadani & Boukerche, 2021). The author mentioned that there are 2 methods for drunk detection direct and indirect. Direct detection is an accurate and trustworthy measurement of a driver's blood alcohol content, The blood alcohol content of the driver can also be determined using breath-based and touch-based sensors.

Driving Behaviour analysis can be utilized for physiological measures such as ECG, heart rate, skin temperature, and electrodermal activity (EDA) with the methods mentioned before. Driving while intoxicated can have a substantial impact on a driver's driving behaviour metrics, such as lateral position, speed, and steering angle. This can be analysed using the changes generated in the sensor’s accelerometer, magnetometer, GPS, and gyroscope, like aggressive detection but different thresholds focus on lane position and speed, or the habit of sudden acceleration or deceleration with a delayed response is typical of a drunk driver. These measures can be combined to determine if the driver is intoxicated.

Real-world data collection presents some difficulties because actual situations are either impossible or would have disastrous results (Azadani & Boukerche, 2021), Simulators may provide useful insight into how drivers behave in risky circumstances, such as determining whether or not they are distracted or intoxicated. However, researchers must create a virtual environment that replicates the real world, they are viewed as an expensive solution. On the other hand, naturalistic data are gathered from the activities of vehicles using the sensors that are built into them. For example, a GPS sensor can directly, indirectly obtain a vehicle's position, speed, and acceleration signals. (Khodairy & Abosamra, 2021).

d) Drowsy Driver Detection

Drowsy or fatigue detection is based on the driver's state, Symptoms of being drowsy while driving include rapid and continuous blinking, head nodding or swinging, and frequent yawning. According to the Naturalistic Driving Study, secondary-task distracted driving increases the risk of crashes and near-crashes by three times, becoming a significant factor in more than 22% of crashes and near-crashes, compared to drowsy driving, which increases the likelihood of crashes and near-crashes by 4 to 6 times (Azadani & Boukerche, 2021).

For drowsy detection is employed two methods, the first and most common is using a front camera to determine visual behaviours blink frequency or PERCLOS throughout physiological signals. The fraction of closed eyes is known as PERCLOS. The many stages of an open eye are depicted in Figure 12. The length of eye closure will theoretically be longer in a weary driver, increasing PERCLOS. As a result, a threshold may be established to show if the driver is experiencing sleepiness that is harmful (Chan et al., 2019). The result demonstrates a high degree of accuracy, coming in at about 95% for moderate and 82% for little sleepiness. Furthermore, it was demonstrated that significant variations in a driver's level of drowsiness had a greater impact on biological and physical measurements than the ability to drive (Azadani & Boukerche, 2021).

Figure 12. The different States of An Open Eye (Chan et al., 2019)

The second idea behind drowsy detection is using the smartphone microphone (Xie et al., 2019) proposed to detect snoring, yawning, and using the steering wheel while drowsy because human movement causes a Doppler shift. Doppler shift is the term used to describe the change in frequency or wavelength of audio signals because of an observer moving away from the source of the signal. At 20 kHz, the speakers first emit acoustic impulses; the microphone then picks up reflected sounds. Before using an FFT to convert the data into the time-frequency domain, band-pass filtering and under-sampling were used to increase frequency resolution without distorting frequency spectra. Long Short-Term Memory (LSTM) network inputs were taken from Doppler profiles of audio signals for each sleepy driving activity and utilised to extract the useful characteristics. Nevertheless, it seems preferable to either employ driving simulators or gather data in a carefully controlled setting for specific tasks as mentioned before (Azadani & Boukerche, 2021).

C. Machine learning categories

1) Algorithms

It is found that Threshold-Based and Fuzzy Logic Algorithms are the most common and the most basic form to extract knowledge from DBA tasks.

a) Threshold-Based

The techniques are based on thresholds to identify driving variations employing fixed criteria, and the correlation between various measures or indicators. Rules can be adjusted using IF-THEN statements to particular detect driving styles or situations (Azadani & Boukerche, 2021). The number of parameters limits the simplicity and interpretability of rule-based algorithms even though they are simple to build.

Analysing the relationship between variables like acceleration (lateral and longitudinal) and speed can be done using a threshold-based methodology. (Carlos et al., 2019) found that developing a g-force diagram to apply this classification acts as a guide to demonstrate whether a vehicle is being driven aggressively or safely. Although this is simple still presents challenges when is analysed across other variables from sensors such as GPS for location, driver states, road state, traffic flow and other mentioned before.

The technological heterogeneity of smartphone sensors influences the retrieved signals and, of course, the threshold of what is regarded abnormal, (Mantouka et al., 2021) concluded that no universal thresholds can be employed. It is also mentioned that the initial step in identifying abnormal driving behaviours is to apply threshold-based techniques, especially in systems with no past knowledge, this can lead to supervised learning. Setting the thresholds is necessary to make sure that the latter is not affected by small device movements, the properties of the sensors, and the orientation and placement of the device. As mentioned before, some techniques can be applied to fixed orientation and calibrate values as part of prepossessing the signal.

The prototype was developed to use this technique to classify the events that the driver does during driving, the prototype system design consists of a scoring system to assist the driver with the events detected, the user can pick up the events and explore the feedback to improve their driving skills. The user can also navigate to different trips to check improvements and the progress bars and graph view provide another vision of driving performance; the prototype was guided by the methodologies found during this research. Most of the specific technique was developed using the thresholds established by (Vavouranakis et al., 2017) research. It establishes a calibration filter for accelerometer signals and processes using conditionals, some of the challenges found are related, to the smartphone positioning that required an extra system for repositioning which was not implemented, calibration process which works well although is very sensible and this varies depending of the DBA schedule task, it is concluded that the smartphone environment is not predictable when is used different mechanisms at the same time. For example, the system is implemented using the accelerometer's x and y axis. However, it was tried also to use the gyroscope and magnetometer to use as a threshold for the Pitch and Roll. However, extracting those values at the same time becomes unpredictable in the sampler system which checks the behaviour events every certain time. Further work will base on extracting events in a controllable environment and analyse them with a machine-learning model.

FIGURE 13. SCORING DRIVING PROTOTYPE ANDROID APPLICATION

b) Fuzzy Logic Algorithm (FL)

Fuzzy logic is a method of processing variables that enables the processing of several potential truth values through a single variable. Fuzzy logic tries to resolve issues using an open, imperfect spectrum of facts. Fuzzy Logic attempt to replicate human reasoning, FL is also a useful method for capturing the potential uncertainty in driving data. Detecting driving style is the primary purpose of this algorithm, as the same Threshold based, FL systems appear to be a useful subject for preliminary research since scoring methods can potentially be expanded to assess numerous aspects of driver behaviour and draw conclusions in the form of average scores for a particular driving scenario like detect driving behaviour aggressive steering, harsh acceleration and braking(Mantouka et al., 2021). Although scoring systems are thought to be an effective way to increase driver awareness, some researchers have emphasised the significance of real savings as an incentive to improve individual driving behaviour, leading to an increase in interest in insurance charging systems over the past ten years. This supports the idea to detect distracted driving.(Kashevnik et al., 2019) found that by utilizing context-relevant data such as route topology, weather, and time of day, drivers can be scored. This is done by employing acceleration, braking, turning, and overseeding. The author indicates that can be detected risky event driving, including sudden or aggressive manoeuvres. Alternatively, this algorithm can be useful to detect drowsy driving (Khodairy & Abosamra, 2021)

Another methodology reviewed by (Chan et al., 2019) employs Speed, acceleration, altitude, throttle signal, immediate fuel usage, and engine revolutions. The gathered data was then used to extract features like average, minimum, maximum, and length of vehicle obstruction. with the same methodology can be identified if the vehicle is on the urban, highway or combine analysing of the speed. Fuel consumption can be calculated by converting consumption metric into a Fussy number where a low value would suggest good fuel usage. Then, the values can be combined to determine the driving style. An interesting methodology is reviewed by (Chan et al., 2019) where information from the driver's profile is combined with the findings of the original driving style classification using a rule-based fuzzy approach. There are two modules in this system. A choice is made based on the output of the first module and the ratio of the number of dangerous manoeuvres to the number of safe manoeuvres in the driver's profile. The first module is in charge of evaluating the current driving move and outputs an initial driving style.

(Azadani & Boukerche, 2021) reviewed another methodology where is determined whether or not drivers are using fuel in an energy-efficient manner. This system accepts a variety of driving data as inputs, including speed, acceleration, and engine load. The result is a score between 0 and 10. The driver acts in a more environmentally responsible manner the higher the score. The suggested technique is utilised to not only grade drivers and offer helpful tips, but also to identify instances of unproductive driving. As seen Fuzzy logic can be useful for applications such as eco-friendly for fuel consumption, evaluating driving events using scoring systems, detect driving styles such as aggressive, distracted, and drowsy driving. The number of parameters available in these approaches is similarly limited. The approaches are more precise the more parameters there are. This is inefficient, though, as adding more factors would result in a significant rise in the number of rules (Azadani & Boukerche, 2021).

2) Machine learning

It is well known that machine learning is used to extract knowledge and predict events, in the case of driving behaviour analysis using a smartphone is used to extract the patterns that can determine events such as hard acceleration, hard breaking, hard cornering etc... in the same case is also analysed the probability to occur certain events such as accident prediction. Therefore, according to (Abou Elassad et al., 2020), Support vector machines (SVM), Neural networks (NN), Bayesian learners (BL), and ensemble learners (EL) are typically the four most popular models; they were all used by 72% his study, and they are also the most accurate Machine learning (ML) models for the analysis of the dimension of the Driving event. In addition, it was found that accuracy (65%), recall (35%), and specificity (32%) are the most common model performance metrics. The following sections explain the contributions of the most important ML techniques used by DBA tasks. A summary of the studies review is presented in **Error! Reference source not found.**. This also shows algorithms that are used in the methodologies, applications showed can be translated into the Application classification in Table 2.

a) Support vector machines (SVM)

SVM is a supervised learning model with associated learning algorithms based on statistical learning frameworks to assess data for classification and regression analysis. The model divides new samples into one of two categories, converting them into a non-probabilistic binary linear classifier (Meiring & Myburgh, 2015). SVMs have the essential capability to translate data to a higher dimensional space through a kernel function, making them relatively resistant to the curse of dimensionality and efficient enough to tackle large-scale issues in both sample and variable space. They are employed in systems that recognize driving events, detect drowsiness (Rachad et al., 2021), and estimate the state of the vehicle.

SVM is used to detect driving characteristics like head movements, and eye state (open or close), and hand cues were taken advantage of to determine the driver's activity state(Abou Elassad et al., 2020), (Chan et al., 2019). This assesses the driver's performance in real-world driving situations. The SVM is a good choice for classification

References	Smartphone Sensors	Algorithm System	Method	Application	Classification accuracy	Challenges and Limitations
(Azadani & Boukerche, 2021)	Accelerometer GPS	Threshold-Based	Acceleration, Breaking, Cornering, Speed, Location	Driving Styles, abnormal behaviour	.	Pre-defined thresholds for some driving behaviour indicators. *number of parameters
(Carlos et al., 2019)	Accelerometer	Threshold-Based	Gear shifts, Lane changes, sudden, braking, Speed, Accelerating	Aggressive or safely	.	Finding one threshold value that yields good results under most conditions is not easy when processing accelerometer data, given the multitude of variable conditions (location of the sensors, individual driving style, state of the road and traffic flow, etc.)
(Mantouka et al., 2021)	Accelerometer	Threshold-Based	Acceleration, Breaking, Cornering Speed, Location	Abnormal driving events, identify road anomalies such as bumps and potholes	.	The accuracy of accelerometer data highly depends on the environment's characteristics (mobile position in the car, vehicle's conditions, road type etc.)
(Mantouka et al., 2021)	Accelerometer gyroscope	Fuzzy Logic	Harsh acceleration, braking, aggressive, steering	Classify driving behaviour on a gradient from smooth to aggressive behaviour with a special focus on the elderly drivers	.	Variety of hardware (sensors and smartphones) positioning of the phone makes not transferable to other systems the knowledge obtained
(Chan et al., 2019)	Accelerometer gyroscope GPS	Fuzzy Logic	Speed, acceleration, altitude, throttle signal, immediate fuel usage, and engine Rotation	Driving Condition, Fuel consumption, the risk level of the driver	.	The position of the smartphone has to be fixed such that the coordinate system of the smartphone and the vehicle are aligned
(Azadani & Boukerche, 2021)	Accelerometer gyroscope GPS	Fuzzy Logic	Speed, acceleration, and engine load	Aggressive, distracted, drowsy, fuel in an energy-efficient manner,	.	The number of parameters available in these approaches is similarly limited. The approaches are more precise the more parameters there are. This is inefficient, though, as adding more factors would result in a significant rise in the number of rules
(Kashevnik et al., 2019)	Accelerometer gyroscope	Fuzzy Logic	Acceleration, braking, turning, and overseeding	Route topology, risky events, normal, Aggressive drowsy events	.	.
(Rachad et al., 2021)	Accelerometer gyroscope	Support vector machines (SVM)	Weaving, swerving, side-slipping, fast U-turn, turning with a wide radius and sudden braking	Drunkenness, stress	.	.
(Abou Elassad et al., 2020)	EMG sensors	Support vector machines (SVM)	Head, eye and hand	Driver characteristics	Accurancy:90%, Recall: 88%	Has very limited success when applied to imbalanced data sets Choosing an adequate kernel function
(Wahlström et al., 2017)	Accelerometers, gyroscopes, and magnetometers	Support vector machines (SVM)	One-sided potholes and road-wide anomalies like speed bumps and train crossings.	Road Abnormalities	.	The development of standardized methods for the detection, classification, and characterization of road anomalies, the effective construction of a map of anomalies and the rejection of spurious detections, and the modelling and consideration of the impact of vehicle suspension
(Chan et al., 2019)	Accelerometer	Support vector machines (SVM), and	Weaving, swerving, side slipping, fast U-turn, turning with a wide radius and sudden braking	Detect abnormal driving behaviour such as weaving, swerving, side slipping, fast U-turn, turning with a wide radius and sudden braking	Accuracy: 95.4% base in 16 features	.
(Chan et al., 2019)	Accelerometers, gyroscopes, and magnetometers	Artificial Neural Network (NN)	Weaving, swerving, side slipping, fast U-turn, turning with a wide radius and sudden braking	Detect abnormal driving behaviour detect aggressive behaviour	Accuracy: 96.6% base in 152 features	Requires a lot of features to rise the accuracy
(Chan et al., 2019)	Microphone	Support vector machines (SVM)	Speech signals	Distractions	Accuracy: 94% trained the based classifier system	Categorize speech signals must be difficult to understand the context if the driver is using the radio to keep himself alertness,
(Azadani & Boukerche, 2021)	Accelerometer GPS	Support vector machines (SVM)	Steering wheel angle and lateral position, drifting weaving	Recognizing different driving events, drunk drivers, driving styles, drivers distraction, and the person behind the wheel	Accuracy: 80% drunk detection	.
(Marafie et al., 2021)	Accelerometer GPS	Support vector machines (SVM)	Acceleration, braking, turning and changing lane	Driving events	Accuracy: 93.4% with 14 features	.
(Abou Elassad et al., 2020)	Accelerometers, gyroscopes, and magnetometers	Artificial Neural Network (NN)	Acceleration/deceleration, braking, lane change and turning	Drowsiness detection, driver attention detection, steering behaviour prediction and fatigue detection	Accurancy:98%, Specificity: 84%, Recall: 92%	.
(Mantouka et al., 2021)	Accelerometers, gyroscopes, and magnetometers	Artificial Neural Network (NN)	Speed and acceleration measurements	Aggressiveness	.	.
(Abou Elassad et al., 2020)	Accelerometer, gyroscope, and magnetometer	Bayesian learners (BL)		The drowsiness recognition	Accurancy:91%, Specificity: 95%, Recall: 88%	Bayesian Networks can be more computationally expensive for high-dimensional data
(Rachad et al., 2021)	Accelerometer, gyroscope, and magnetometer	Bayesian learners (BL)	Detects sharp turns, sudden lane changes, acceleration, and braking events	Safe or unsafe driver behaviour	.	.
(Chan et al., 2019)	Accelerometer,	Bayesian learners (BL)	Detects sharp turns, sudden lane changes, acceleration, and braking events	Drivers' stress detection, manoeuvre detection, and recognition of driving styles, normal, drunk, Drowsy, and fatigue	.	.
(Kanarachos et al., 2018)	Accelerometer, gyroscope, and magnetometer	Bayesian learners (BL)		Transportation mode detection	Accurancy:94%,	.
(Chan et al., 2019)	Accelerometer, gyroscope, magnetometer, GPS	Ensemble Learning	U-turn turns or lane change	Congested or not congested, driving events	Accurancy:94%,	The main drawback of this system is the large number of algorithms that make it complicated to implement in a real system, requires a system with a high level of computation power to run all the algorithms
(Chan et al., 2019)	Accelerometer, gyroscope, and GPS	Ensemble Learning		Driver distraction	F1-score: 87%	That requires a high computational effort
(Chan et al., 2019)	.	Ensemble Learning	Lane change and turns, hard acceleration and deacceleration	Driving event	Accurancy:95%,	.
(Azadani & Boukerche, 2021)		Ensemble Learning		Detecting driving events, drunk drivers, driving styles, drivers' inattention	.	.
(Chan et al., 2019)	Microphone and speakers	Long Short Term Memory (LSTM), Neural Network		Drowsy detection	Accurancy:94%,	Computational cost, the large amount of data required to train the classifier, and road conditions also affect the accuracy
(Li et al., 2020)	Accelerometer, gyroscope, magnetometer, GPS	Long Short Term Memory (LSTM), Neural Network	Going straight, left turn, right turn, and U-turn	Detect vehicle manoeuvres	The precision of 0.97, recall of 0.98, and F1-score of 0.98	Computational cost, the performance of stacked-LSTM can be improved by adding more layers or trying more combinations of different hyperparameters
(Chan et al., 2019)	Accelerometer readings	Long Short Term Memory (LSTM), Recurrent Neural Network (RNN), Gated Recurrent Neural Network (GRU)	Aggressive braking, aggressive acceleration, aggressive left turn, aggressive right turn, aggressive left lane change, aggressive right lane change and non-aggressive event	Classify driving events as safe and aggressive events	Accuracy:95%	.

TABLE 3. DBA SMARTPHONE BASES SUMMARIZE METHODOLOGIES

issues involving duplicate data sets due to its great capability to handle redundant features, and non-linear, high-dimensional, and limited samples. This method is also utilized for driver sobriety evaluation to prevent driving under the influence of alcohol, and SVM is also used for driver stress detection (Rachad et al., 2021).

(Wahlström et al., 2017) discovered that SVM is also utilized to distinguish between one-sided potholes and road-wide anomalies like speed bumps and train crossings. The development of standardised methods for the detection, classification, and characterisation of road anomalies, the effective construction of a map of anomalies and the rejection of spurious detections, and the modelling and consideration of the impact of vehicle suspension are some of the challenges identified for this category.

(Chan et al., 2019) discovered that SVM was used to categorise speech signals acquired by the smartphone microphone to determine whether or not the driver was distracted. This case is difficult, and it can also be misunderstood if the radio is on because it might sometimes keep the driver focused. The author also found that SVM in combination with NN is used to determine smartphone orientation and detect abnormal driving behaviour. In addition, (Chan et al., 2019) emphasised that whereas NN used all 152 features for training, SVM only employed 16 fundamental features. Based on this implementation, SVM and NN both achieved an accuracy of 96.9% and 95.4%, respectively. A straight comparison between them can be very skewed because various features were used by different classes.

(Marafie et al., 2021) showed that the most effective ML algorithms for signal classification are SVM and KNN, which are used in various fields, including pattern recognition and regression. Ten cars of various makes, sizes, and driving circumstances were the subject of a collection of raw sensor data that was labelled for the training model. They discovered that adding Feature 14 greatly improved classification accuracy, which now stands at 93.4%. (SVM). This function makes use of sensor data to determine whether an event takes place when the signal rises beyond a predetermined threshold. The event is likely to be a turn or lane change when the accelerometer's x-axis signal initiates the detection; otherwise, it is an acceleration or braking. Using SVM, they successfully classified 12 instances.

(Azadani & Boukerche, 2021) learned that SVM is used to assess whether a driver is impaired by alcohol, and can have a significant impact on measures of a driver's driving behaviour, particularly those that differ significantly depending on the driver's driving states, such as lateral position, speed, steering angle, etc. This is calculated using the vehicle's lateral position range. Additionally, when driving while intoxicated, a driver's range and normal variation of steering wheel angle are larger. The SVM model has been shown to classify normal and drunk drivers with an accuracy of 80% in the literature examined by the authors. Additionally, they discovered how important steering, vehicle acceleration, and hard braking are correlated. Therefore, SVM is a promising algorithm that has been widely used for a variety of DBA tasks, including identifying various driving incidents, drunk drivers, driving patterns, driver distractions, and the person operating the vehicle.

b) Neural networks (NN)

An artificial neural network (ANN) is an intelligence system that simulates the biological connections of the nervous system like a brain and is made up of numerous, highly interconnected processing components that work together to solve issues. Signals are transferred in an ANN through connections between network nodes (neurons), each of which is given a distinct and programmable weight (Meiring & Myburgh, 2015). The network may be trained and optimized using a learning algorithm thanks to the movable weights. This weight is the multiplier used in a typical ANN to alter the input to get the output value. To address issues in diverse sectors, numerous forms of ANNs do exist.

Artificial Neural Networks (ANNs), which primarily rely on computer vision techniques, are used in drowsiness detection, driver attention detection, steering behaviour prediction and fatigue detection (Rachad et al., 2021). (Abou Elassad et al., 2020) discovered that deep learning techniques can be seen as an improved extension of conventional artificial neural networks (ANNs), which are composed of more layers and allow for higher levels of abstraction and improved data analysis. Their study contrasted Deep Neural Networks (DNNs) to conventional ANNs, and the model accuracy was 98%. Furthermore, 57% of the selected papers that employed DNNs for DB analysis used them, while 43% used conventional ANNs. It has been demonstrated that ANN has good generalization, learning, and adaptability capabilities and that it performs consistently with noisy input. (Azadani & Boukerche, 2021) claims that the neural network's layers are in charge of bringing out any hidden temporal dependencies present in the data.

(Chan et al., 2019) studied the use of ANN and a picture captured by a smartphone front camera and focused to obtain the driver's eyes. An ANN with 16 hidden neurons was then used to categorize the states of the eyes. Another work reviewed by the author used fuzzy logic in conjunction with a neural network for aggressive driving detection using the smartphone's gyroscope, accelerometer, and magnetometer. A quadratic sum of weights penalty factor was introduced into the error function to minimize underfitting and overfitting. To assess each driver's driving behaviour, the system compared their actions against samples of aggressive and safe driving. Four steps of the system assess sensor segment segments.

According to (Mantouka et al., 2021), speed and acceleration readings were used to determine the level of a driver's aggression using artificial neural networks. They discovered that the neural network performs better at recognizing driving movements than the other techniques. However, due to the large increase in processing power needed for the models' training and validation, several tasks must be carried out offline. As a result, ANN is useful for categorizing occurrences and can be integrated with other techniques for improved outcomes and pattern recognition.

c) Bayesian learners (BL)

Bayesian learners can be helpful by adopting a probabilistic model based on dynamic Bayesian networks, it is possible to perform driving style categorization in real-time amongst four driving styles, including normal, inebriated, drowsy, and weariness (DBNs). Contextual data on the environment, the vehicle, and the driver are combined. The dynamic behaviour model accurately and reliably detects the driver's behaviour by capturing both its static and temporal components. (Meiring & Myburgh, 2015) explained how a driver behaviour detection application uses a Bayesian approach to deal with the issue of partial data. As a result, it is combined with other models to improve accuracy. In addition to explicitly modelling the time-dependent nature of the driver state and allowing the incorporation of contextual elements that affect DB, (Abou Elassad et al., 2020) explained that BL also could infer the state of an unobserved variable from the state of observable variables. Additionally, it has been demonstrated in the reviewed study that BL can be more analytically challenging when the dimensionality is involved, but still manageable and economical when employing flexible inputs. in the author's view, models such as Naïve Bayes and Baseline Bayesian are computationally efficient, while other, more elaborate methods such as Bayesian Networks and Tree Augmented Bayesian Networks can be more computationally expensive for high-dimensional data. on the other hand, (Rachad et al., 2021) discovered that BL used smartphone sensors like the accelerometer, gyroscope, and magnetometer to classify driver behaviour by risky driving events. The app detects sharp turns, sudden lane changes, acceleration, and braking events and uses a Bayesian classifier to determine whether a driver's behaviour is safe or unsafe. As the same indicated by (Wahlström et al., 2017).

(Chan et al., 2019) discovered that Bayesian algorithms for computing probabilities are based on the Bayes theorem. An example of a probabilistic graphical model is a Bayesian network, which may be used to forecast the likelihood of various classes of occurrences. Bayesian networks depict conditional dependency between random variables by edges in a graph. These networks have been utilised for manoeuvre detection, driving style recognition, and stress detection in drivers. Finally, (Kanarachos et al., 2018) found that Neural Networks outperformed Support Vector Machines (SVM) and that Bayesian Networks outperformed SVM. SVMs were outperformed by Bayesian Networks by 2.5% in the training set and 7% in the test set. With a classification accuracy of 95%, neural networks, k-nearest neighbours, and naive Bayes all fared similarly. It was used in this case to detect transportation mode. This shows how successful it is to categorise occurrences, and, how this machine learning model can combine those properties with those of other models to increase classification accuracy.

d) Ensemble learners (EL)

(Azadani & Boukerche, 2021) suggested using ensemble algorithms to integrate the outcomes of various models that were individually trained. The key goals of DBA include recognising driving events, drunk drivers, driving patterns, drivers' inattention, and drivers themselves. Random Forest is a well-known ensemble method that uses individual decision trees. Although Random Forest was used in most research in the literature, there are other works based on alternative ensemble algorithms, including Gradient Boosting, Adaboost, bagging, and an ensemble of various traditional machine learning techniques.

(Chan et al., 2019) conducted research and discovered that certain methodologies increase detection accuracy and are used to gather reliable data. As a result, common methodologies are found throughout the papers, and as previously mentioned, the smartphone must be placed in a specific location before being calibrated to align its axes with the axes of the car. The t-SNE algorithm was then applied to the raw data to extract features relevant to different labels, or it was filtered with a low pass filter and Kalman filter to remove noise caused by road anomalies. Methodologies suggested applying filters to the raw data by a moving median and moving mean filter for noise removal. Following this, classification techniques such as the well-known C4.5 decision tree type, Radial Basis Function RBF, or ensemble learning with KNN, Logistic Regression (LR), Nave Bayes (NB), and RF were utilised, where the output from each classifier was combined to produce the final output. A Fuzzy Inference System (FIS) is also helpful at the end to assess the driver's level of danger. Additionally, based on the speed calculated from GPS and the zero-crossing rate of the data gathered by the y-axis of the accelerometer, it is possible to detect driver distraction, driver manoeuvres, and traffic conditions such as congestion or no congestion.

By considering the zero-crossing rate, variance, minimum, and maximum of the data gathered by the z-axis of the accelerometer, MLP was once more applied to classify the types of cars into high and low-sensitivity cars. The safety or hazard of a manoeuvre was then determined using the K-nearest neighbour (KNN), MLP, and SVM with RBF fusion, which is another intriguing methodology. For models that employ ensemble learners, it may be able to reach an accuracy of 95% or an F1 score of 87%. It is crucial to emphasise that thresholds are employed across many techniques and that they can be altered depending on several factors, such as the sensitivity of the sensors, the smartphone, the type of automobile, the wheels' shock absorbers, etc. As a result, the requirement for approaches where the model learns as the variables change is apparent, and the necessity to use deep learners is consequently evident, they can extract hidden features and temporal dependencies existing in data.

3) Deep learning

Neural Network with Long-Short-Term Memory It has been demonstrated that deep learning techniques perform better when learning sensor data than other machine learning techniques. Furthermore, previous research suggested that LSTM produced superior outcomes than others. (Azadani & Boukerche, 2021) exposed deep neural networks (DNN), convolutional neural networks (CNN), and recurrent neural networks (RNN) for processing. (Khodairy & Abosamra, 2021) suggested that deep learning techniques are not frequently employed, using LSTM for driver identification. High computing costs and implementation complexity are some of the difficulties in this field; as a result, several studies do their analysis offline. In addition, the advantages of using real-time smartphone technology have not been conclusively demonstrated.

a) Long Short-Term Memory (LSTM)

According to (Li et al., 2020), LSTM networks are utilised for smartphone-based human activity recognition. In comparison to SVM Convolutional Neural Network (CNN), DTW, etc., the results showed that LSTM had the highest accuracy. In addition, as a result of its distinct memory cell design, which includes three gates to regulate when to forget or remember specific information, the author claimed that LSTM can learn from time-series data more effectively than other neural networks. On the other hand, Due to its successful performance on time-series data, (Li et al., 2020) discovered a Long Short-Term Memory (LSTM) neural network for the detection of vehicle motions. Since it added the memory cells to decide when to forget specific information, LSTM is capable of learning long-term dependencies. The forget gate and the output activation function were identified as the two LSTM components that are most important for the algorithm's ability to adapt to its environment. In contrast to RNN, LSTM features three distinct gates. How much of the previous step memory cell is forgotten is determined by the forget gate. The updateable values are chosen by the input gate. The hidden state's output is decided by the output gate. With the addition of these unique gates, LSTM can now maintain information over lengthy timestamps more easily. (Azadani & Boukerche, 2021) found the effectiveness of several deep learning models for driver detection, including CNN, LSTM, and convolutional LSTM. The outcomes showed their benefits in capturing temporal dependencies in data compared to numerous standard machine learning models. Additionally, it was utilised to determine driving styles by automatically learning elements from GPS data.

(Chan et al., 2019) found an intriguing proposal, which employs the speakers to transmit acoustic impulses at a frequency of 20 kHz, followed by the microphone picking up the reflected signals, to detect drowsiness. Then, before converting the signal to the time-frequency domain using FFT, band-pass filtering and under-sampling were used to improve frequency resolution without distorting frequency spectra. Long Short-Term Memory (LSTM) network inputs were taken from Doppler profiles of audio signals for each sleepy driving activity and utilised to extract the useful characteristics. For this idea, two LSTM models were trained. The first LSTM divides the condition into three categories: normal, nodding, and yawning. The second LSTM divides steering function into normal and abnormal. To determine whether the driver is drowsy, a NN is provided with the outputs from both LSTM models. The approach claimed a 94% accuracy rate for identifying drowsy drivers. The classifier must be trained with a lot of data, which is the key limiting issue. The precision of such a system is also impacted by the state of the roads. It was discovered that low detection accuracy occurs when the driver must use the steering wheel more frequently on an uneven route. Furthermore, it is uncertain whether the presence of passengers will impact the accuracy because passenger movement will also influence the Doppler shift. Also uncertain is whether LSTM or NN can be trained in a smartphone context.

Long Short-Term Memory (LSTM) is also employed for the classification of driving behaviour (Chan et al., 2019), and the usage of the camera is another working methodology. As LSTM can enable the exploitation of inherent dependency and correlation between diverse sensor data gathered at each time step of real driving sessions, the objective was to minimise the tedious handcrafting of feature extraction. On the other hand, other works use various algorithms to process the sensor information. For instance, three algorithms like Recurrent Neural Network (RNN), Gated Recurrent Neural Network (GRU), and Long Short-Term Memory (LSTM), were utilised to perform driver behaviour profiling. According to (Chan et al., 2019), this study was based solely on accelerometer readings and attempted to differentiate between aggressive braking, aggressive acceleration, aggressive left and right turn, aggressive left and right lane changes, and non-aggressive events. The performance of this method archives 95%. However, the number of neurones had a simple impact on the LSTM's accuracy. Furthermore, two categories of aggressive left and right lane changes again yield an unbalanced dataset when compared to the other categories. Furthermore, information was gathered in weather ideal conditions on a dry route. There is no data to show if it is affected by other weather conditions. Additionally, the smartphone's position must be maintained throughout the journey despite potential interference from road irregularities like potholes or speed bumps. Finally, model training and validation were done offline because it isn't known if model training can be done on a smartphone or if the strong performance holds for streaming data. Deep learning, therefore, presents challenges at various stages of data collection, filtering, and processing, even though it improves classification.

b) Deep neural networks (DNN)

Deep neural networks (DNNs) are a potent subclass of machine learning models that employ several secret layers to extract hidden features from data. In comparison to traditional machine learning techniques, the training of these networks requires a significant amount of processing power. However, DNNs are more effective at identifying hidden characteristics and temporal connections in data. Convolutional neural networks (CNN), recurrent neural networks (RNN), and deep autoencoders are just a few examples of the several types of DNN that are frequently employed in DBA tasks, similar to other machine learning models. (Azadani & Boukerche, 2021) indicates CNNs are a key deep-learning method for processing spatial data and developing a representation of the feature space concealed in data. CNN's have demonstrated effective results for time series classification, particularly for driving style detection and driver identification, even though they are mostly utilised for computer vision applications. RNNs, a different kind of neural network, are created primarily to manage sequential data and capture temporal connections in data. They have been used for some DBA tasks, such as driver identification, driver style detection, and driver distraction detection. A deep autoencoder is a kind of neural network that attempts to regenerate the input at the output and is mostly used for dimensionality reduction purposes useful for unusual event identification and drunk driving detection.

As Deep Neural Networks are best suited for handling noisy sensor data and discovering underlying patterns, (Kanarachos et al., 2018) explained that the deployment of deep learning algorithms for processing smartphone data for ITS is projected to expand significantly. Recently, successful instances that are not based on smartphone data or have a different scope have been created. The manual feature-creation procedure is eliminated by Deep Neural Network (DNN). However, (Chan et al., 2019) countered that DNN also increases recognition accuracy. While the deeper layer can combine several low-level features to extract higher-level features to represent more abstract driving behaviour, the shallower layer may extract low-level features to reflect more focused driving behaviours. However, the biggest obstacles to utilising DNNs include having adequate data, knowing how to pre-process data, adjusting hyper-parameters, and employing the right structure. Lack of data lowers the network's capacity for generalisation, which results in over-fitting. Finally, it is unknown whether training and updating of the algorithm can be done in a smartphone environment for most of the approaches mentioned.

4) Performance

Along with this research was found that different models are evaluated against different model measures the most often found is accuracy, however, other works used specificity, recall, precision and F1-score. The most logical performance metric is accuracy, which is just the proportion of properly predicted observations to all observations. It is an excellent indicator but, it does not work well with imbalance datasets, and as expressed before imbalance can be found across the classes detected for driving events. Precision is the proportion of accurately predicted positive observations to all expected positive observations. Low false positive rates are related to high precision. Therefore, it can be expressed in this scenario as all events were labelled and which were not identified. Recall or sensitivity, on the other hand, is defined as the proportion of accurately predicted positive observations to all the actual class observations, often used to classify the driving behaviours. And F1-score is often used when there is an imbalance class, it is beneficial due to the weighted average of Precision and Recall. Then, both false positives and false negatives are considered while calculating this score. Specificity indicates the percentage of genuine negatives that the model accurately detects. This suggests that there will be a further percentage of genuine negatives that were anticipated as positives and may be referred to as false positives. Low specificity indicates that the model is mislabelling a large number of negative findings as positive, whereas high specificity indicates that the model is accurately detecting the majority of the negative results.(Abou Elassad et al., 2020) assessed the different models discussed here, including SVM, NN, BL, and EL, for accuracy, specificity, and recall in terms of driving event detection. They found that SVM and EL are more accurate and precise than BL and NN, but the SVM performs much better than the others in all measures. Then, as a result of the same outcome, the most frequently employed performance metrics in primary investigations are Accuracy, Recall, and Specificity. Most ML models' overall estimation accuracy is within acceptable bounds. The analysis of the dimension of the Driving event revealed that ML models' arithmetic means of Accuracy roughly range from 73% to 98%, Recall from 82% to 96%, Specificity from 84% to 97%, and F1-score around 98%.

V. DISCUSSION AND CHALLENGES

Understanding and modelling driving behaviour is a difficult study topic today. The wide purposes brought several areas to apply the different methodologies found. The literature review showed several terminologies that were classified into common categories for better understanding and leave open for future work and applications as was shown in FIGURE 6 in the ITS environment. As shown in the results the most common methodologies identified vary depending on a range of factors, to classify those factors (Azadani & Boukerche, 2021) research classified algorithms into three categories Threshold-Based and Fuzzy Logic Algorithms, Classical Machine Learning Algorithms, Deep Learning Algorithms to determine driving events applied for ITS. Several algorithms for different applications were deeply studied by (Meiring & Myburgh, 2015), (Wahlström et al., 2017), (Chan et al., 2019), and (Abou Elassad et al., 2020) fill in those categories, where (Abou Elassad et al., 2020) indicated that Support vector machines (SVM), Neural networks (NN), Bayesian learners (BL), and ensemble learners (EL) are generally the four most popular models; they were all adopted by 72% of participants in their study, and NN, IB, BL, and SVM are the most accurate Machine learning (ML) models for the analysis of the dimension of the Driving event or event driving behaviour. It also concluded that the most model metrics performance used is Accuracy at 65%, recall at 35% and specificity at 32% also identified in this study. Deep learning algorithms are not very often used, however were founded some applications that use those methodologies.(Khodairy & Abosamra, 2021) used LSTM for driver identification, but (Azadani & Boukerche, 2021) uncovered Deep neural networks (DNN), Convolutional Neural Networks (CNN), and Recurrent Neural Networks (RNN) for processing.

Table 2 were summarized the classification terminology and the areas that can support in ITS environment, this showed the applicability of the methodologies reviewed. However, challenges and limitations in this area are presented at different levels in Driving behaviour analysis tasks, they are associated with the collection, quality, and processing of the data before applying the models as proposed by (Mantouka et al., 2021). across different sectors of society and demonstrating an interest in road safety.

One problem that remains across the literature is the engagement of the user to auto encourage to improve driving styles using applications that support these tasks. (Rachad et al., 2021) research multiple applications with the purpose to promotes the user's active interest to improve their driving behaviours, in general, find Mobile applications that purpose to enhance user skills, engagement, or behaviour with incorporate gamification techniques into their design. Another technique includes the auto start and notification engagement when is detected that the user is driving, but the backwards of this method can be a little intrusive, difficult to determine if the user is driving, and calibrating scenarios to get quality data. as mentioned before, mobile positioning and calibration are crucial for many of driving style detection. (Mantouka et al., 2021) research also indicates that incentives are effective to captivate the attention of users. Another method that evidences effectiveness is to share performance and built social groups where it discusses data around this area. future research should look for evidence of improvement using this method from the source of driving learning such as driving schools, or encouragement from government which use writing and driving test to approve license. Driver behaviour analysis systems sound that are a great solution to attempt to increase road safety, however, the diversification of these systems is not supported yet and as I stated before required promotion and encouragement from entities that regulate driving in every government, thus they can raise awareness and change attitudes to this subject.

Another challenge evidenced is the data availability and quality, as mentioned before processing data collected from the sensor is not an easy task and vary depending on the device and different circumstances. Most of the literature found it problematic to have linear data that can be easy to understand and use by algorithms or machine learning algorithms. Dynamic positioning and calibration are widely investigated to counter this problem (Vlahogianni & Barmpounakis, 2017) research explore this by trying to apply strategies that match the car orientation with the smartphone by computing the Euler angles and calibrating the signal with rough set theory.

Data availability is associated with privacy and security, consequently, there are different concerns here. The first is the data collected from users, and many policies are applied to this area by the government to ensure the correct use and manipulation. Second, the users may feel disturbed by the idea that they are vigilantes, and this kind of application can affect them on different levels of implications. Another concern is related to the device's capability, although they are powerful machines are limited by the batteries and the use of many sensors at the same time can drain the battery fastest, for example, drowsy detection uses the front camera to monitor the eye, this function requires image processing just using the mobile which can drain the phone fast (Kanarachos et al., 2018).

As mentioned before, there is much research in the area of driving style behaviour, however, the challenge presented is that there is not a universal driving behaviour profiling framework. Therefore, is not established how much data should be collected to detect any style, then this requires future development to standardize this practice. On the other hand, it is well known that machine learning models required datasets to train the model, however, driving available datasets are usually imbalance, and useful data such as accidents or abnormal driving data are very rare as cited by (Mantouka et al., 2021), in some cases is reported that is necessary input data manually. (Azadani & Boukerche, 2021) bring together and explain the best datasets for driving behaviour analysis used for different driver style detection.

It is also a challenge and controversial the usage of mobile phones during driving, and the methods proposed widely do not mention how to face this issue. Some propose different places to position the smartphone (Vlahogianni & Barmpounakis, 2017) and use another application while they are driving. It is well known that most people use their phones for navigation, and it is widely used applications such as google maps, or Waze. This may interfere with the data collection or quality of data. Therefore, it is required to develop work in the background. It was not found analysis to explore how it affected the DBA tasks, which demand quality and a huge amount of data, with other systems that are requiring the same data. Then, this issue requires future research.

VI. Conclusions

Driving behaviour Analysis has the potential to enhance road safety, traffic management, fuel consumption and road support through the performance of drivers. The adoption of some practices has the potential to make efficient Intelligent Transportation Systems. This investigation identified the most recent research on DBA using smartphones. Trends around this area were explored and concluded that has an important interest across different areas such as the applications in ITS. Different terminology was identified and classified to support the applicability of several applications. Then, it was categorized applications by strategy, tactical and reactive. Smartphone sensors were identified that can support the identification of driver performance, and some driving styles were examined to identify their methodologies. Also, it provided the most common algorithms, Machine learning, and deep learning used to distinguish driver performance and driving styles, Finally, it was discussed the results and challenges found in this field. This research supports those who want to immerse in this domain in future works.

Overall, it is concluded that DBA is a difficult study and needs a framework for its development, related works use widely different concepts making harder this study. Interpretation of outcomes can be explored in diverse ways, for instance, sudden braking can be interpreted as aggressive by the systems, but it is necessary to explore the reasons for such events. In addition, it’s important to highlight that the entire smartphone device can be useful from the point of view that the access to driving data through apps installed in the devices could be massive due to the world population being the owner of this device. However, the device also has its limitations in terms of driver use, road safety standards and capabilities of the device. Although smartphone sensors are improving their quality through the years, it is difficult to determine the variability in values between mobile phones and sensors from different generations, as well the sensor fusion may influence its functionality of itself as indicated by (Kanarachos et al., 2018). Advancements in sensor technology, communication protocols, and road maps may be advantageous for upcoming implementations. Smartphones will continue to provide scalable and user-friendly telematics platforms for many years to come, despite some claims that the growing number of automobiles with factory-installed telematics systems will eventually turn smartphone-based solutions obsolete for this applicability.

On the other hand, Vehicles have different characteristics such as type, shock absorbers and wheels that can affect the raw data captured. In addition, weather, state road, road topology, passengers, computational complexity, and imbalanced dataset add complexity to standard a methodology. Therefore, the challenges are presented in the variation of each device to another, vehicles, quality of sensors, quality of raw data, energy consumption, privacy and security, and the methods to access driver data.

DBA tasks such as aggressive detection, distracted detection, drunk detection, and drowsy detection are broadly researched for their significance factor. These human factors are one of the main causes of fatal driving accidents. The literature review revealed that those DBA tasks have not been proven on a massive scale to determine the real impact on road safety. Neural networks (NN), Support vector machines (SVM), Clustering (CL), Instance-Based (IB), Decision trees (DT), Bayesian learners (BL), Ensemble learners (EL), Fuzzy & Neuro-Fuzzy based (NF), Inductive Rule Based (IR), Evolutionary algorithms (EA), and Miscellaneous were the broad categories used to classify machine learning techniques. SVM, NN, EL, and BL are the most often utilised among them. The three-performance metrics that are most frequently employed in primary research are accuracy, recall, and specificity. Most ML models' overall estimation accuracy is within accepted limits(Abou Elassad et al., 2020). The difficulty of finding labelled data or labelling it for DBA due to the lack of or sparse labelling of real-world data has brought attention to the need for semi-supervised approaches. it was evidenced that although deep learning approaches bring improvements to the DBA tasks, it is preferable to use systems that require less computational power and the least complexity for a smartphone environment.

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