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Taxonomy, Open Challenges, Motivations, and Recommendations in Driver Behavior Recognition: A Systematic Review

Mohammed Basim Omar[1],Mohamed A Ahmed[1], Harith A Hussein[1], Z.T.Al-Qaysi [1], Mahmood M. Salih[1],SA Hamddi[1], Qabas A Hameed[1], Reem D Ismail[1]

[1]Tikrit University, College of Computer Science and Mathematics, Computer Science Department, Iraq

*Corresponding Author: Mohamed A Ahmed

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ABSTRACT: Driver behavior has a major role in many of the unpleasant things that happen when driving, such as crashes or accidents, heavy traffic, abrupt braking, and acceleration and deceleration. Numerous investigations have been carried out to look into the variables influencing driving behavior. To offer a thorough analysis and classify these findings according to a logical classification, further research is required. The goal of this systematic review is to enhance knowledge about the variables influencing driving behavior. A taxonomy on the subject of driver behavior in various ITS domains and their categories was also produced by this work.
A systematic review of the literature was performed in accordance with PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines to gain insight into driver behaviour recognition.
Specifically, IEEE Explore, ScienceDirect and Springer databases were searched to identify any relevant articles with a focus on "driver behavior," "driver style," "driver pattern," "driver simulator," and "visual attention," from 2008 to 2021 (15 April).
Several filtering and scanning procedures were performed on all 606 retrieved articles in compliance with the exclusion/inclusion criteria; nonetheless, only 50 articles met the requirements. The criteria-compliant references were examined and evaluated. Furthermore, every piece that was included was classified using a taxonomy. The four categories created by the taxonomy are review, experiment, framework, and other study types. To illustrate the main gaps in the literature regarding the identification of driving behavior, a discussion and analysis were presented. This thorough analysis has highlighted the issues and reasons while also pointing forth fresh research directions.

Keywords: Driver behavior, Systematic review, Driver style, Driver simulator, Visual attention, ADAS, Advanced driver-assistance systems.

INTRODUCTION

Road traffic injuries and deaths are a serious public health concern that has a negative impact on economic and social development around the world. That 74 percent of road crashes are caused by driver errors and traffic offenses. As a result, understanding the impact of driver behavior on crash risk is critical for reducing road accidents [1]. One of the most critical variables affecting road safety is driver conduct and error, external factors, and vehicle-related factors. As a result, driver behavior monitoring and detection systems have recently become a hot topic of research. Some systems monitor the driver's behavior in isolation, while others combine the driver's behavior, the vehicle's state, and the surroundings to monitor the driver's status. However, there is currently no reliable monitoring system that can reliably detect all aberrant behaviors of a driver [2]. Meanwhile, in both legislation and research on road safety, driver behavior remains a major concern, Human errors, aggressiveness, and other human-involved elements are likely to have a significant influence in numerous unpleasant events, such as traffic jams and deadly accidents. For example, people are still at risk of being engaged in traffic accidents today as a result of human error, particularly because of selfish, irresponsible driving such as high speed and abrupt lane changes without turn signals, Aggressive driving is the term used to describe this type of behavior [3]. On the other hand, also researchers looked into driving intention, categorizing distinct types of driver intentions such as traffic context awareness, driver state, and vehicle dynamics. In addition, several approaches for monitoring driver performance have been launched in recent years; however, these methods have been associated with increased costs and delayed development [4]. There is much research in the literature on increasing road safety to avoid such difficulties through developing driver monitoring system. The automotive industry is creating creative ways to provide security[1] through technologies known as advanced driver

*Corresponding author: author@organization.edu.co

assistance systems (ADAS). ADAS is effective for decreasing traffic accidents and promoting more fluid and efficient transportation in order to deal with some prevalent causes of accidents. Generally, external parameters like as the distance between vehicles, the intensity of the illumination, the road, and other factors are monitored by assistance systems in order to provide a warning to the driver in the event of a threat [5]. ADAS can be divided into vertical systems and horizontal systems, vertical systems regulate the vehicle's front and rear behaviors, whereas horizontal systems control the vehicle's left and right behaviors. Adaptive cruise control (ACC), which manages a vehicle so that it maintains a set distance from the vehicle in front, and an autonomous emergency braking system (AEBS), which automatically prevents a collision when a front-collision danger exists, are examples of vertical ADASs. A lane departure warning system (LDWS), which keeps the car in its lane, and a blind-spot warning system (BSWS), which informs the driver if there is a vehicle in the driver's blind area, are examples of horizontal ADASs [6]. Besides that, intelligent vehicles with varying levels of automation and driver interaction will most likely be blended in large-scale diversified traffic scenarios in the near future. To increase driving safety, more study and understanding of vehicle and driver monitoring is needed in these mixed assistive driving settings [7]. This study provides a thorough mapping of significant data on driver behavior evaluation methodologies. The main goal was to figure out which approaches had been employed in previous studies, as well as the characteristics of such approaches, such as their origin, type, and style of execution. This mapping provided conclusions on the state of the art in this subject and led to the creation and refinement of driver behavior evaluation methodologies. In addition, the current study used a systematic review process, a taxonomy of essential factors, a mapping of data gathering methods, and a discussion of past research (i.e. motivations, challenges, and recommendations). The following is how the paper is structured: Section 2 explains the article survey search strategy (Method); Section 3 explains the taxonomy of essential factors, and Section 4 explains the mapping of data gathering methods. Section 5 examines motives, challenges, and recommendations; Section 6 focuses on in-depth analysis; Section 7 depicts the recommended pathway solution's future direction; Section 8 outlines the study's limitations; and Section 9 wraps up the research.

1. METHOD

This study is a systematic literature review based on PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines[2-8]. This review focuses on what is done and discovered in the literature, which determine the importance of the systematic review. The content of reports for systematic reviews varies, as for other publications, making it difficult for readers to understand the motivation, challenge, and recommendations of the reviews. Figure 1 illustrates the steps involved in the methodology for collecting related resources.

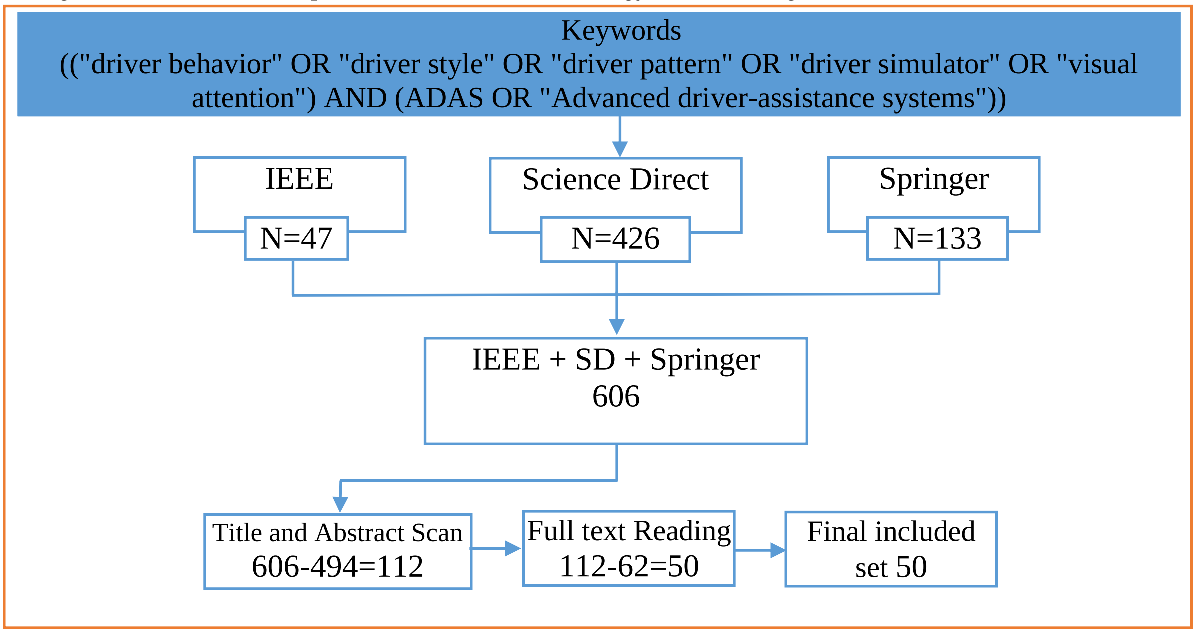

Figure 1. Flowchart of study selection, including the search query

1.1 INFORMATION SOURCES

To gather relevant papers from highly reputable publications in the disciplines of transportation engineering and computer sciences and technologies, the following digital databases were chosen: (1) ScienceDirect, (2) IEEE Explore, and (3) Springer. These databases cover scientific and technical literature and give a wealth of information about researchers' work across a wide range of subjects. Articles were chosen from these sources of information to meet the objective of this review.

1.2 SEARCH

In September 2021, a search was undertaken on the databases "ScienceDirect," "IEEE Explore," and "Springer." a variety of keywords in various formats were used, Using the following query string as a starting point: (("driver behavior" OR "driver style" OR "driver pattern" OR "driver simulator" OR "visual attention") AND (ADAS OR "Advanced driver-assistance systems")).

1.3 STUDY SELECTION

The search on related papers using three sources of information using different keywords "driver behavior," "driver style," "driver pattern," "driver simulator," "visual attention," "ADAS," and "Advanced driving-assistance systems" combined by the “OR” operator. Furthermore, this research concentrated on English-language articles. However, the search results may include articles that are unrelated to the topic of the search. Therefore, three iterations of screening and filtering were performed on gathered references to pick the relevant studies, and the filtering stages are depicted below:

- In the first step filtering, duplicate articles were removed, and items published between 2017 and September 10, 2021, were gathered using the database's Advance search.
- In the second step filtering, articles were filtered by title and abstract, and those that did not fit within the fields of interest were eliminated.
- In the third step filtering, articles were filtered using full text reading, and those that did not fall within the scope of the domains of interest or did not fulfill the criteria were removed.

1.4 ELIGIBILITY CRITERIA

A set of criteria has been set up in order to find relevant articles and to exclude articles that do not meet these requirements.Via three iterations of filtering and checking, items that did not fit the inclusion/exclusion criteria were eliminated. The following are the exclusion criteria:

- Articles written work in a non-English language.
- We just looked at the driver's face and the things that affected him or her, such as drowsiness, exhaustion, visual attention, and so on.
- Traffic signals and articles indicating items on the road were not included.

1.5 DATA COLLECTION PROCESS

The final group of articles had a total of 50 articles, as illustrated in Figure 1. The articles were read in their entirety and analyzed in Microsoft Excel. To make the next steps easier, articles were categorized in detail using taxonomy and a big collection of highlights and comments. Different categories (and subcategories) were offered, including experiment, framework, review, camera, and sensor. Microsoft Excel was used to save the data collection and essential information. To present an overview of the issue, all articles from various sources were thoroughly examined. The following questions were addressed in the current study:

- What are the most significant influences on driving behavior?
- What are the most common reasons, difficulties, and recommendations?
- What factors were used in previous studies?
- What possibilities can be presented to future researchers?
- What are the probable flaws in this sector that researchers should be aware of?

2. RESULT

Over the period of 2017 to 2021, the original keyword search yielded 606 articles: 133 from Springer, 426 from ScienceDirect, and 47 from IEEE Xplore. Following a review of the titles and abstracts, 494 additional articles were eliminated, leaving 112 pieces. After excluding 62 articles from fulltext reading, the final set of papers included was reduced to 50. Those publications were thoroughly examined with the goal of establishing a general framework for future research on this burgeoning issue. The majority of the articles (6 percent; 3/50) are review papers that use actual applications or literature to describe current driving behavior for a specific behavior Analyzing, or purpose, or to provide a broad summary of the new trend. The next-largest percentage of publications (84 percent; 42/50) conducted diverse investigations (experiment), ranging from evaluating samples from the flowing current of driver behavior to analyzing the desired characteristics that people would like to have in their newly discovered assistive technology.

Several academics rode the new wave, presenting real-world initiatives to improve their driving behavior or sharing their experiences doing so. Proposals for frameworks or models that handle the functioning of apps or their development in a more general setting made up the final and smallest number of works (4 percent; 2/50). There are three articles (6 percent; 3/50), one of which deals with assessment and the other with an interview and a questionnaire. While I dealt with the last article, Development two-stage learning for driver lane change intention inference. These patterns were noticed, the main categories of research papers were captured, and the classification was refined into the literature taxonomy illustrated in (Figure 2). We were able to discern various subcategories within the primary classes, however there were some overlaps. The observed categories are listed in the following sections, with simple statistics used throughout the discussion.

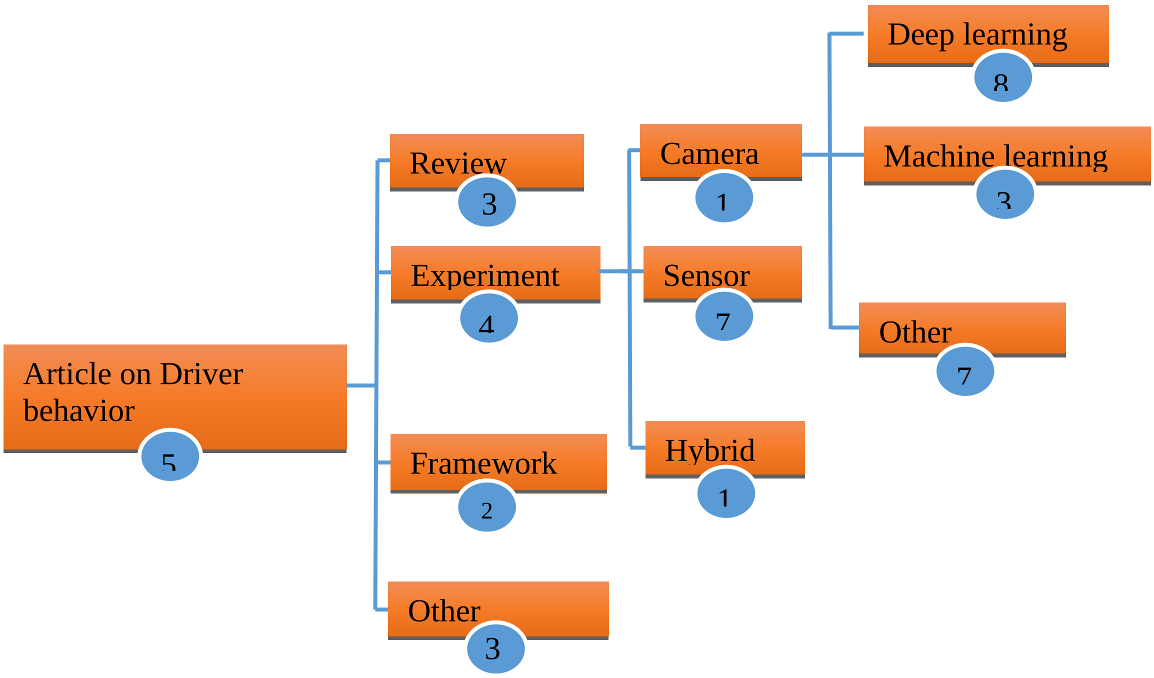

FIGURE 2. - taxonomy of research literature

2.1 EXPERIMENT ARTICALS

It's no surprise that the majority of studies on driver behavior are experiment articles focused at capturing the new phenomenon, introducing it to the scientific and industrial communities, and generating descriptive data, all while attempting to grasp the ramifications and potentials. The easiest and largest class to notice is the experiment based on a Driver behavior study (42/50 articles). Examples of this category include the driver behavior Monitoring through the camera eight articles [8-15] included through deep learning, while [16-18] three articles listed under machine learning, others used the camera for evaluation, statistical analysis, and other methods of examination, which were gathered in a section called (Other) [19-25] the number was seven articles. As for behavior monitoring through the sensor, it has included also seven articles [2, 3, 6, 26-29], While, hybrid used between camera and sensor have included seventeen articles [4, 5, 30-44].

2.2 REVIWES ARTICALS

The usefulness of review papers is recognized by the importance of capturing, integrating, and presenting new phenomena to the research community, as well as extracting descriptive statistics to comprehend the possibilities and impacts of phenomena to bring about change, despite the importance of this type of the articles, only 3 of the 50 papers are reviews and surveys. One of these articles involves, focus on naturalistic driving studies with the goal of analyzing driver behavior from many modalities and the incentive of contributing to more intelligent driver-vehicle systems, and attempting to answer the research questions. which are the: (1) how can we get adequate data, (2) how can we assess and understand driving behavior, and (3) how can we effectively transmit information to drivers [7]. The other review paper also provides a complete picture of goes over the tactics for improving driving behavior utilizing naturalistic driving research to improve road safety that has been mentioned in the literature. Driver characteristics, distraction, environment, enforcement, and highway characteristics are all elements that influence driving behavior, according to studies on naturalistic driving behavior [1]. Discussed the last article detailed summary of research on the prediction and detection of lane change maneuvers. Where, the interplay between the driver and the environment influences the lane change decision. Therefore, a wide range of driver behavior and lane change modeling studies were reviewed [45].

2.3 FRAMWORK ARTICALS

We recommend defining some of the literature articles in this part as belonging to the previous group because they produce new applications and complete frameworks, as well as focusing on the work of an integrated practical system that develops new applications and research expertise. It could be useful to future researchers. Articles in this class (2/50) include works focusing on models and methods for the design in full. One of the proposed studies aims to create a mobile app for an Android smartphone that can recognize driver behavior and provide recommendations while driving in a dangerous situation caused by driver drowsiness and/or distraction, the primary goal of driver behavior analysis is to identify unsafe circumstances and generate recommendations at reducing or eliminating the likelihood of accidents. This is accomplished by utilizing the smartphone's functionalities in this reference model, which allows the other model components to connect with one another through it. The front camera, built-in smartphone sensors and local database are among them [46]. Another study also uses a smartphone to determine the driving style of a person. In the beginning, data from sensors is received via a smartphone in a moving car. While, the camera data is utilized to determine traffic direction signs, and the data collected by the other sensors is used to determine the driver's speed and maneuverability. The deep learning algorithm proposed calculates driver speed and maneuver, as well as traffic direction signs, all at the same time. The driver's driving style profile is then determined by matching these facts [47].

2.4 OTHER STUDY

This category accounts for 6% (n = 3/50) of the articles, which were not included in the previous categories, such as articles that how car data from the Naturalistic driving study may be used to discover differences in driver behavior and driving context in the Chinese, Swedish, and US markets. In ADAS design. as well, this study provides a better way to consider infrastructural and cultural variations [48]. In another article, Researchers find that it is significant to understand the comprehend the implications of partial automation systems (PAS) on drivers' comprehension and behavior. In order to adapt to new car technology. so it was, the researchers performed in-depth semi-structured interviews with individuals to learn about their personal experiences with PAS [49]. Of the articles, which were beyond the scope, the researchers began developing a two-stage learning framework for predicting driver lane change intentions [50].

2.5 DATASET

The dataset is a valuable and necessary resource. Such datasets are an important aspect of learning and understanding driver behavior. Although there are not many datasets dedicated to learning and understanding driver behavior. Therefore, Participants' familiar automobiles should be equipped with various cameras and sensors that capture vehicle motions and unobtrusively driving behaviors and without disturbance. But this data collecting will be time-consuming and more costly, as well as difficult to coordinate [7]. Many studies have concentrated on a selective set of data, some of which may have been collected over a period by researchers. We discovered a public dataset and own dataset (self-built) through our study of the set of articles. Which are covers the many types of real-world driver behavior. Table 1. provides more information on the database utilized in the majority of past studies, including the dataset type, dataset name, number of participants in the trial, and sample amount/size.

Table 1. - Description of Dataset used in the literature

Ref.	Dataset name		Participant		Size	
	Self-built	Public	Self-built	Public	Self-built	Public
[9]	-		10		91 sets of eye-movements data	
[10]	-		60		-	
[11]	transport vehicles in Zhenjiang		-		29,813 data	
[12]	-		13		320 trips totaling 167.7 h.	

[13]	-		20		356 take-overs	
[14]	The Smart Mobility Research Center of Tokyo University of Agriculture and Technology.		4		-	
[15]	-		14		100 m before crossing each intersection.	
[16]	-		25		The driving performance, eye movement, and EEG data on each road segment were collected from 100 m after passing the previous intersection to 100 m before arriving at the next intersection.	
[17]	VCCNDS cohort & DAF NDS		50 120		1500 h—or 12% of the study duration 1,178 h—or 17 %	
[18]	SHRP2NDS database		3100		581 events	
[19]	-		3		21411 samples	
[20]		ACCV drowsy driver dataset		-		-
[21]		dataset Taamneh et al.		68		-
[22]		KAGGLE’s		26		123561 image
[23]		CranData		3		150 miles of naturalistic data
[24]	SEU-real-Driving dataset	Kaggle-driving dataset	-	-	16,905 images	47,424 images
[25]	SEU-real-driving dataset	Kaggle-driving dataset	-	-	33,162 images	22,424 labelled/25,000 unlabeled images
[26]		COCO dataset	6	-	200 Image	
[27]		OpenXCTM platform (http://openxcplat form.com/about/data-set.html)	-	15	-	-
[28]	CranData	Brian4Car dataset	3	10	47,111 samples	36,760 samples
[29]	ZJU and the created database of the authors.	ZJU dataset	20	4	4841 images, including 2383 closed eyes and 2458 open eyes	4157 images (2100 open and 2057 close images)

2.6 DATA COLLECTION DEVICES

The studies that were selected used a variety of devices to observe driver behavior in a real driving environment. Researchers have utilized a variety of equipment to study these, including the Global Positioning System [3, 27, 28, 32, 34, 35, 43, 46-48], accelerometer [34, 46, 47], camera [4, 10-12, 17, 18, 30, 34, 35, 39, 43, 44, 50], radar/LiDAR sensors [30], and eye-tracking devices [19, 23-25, 35, 40]. To observe the overall driver's behavior, these gadgets continuously collected vast amounts of data from the driver, vehicle, and surroundings. Table 2. Provides more details on the Device Names, Pictures, and Specifications of these devices that were employed in our study of a few selected articles.

Table 2. - Type of Input Devices mentioned in literature review

Ref.	Device Name	Device Description	Device image
[20]	D-Link DCS-932L	The camera is equipped with infrared LEDs because it is a surveillance digital camera, allowing it to catch the driver at night. Infrared lighting is also included in this camera, which aids in the capture of people who wear glasses. The video was shot at 30 frames per second frame rate.	
[9]	Tobii Pro Glasses II	Tobii Glasses 2 is designed to make collecting easy, eye-tracking data simple, precise, and efficient in a range of research contexts. In both qualitative and quantitative real-world research, the discrete, ultra-lightweight design promotes natural behavior and study validity. In uncontrolled scenarios and real-world settings, accurate data and effective eye tracking capabilities can be relied on. Tobii Glasses 2 is designed to be utilized in human behavior research, including eye movements.	
[10]	Seeing Machines faceLAB eye-tracker	faceLAB 5 is a hardware eye-tracking device from Australian "Seeing Machines". In comparison with other similar devices, this system has its own specific construction. faceLAB 5 is based on two separate cameras with emmiters. Position of those emmitters can be changed in accordance with user's needs. Such approach makes it possible to use this device in various environmental conditions. This device measures such paramters as user's sight direction, positions and diameters of pupils, frequency and time of blinking.(https://www.eyecomtec.com/3132-faceLAB).	
[11]	Driver State Monitoring System (DSMS)	The driver state monitoring system (DSMS) is a camera-based system for monitoring driver attentiveness that not only recognizes but also tests the driver's level of awareness. When indicators of tiredness or distraction are detected, the Driver Monitoring system will inform the driver.https://www.truckindia.co.in/Driver_State_Monitoring_System_DSMS_by_BharatBenz_10thfebruary2021.html	
[12]	Blackvue forward-facing camera	is a budget-friendly dashcam for drivers who desire all-around protection and front and rear recording. This two-channel dashcam system captures video from two dashcam lenses, which are typically positioned on the front and back windshields, and records the footage to a single memory card. a forward-facing dashcam with excellent quality, Full HD 1080p recording, and extremely smooth 60FPS (frames per second) video that is WiFi and Cloud capable.	
[12]	Mobileye Camera	The Mobileye Camera Development Kit is perfectly suited for sensor fusion systems, on-road Advanced Driver Assistance and automated driving research. https://autonomoustuff.com/products/mobileye-camera-dev-kit	

[12]	steering wheel angle sensor	This sensor is designed to measure rotational movement and angular speed, e.g. steering wheel angle and steering wheel speed. https://www.bosch-motorsport.com/content/downloads/Raceparts/en-GB/54425995191962507.html	
[30]	Tobii X120 eye-tracking system	Tobii's X60 and X120 Eye Trackers are stand-alone eye tracking machines that can be used for investigations on any surface. They allow for a range of stimuli settings, including a TV or other displays, a projection screen, a physical object, or a scene. They're our most adaptable eye trackers, and they're ideal for research that necessitate specific stimulation configurations. Automatic tracking saves time and money, allowing eye tracking to be used in far more applications than ever before.	
[13]	Smart Eye Pro eyetracker	The Smart Eye Pro is a 3D eye tracker system available in 60 or 120 Hz, and has been designed to be completely flexible, allowing for free camera placement in even the most demanding environments. https://brainbox-neuro.com/products/smart-eye-pro	
[31]	Mobileye	The forward-facing camera constantly monitors the road in front of the vehicle. It identifies potentially dangerous situations, and provides audio and visual alerts to assist the driver.	
[27]	Emotive Epoc EEG	The electrical activity of the brain is measured with an EEG examination[32]. EEG scans are performed by putting EEG sensors on your scalp, which are little metal discs also known as EEG electrodes[33, 34]. The electrical activity in your brain is picked up and recorded by these electrodes[35]. The gathered EEG signals are amplified, digitized, and then stored and processed on a computer or mobile device[36].EEG data analysis is a fantastic technique to learn more about cognitive processes[37, 38]. It can assist doctors in making a medical diagnosis, researchers in better understanding the brain processes that underpin human behavior[39, 40].	
[41]	CMOS cameras	Extremely compact cameras with high-speed CMOS sensors were created with the goal of being small and light. The cameras can be simply integrated into a wide range of systems. A plastic housing with a CSmount lens adapter is available for these cameras. Because the CMOS sensors employed have a linear response to light up to very close to saturation, so, cameras can be utilized for scientific applications.	
[41]	Velocity BOX (VBOX) datalogger	The VBOX datalogger can record a wide range of vehicle dynamic data, including velocity, acceleration, heading, and location. is a high-performance GPS receiver.	
[15]	Smart Eye Pro	The eye-tracker allowed collecting the head and gaze directions with respect to the vehicle axis (which was fixed in the eye-tracker system configuration).	
[42]	EMR-9 eye tracker	eye tracking measurement and analysis technologies at their most advanced. The EMR-9 is a completely transportable eye measuring system that is far smaller and lighter than typical eye measurement systems. This permits the subject to walk around in their native environment freely and unfettered. The EMR-9 saves information to a small SD memory card. This SD memory card can then be used to transfer the data to a computer for statistical analysis. Finally, the EMR-9 has detection and sampling speeds of up to 240 Hz,	

		making it perfect for active and mobile users.	
[43]	Xsens MVN Animate	The proprietary motion capture software from Xsens MVN Animate transmits or exports all data to your 3D package. The motion capture equipment is used to acquire highly precise data based on a series of experiments. Your work benefits from quick and easy calibration, real-time visualization, easy playback and reprocessing of your motion capture data.	

2.7 IDENTIFIED DRIVER PATTERN

In this section, we'll go through the many types of driving behaviour that the researchers aimed to identify, as well as how they influenced the ultimate decision. Many studies focused on recognizing chatting, yawning, looking away, eye movements, eye blinking, face deformations, driver weariness, Front nodding, Assent of the head to the left, and Assent of the head to the right as indicators of driver drowsiness. Furthermore, driver sleepiness may be detected using biomedical signals such as respiratory rate variability, heart rate variability, and respiration rate parameters [12, 20, 29, 44-46]. There is also, Researchers monitored the driver and his use of the tablet, book, cell phone, and laptop or gazes into the windscreen, into the instrument cluster, and towards both rear-view mirrors. Are used as an effective driver visual attention feature [10, 13, 26, 47]. Researchers have also analyzed (head pose, gaze and pupil metrics, and eyelid opening. in addition, head pose and eye movements, Lane Change, Left Turn, Right Turn, Traffic Junction, Left Turn, Right Turn, talking to co-passengers, Aggressive Lane change, Traffic Junctions (city traffic lights), Vehicles up front, Vehicles Blind spots, Vehicles Side Lanes, Sudden Obstacles, Use of Cell phone, Moving/adjusting/monitoring objects in vehicle, passenger interaction, Talking/Singing, audience unknown, Drinking or eating or smoking, personal hygiene, external distraction) to see if the driver's attention is focused ahead and if the driver is distracted[12, 18, 22, 33, 46, 48-50]. Researchers use features to detect aggressive driving and braking habits in drivers by monitoring the driver's right leg[43, 51]. such as features right upper leg (RUL), right lower leg (RLL), right foot (RF), and right toe (RT), Sudden acceleration, Sudden braking, Sharp left turn, Sharp right turn. Table 3. Delves more into the set of features and their use in the selected articles.

Table 3. -Different classes mentioned in the literature review

Detection	Tools	classes	REFERENCES																
			[24]	[20]	[25]	[26]	[44]	[12]	[47]	[27]	[41]	[21]	[48]	[17]	[28]	[18]	[51]	[19]	[52]
recognize driving behavior	camera	Normal driving	*		*					*					*				
	camera	Hands off the wheel			*														
	camera	Calling mobile	*		*	*													
	camera	monitoring objects in vehicle														*			
	camera	passenger interaction														*			
	camera	external distraction														*			
	sensor	Lane Change											*				*		
	camera	Smoking	*		*											*			
distracted driving	camera	Playing on Mobil phone	*										*			*			
	camera	Drinking or eating	*		*											*			
	camera	Talking with passengers	*		*								*			*			
	camera	eye movements											*						
	camera	Texting right	*		*														
	camera	Calling right	*		*														
	camera	Texting lift	*		*														
	camera	Calling lift	*		*														

Detection	**Tools**	**classes**	**REFERENCES**																
			[24]	**[20]**	**[25]**	**[26]**	**[44]**	**[12]**	**[47]**	**[27]**	**[41]**	**[21]**	**[48]**	**[17]**	**[28]**	**[18]**	**[51]**	**[19]**	**[52]**
	camera	Operating the radio	*		*														
	camera	Reaching behind	*		*														
	camera	Hair and makeup	*		*														
	camera	eye movements					*												
	camera	drowsy		*			*	*					*						
	camera	head motion						*			*		*						
	camera	still condition (no movement)		*															
	camera	yawning		*			*												
	camera	looking aside		*															
drowsiness detection	camera	face deformations					*												
	camera	fatigue					*												
	camera	Front nodding					*												
	camera	Blink detection					*												
	camera	Assent of the head to left					*												
	camera	Assent of the head to the right					*												
	camera	Distraction to left					*												
	camera	Distraction to right					*												
visual attention	camera	eye gaze							*										
	camera	head motion							*				*						
	camera	Calling mobile				*													
	camera	tablet				*													
	camera	car interior				*													
	camera	book				*													
	camera	laptop				*													
lane change intention inference	camera	eye gaze									*								
lane change intention inference	camera	head motion									*								
lane change intention inference	camera	hand motion									*								
lane change	camera	head motion									*								
lane change	camera	hand motion									*								
lane change	camera	usage of the turn signal									*								
analyzing the driver	sensor	Heart rate										*							
	sensor	Breathing rate										*							
	sensor	gravity																*	
	sensor	throttle of the vehicle																*	

Detection	Tools	classes	REFERENCES																
			[24]	[20]	[25]	[26]	[44]	[12]	[47]	[27]	[41]	[21]	[48]	[17]	[28]	[18]	[51]	[19]	[52]
	sensor	Speed										*						*	
	camera	Right. Pupil diameter										*							
	sensor	Acceleration										*		*			*	*	*
	sensor	Brake										*							*
	sensor	Steering										*							
	camera	Left. Pupil diameter										*							
analyzing driver behavior (physical behaviors)	camera	emotional													*				
detection aggressive	sensor	Acceleration															*		
	sensor	Brake															*		

3. DISCUSSION

A retrieved literature information pattern resulted from the data extraction and search technique. This section aimed to discuss and highlight three major components: (1) issues and problems identified in earlier and current research and academic studies; (2) motivations relating to the topic's benefits and significance, as well as concepts explained by researchers; and (3) recommendations, in which the writers express their future thoughts and hopes for further research.

3.1 MOTIVATION

Various aspects of motivation are found in the literature that clearly and convincingly characterizes the study of driver behavior. Whether it is about optimization, alerting, or the interaction between humans and automation. This section discusses some of the several motivations that have been cited in this literature. Figure 3**Error! Reference source not found.**. Presents the classification of categories on motivations.

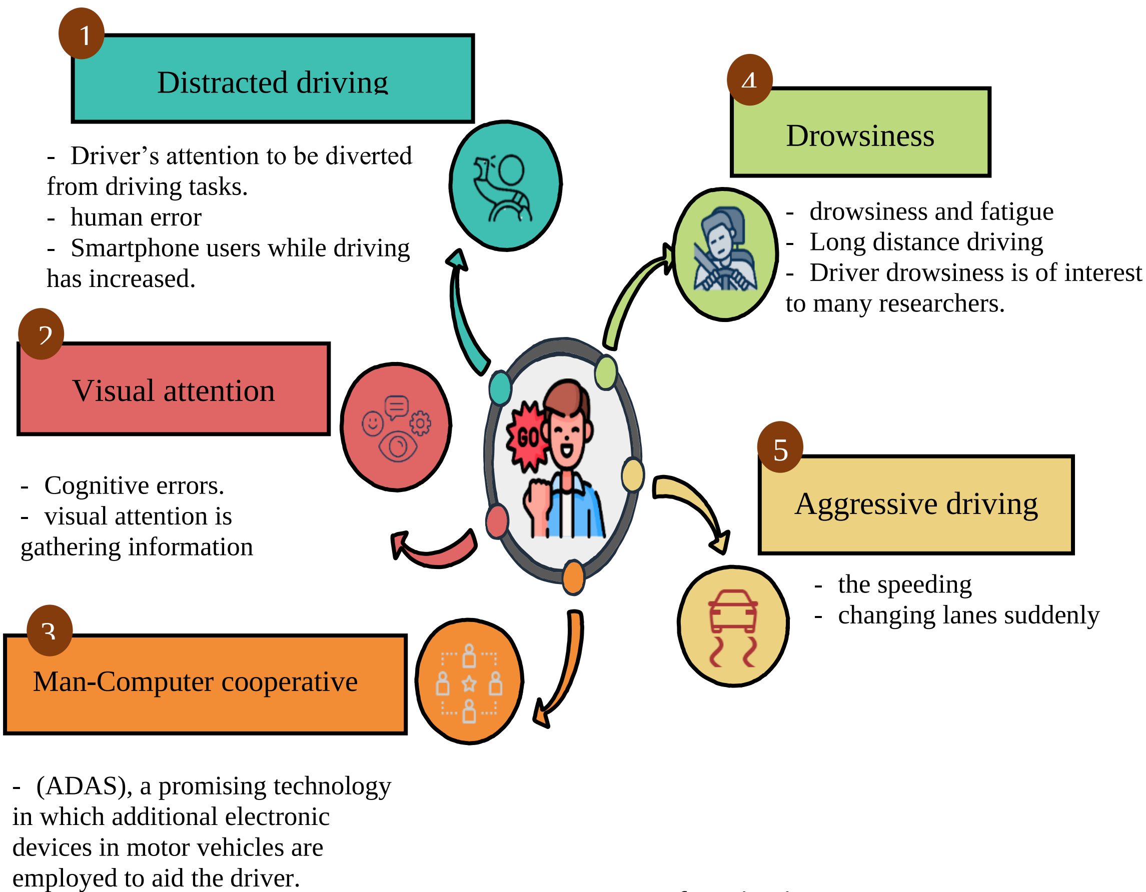

FIGURE 3. -**Category of Motivation**

3.1.1 DISTACTED DRIVING

Previous studies in driver behavior indicate various factors that lead to a large number of accidents, such as driver distraction [22, 47, 53]. Distracted driving during a specific event or activity inside or outside the car causes the driver’s attention to be diverted from driving tasks and this is the reason why studies are interested in studying distracted driving to ensure road safety and reduce accidents [18]. Furthermore, according to another study, driver distraction induced by using a cell phone or smoking is responsible for more than 80% of traffic accidents [24, 25, 49, 54, 55]. Distraction, or paying attention in the wrong location, is thought to be the major cause of car accidents [56]. In the United States, roughly 94 percent of serious road accidents are caused by human error. Similar numbers can be found in nations around the world, including Ecuador, Chile, and France, where up to 80% of traffic accidents are caused by driver's and pedestrians' incapacity or recklessness. In 2017, 3,166 people were killed in road incidents caused by distracted driving. and this classifies distraction as one of the main causes of human errors while driving.[57]. Road traffic injuries (RITs) In another study, are said to be the world's eighth biggest cause of death. Poor driving conduct, particularly driver distraction, is thought to be a direct cause of traffic accidents [58]. On the other hand, due to the technological development in the means of human communication and the expansion of communication services, the number of smartphone users while driving has increased, leading to a new storm of driving distractions [30]. Pedestrians, cyclists, and motorcyclists, on the other hand, continue to face risky scenarios. According to statistics, 83 percent of these collisions occurred on straight roads, and 35 percent were caused by careless driving [14]. In another study, every year, over 7600 people in Europe are killed in collisions involving bikes and pedestrians. Bicyclists and pedestrians are particularly vulnerable in collisions with motor vehicles, and truck collisions can result in serious injuries [59].

3.1.2 VISUAL ATTINTION

When analyzing driver behavior, it is critical to understand and be aware of the drivers of visual attention in order to reduce the risk of road accidents and maintain safety. Previous research has shown that a 90 percent increase in car accidents is related to a human mistake caused by cognitive errors such as failing to attention eye in the needed area and in the correct method [9]. During a driving task, visual attention is the initial stage in gathering information, picking relevant elements in the field of view, and allowing them to appear in central vision, where the human visual system delivers greater color and detail perception [15].

3.1.3 MAN-COMPUTER COOPERATIVE

Intelligent vehicles based on electrification, intelligence, and network connectivity have become a prominent trend in the automobile industry due to the rapid growth of computer technology, Internet technology, communication technology, and artificial intelligence [11]. Various advanced driver assistance systems (ADAS) have been created to improve drivers' behavior and perceptual skills; nevertheless, field operational studies are required to determine whether these ADAS have any demonstrable influence on driving performance [31]. Driver profiles are involved in circumstances where they must be known in order for ADAS to function properly. If a person's driving style is predetermined, ADAS may be able to do a better job of helping the driver at the wheel [60]. On the other hand, the transportation sector and the research community are trying to ascertain the impact of self-driving vehicles (AV) on consumers, as well as the various elements that will influence their adoption, to keep pace with technological advances in autonomous driving [61]. In another study, with the advancement of smart vehicles, it is becoming clear that human drivers may be excellent teachers to their smart counterparts, the design of a human-centered intelligent system can benefit from a comprehensive examination of human driver behaviors, patterns [28]. Also on the other, It is the responsibility of safety experts and industry professionals to determine any potential risks associated with the implementation of sophisticated vehicle technologies, to mitigate fatal accidents and road safety [17]. Driver assistance systems in the vehicular environment have advanced significantly over the last ten years, to Advanced Driver Assistance Systems (ADAS), a promising technology in which additional electronic devices in motor vehicles are employed to aid the driver in particular scenarios[48, 62].

3.1.4 DROWSINESS

Driver drowsiness and weariness are two of the most common causes of car accidents [9]. Road accidents are caused by a variety of factors, one of the most common of which is "drowsiness", driver sleepiness detection could be a viable tool for preventing accidents [14, 17[63-66]. Driver sleepiness detection technologies, on the other hand, have piqued the interest of numerous researchers as a means of preventing car accidents [18]. Meanwhile, many drivers today have to drive a lot and can get into risky situations as a result of long-term driving. Drivers are sometimes unaware that they are in a perilous situation. Microsleeps or reduced focus, for example, may go unnoticed by drivers but result in road accidents [46].

3.1.5 AGGRESSIVE DRIVING

Human error exposes people to traffic accidents, and this is due to selfish and careless driving, such as speeding and changing lanes suddenly and without warning the turn signal. The term used to describe this type of behavior is called aggressive driving[51]. Reckless driving is to blame for the majority of deadly car accidents[52]. In another study, over 90% of road accidents are caused by human error, and most of these accidents are related to the driver's braking or braking-related behaviors[43]. In recent years, scholars, businesses, and government agencies have paid more attention to road safety. According to a data released by the United States Department of Transportation, 36,560 individuals died in motor vehicle-related incidents in the United States in 2018, averaging nearly 100 deaths per day. Human mistake is at blame for 94 to 96 percent of all car accidents. As a result, autonomous driving technology has piqued the interest of scientists for decades[67]. On the other hand, a lane change is a dangerous driving maneuver that helps accidents happen[68]. Furthermore, of the 44,583 traffic accidents caused by the driver, 19,367 (43 percent) were caused by speeding, talking on the phone while driving, operating devices in the vehicle, and failing to maintain one's eyes forward, showing a significant risk of front collision while driving[69].

3.2 RECOMENDATION

Correct knowledge of driver behaviors aids in the reduction of traffic accidents, the improvement of road safety, and the development of active safety systems. As a result, researchers have made the following recommendations Figure 4.

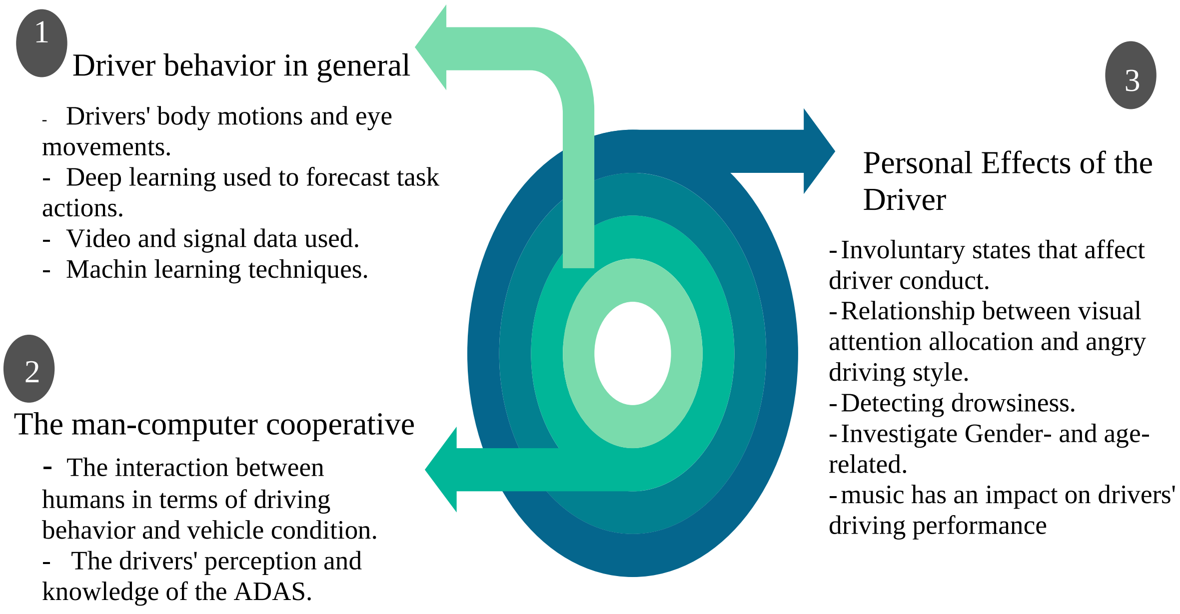

FIGURE 3. - Category of Recommendations

3.2.1 DRIVER BEHAVIOR IN GENERAL

Important guidelines for driver behavior, movement analysis, and driving style are included in this subsection. More sensor-based data, such as drivers' body motions and eye movements[44], should be analyzed, and deep learning used to forecast task actions, such as right-turning or drivers' movements before braking[19, 26[70-72]. Meanwhile, it is suggested that video and signal data be used to apply deep learning in various ways, with unsupervised learning being used to classify the data. Hence, supervised learning can be used to anticipate the state of drivers [4]. On the other hand, in addition to the neural network, more research is needed to construct a driver behavior model employing other artificial intelligence techniques [6]. Finally, there is a need for in-depth research on the Future research will need to look into driver behavior in a variety of vehicles [42]. In addition to using the gathered data to estimate the behavior of a broader population of drivers and incorporating these estimates into counterfactual simulations aimed at evaluating the safety benefits of Automatic Emergency Braking [43].

3.2.2 THE MAN COMPUTER COOPERATIVE

To increase the overall driving skill of the driver and human-computer cooperative driving, researchers are looking into the interaction between humans in terms of driving behavior and vehicle condition [21]. Meanwhile, the researchers recommend, the building of a holistic driver reasoning system based on multi-modal driver status and a full analysis of the driver's purpose toward a more intelligent driver-vehicle partnership [32]. Identifying human-related issues affecting the use of ADAS, such as the drivers' perception and knowledge of the system, is one of the recommendations. To ensure that the needs of users are addressed, next-generation systems must be designed with all influencing elements in mind [27]. It is also suggested, investigate the impact of a different type of ADAS smartphone app warning, such as vibrotactile feedback or augmented reality[73], to compare the benefits of these methods to those offered by using an audible signal to refocus the driver's attention back on the road, as well as the impact on long-term driver behavior [23]. Meanwhile, researchers consider, taking away a driver's task may result in underloading and weariness, resulting in poor driving performance. This is due to an overabundance of Over-trust and dependence on driving automation [38]. Researchers recommend refining the size of time windows for better performance, investigating additional learning algorithms such as online learning, and cooperatively calculating the probability of accident risk in vehicular networking by combining drivers' behavior and environment status [2].

3.2.3 PERSONAL EFFECTS OF THE DRIVER

This section contains recommendations for involuntary states that affect driver conduct. Such as emotional state, one of the recommendations is represented the driver's emotional state while driving will also be examined, as well as the driver's essential statistics [47]. Driver emotion identification will aid vehicle automation in providing appropriate assistance and warning signals to humans suggests understanding driver emotion in smart future vehicles is essential to better assisting humans in difficult situations; in addition, the multi-modality system and in-cabin speech analysis can be further combined in the future to provide greater information on driver mental states [39]. On the other hand, is recommended to conduct in-depth research, the researchers could further look at the causal relationship between visual attention allocation and angry driving style, as well as how angry drivers are trained to make impulsive judgments to change lanes [24]. Particularly, A function for establishing a link between the traffic environment and the proper driving technique might be derived. The next difficulty is to combine head-pose estimation with eye-tracking to obtain an accurate driver behavior. This could be improved further by combining eye-tracking and gaze-pattern estimation techniques. This work is expected to serve as a springboard for others to continue their research in this area in the coming years [34]. Besides that, Researchers recommend Combination of Time Skips Long Short-Term Memory (LSTM) can be employed in action recognition because it is good at detecting drowsiness. Instead of using solely face detection, the face tracker method will be used. Implementing a distributed program with parallel advantage for the system, which can speed up processing time, is another stage. The final option is to use additional facial characteristics in addition to the eyes and lips [9]. There is a need to investigate Gender- and age-related disparities in post-congestion effects in the future. The reactions of drivers with various personalities would be a fascinating research topic as well. Furthermore, music has an impact on drivers' driving performance as well as their physiological responses. Music intervention tactics can be incorporated into the design of assistance systems to assist drivers in reducing the negative impact of traffic congestion [37].

3.3 CHALLENGE

All issues and obstacles confronting driver behavior were discovered after researching the literature. In the subsections that follow, the major challenges are discussed. The classification of challenges is illustrated in Figure 5.

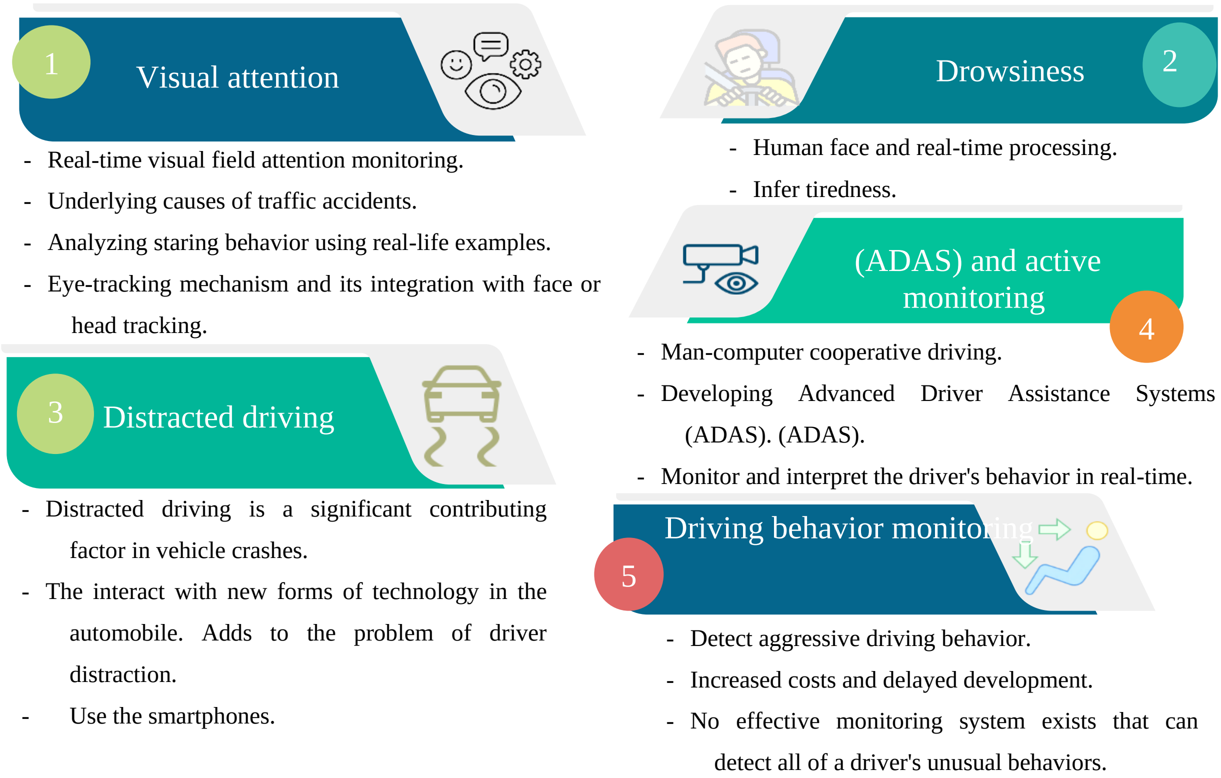

FIGURE 4. - Category Challenge

3.3.1 DRIVER VISUAL ATTINTION AND EYE TRACKING

Long periods of monitoring or supervision may be required to maintain a continuous state throughout the research trip and collect data. Some difficulties were discussed in this sub-section. Real-time visual field attention monitoring, for example, is at the heart of future safety systems and has the potential to minimize the frequency of accidents and improve road safety [31]. As a result, computer driving simulations and simplified road experiments are unable to account for the underlying causes of traffic accidents. Furthermore, there is a paucity of research on analyzing staring behavior using real-life examples [33]. In addition, Despite the fact that the driver assistance systems panel has been completed to a high standard, there are still gaps to be filled, including the development of a reliable eye-tracking mechanism and its integration with face or head tracking [34].

3.3.2 DROWSINESS

The issues of drowsiness are described in this subsection, based on some of the literature; The current study looked at many parts of the difficulties. Where the algorithm's tolerance to variations in the human face and real-time processing capabilities are the primary hurdles [9]. In addition, Drowsiness detectors are divided into three categories: vehicle-based, signal-based, and facial feature-based. Vehicle-based approaches attempt to infer tiredness from changes in steering wheel angle, acceleration, lateral position, and other factors. These methods, on the other hand, are too slow for real-time jobs [14]. At the same time, the critical problems of dividing the aforementioned three drowsiness detectors include: (1) Systems that use physiological signals to determine the driver's status are extremely accurate. Most physiological sensors, on the other hand, interfere with car control, making them unsuitable for use in real-world circumstances due to their intrusive nature. Furthermore, (2) the usage of systems based on vehicle dynamics data is fraught with difficulties, and poor performance is to be expected as a result of external factors such as road geometry, traffic, vehicle characteristics, and slow processing speeds. (3) In a controlled laboratory, the utilization of driver's facial photographs and data extraction from the driver's blinking, movement, head twisting, and yawning produces satisfactory results. However, due to non-ideal variables such as unforeseen changes in the environment, the performance of such systems suffers dramatically in real-world settings [18]. Although an increasing number of positive results have been reported in terms of its robustness and accuracy about real-time object tracking and driver drowsiness detection, it is a challenging area of research. Especially when it comes to applying these methodologies to real-world problems, where often concerning tracking conditions there is no unambiguous data [12]. Despite this, researchers consider that driver sleepiness is a serious public health issue that has previously been connected to an increase in the likelihood of drivers engaging in visual distraction [22].

3.3.3 DISTRACTED DRIVING

According to the literature, one way to improve road safety is to use sensors to track a driver's behavior and analyze the data obtained; we will go through that in this subsection. Despite the fact that distracted driving has been established as a significant contributing factor in the occurrence of right-turn vehicle crashes, it is difficult to adopt immediate countermeasures to minimize distracted driving behavior [42]. At the same time, In-vehicle technology, often known as in-vehicle information systems (IVISs), adds to the problem of driver distraction. As they interact with new forms of technology in their automobiles, such as media players and navigation gadgets, drivers are more likely to become distracted. To address driver distraction, a variety of solutions have been proposed, including the use of computer vision technologies and deep learning. Most of them have achieved satisfactory results in driver distraction detection, but they have failed to develop a system that combines a lightweight detection module with a comprehensive training module and real-time monitoring and analysis capabilities [13]. From another perspective, a growing percentage of drivers have admitted to using their smartphones in their vehicles to access the Internet, read or answer e-mails, and read or update social media networks, culminating in roughly one-fourth of all drivers going online while driving. Furthermore, using a cellphone while driving is not just a problem for teenagers; large percentages of drivers over the age of 40 have been documented [23]. On the other hand, many drivers abruptly braking, or their braking-related behaviors, are responsible for many accidents. However, collecting data on drivers' pre-braking behavior using sensors put on vehicles is difficult [26].

3.3.4 ADVANCED DRIVER ASSISTANCE SYSTEMS (ADAS) AND ACTIVE MONITORING

Although different degrees and functions of intelligent vehicle technology are fast advancing, achieving a completely functional automatic driving car in the short future has proven impossible. We are only at the beginning of the man-computer cooperative driving stage, in which drivers and automated driving systems interact, and intelligent cars from L1 to L4 levels must deal with man-computer cooperative control issues. Furthermore, in the progress of man-computer cooperative driving, the allocation of driving rights and collaboration has been the most significant component. It was also agreed that determining the driving rights between the driver and the control system is a vital aspect of man-computer collaboration [21]. Microsleeps or reduced focus, for example, may go unnoticed by drivers but result in road accidents. Car manufacturers all over the world are looking into this issue and developing Advanced Driver Assistant Systems (ADAS), which assist the driver in analyzing the situation and controlling the vehicle. In addition, some automakers equip their vehicles with specific equipment that detects driver behavior. However, automobiles with this equipment are pricey and not available to the general public [46]. Despite the fact that developments in computing have powered increasingly complex and intelligent systems for active safety support in driving, active monitoring remains a problem for the adoption of Advanced Driver-Assist Systems (ADAS) [36]. Advanced Driver Assistance Systems (ADAS) help drivers become more aware of their surroundings while driving. Yet, not all users embrace and use it, indicating a lack of trust in automation and skepticism among drivers. Automation, for example, helps to reduce the workload of driving, which leads to a reduced awareness of the driver's situations, which must be taken into account while predicting the driver's vehicle handling [44]. However, if a driver's reaction time is quick and they drive actively, it's best not to issue a warning if they are aware of the collision risk ahead of time, because issuing collision warnings too frequently can reduce the reliability of the warnings and cause dissatisfaction or promote disregard while driving [6]. The classifications for these systems, Level 2 partial automation, and Level 3 conditional automated driving. The difficulty of transitions between machine and driver, in Level 3, is an active research topic in which the system hits its limits and the driver must regain control of the vehicle in a limited amount of time. Human capacities can decline owing to task switching and a lack of situation awareness. These consequences also apply to modern car assistance systems. If these theoretical constructions apply to automobiles with advanced driver assistance systems, is how long do drivers need to retake safe control of their vehicles [25]. The majority of effective ADAS technologies, such as lane departure warning (LDW), adaptive cruise control (ACC), and side warning assist system (SWA), are meant to provide additional driver support. While most of these technologies fail to monitor and interpret the driver's behavior in real-time [50[74].

3.3.5 DRIVING BEHAVIOR MONITORING

The main challenge here is whether we can detect aggressive driving behavior just by looking at detailed measures taken Driving is a multi-tasking operation that requires substantial human-machine interaction at this time and frequently involves four essential steps: surrounding monitoring, predicting, making decisions, and performing maneuvers. Many factors can influence a driver's performance and safety while driving[75]. To increase driving safety, a better understanding of vehicle and driver monitoring is required in these mixed assistive driving scenarios [7]. Sensing technologies for drivers, cars, or both are necessary, for example, recognize aggressive driving, it has been a variety of equipment has been used, including inertial measurement units (IMUs), on-board diagnostic (OBD) devices, and cellphones[66], among others. Their inertial sensors, in particular, are capable of delivering accurate motion data continually. However, they are unable to immediately measure vehicle conditions such as speed and steering because they are not directly connected to automobiles like OBDwith a smartphone [3]. In this context, when examining the impacts of traffic congestion, experts have primarily focused on driver behavior. Congestion can induce unpleasant feelings and aggressive driving behavior on non-congested highways following, referred to as post-congestion roads. In fact, in post-congestion scenarios, crashes occurred even more frequently. However, driver behavior in post-congestion scenarios is still ambiguous [37]. On the other hand, several approaches for monitoring driver performance have been launched in recent years; however, these methods have been associated with increased costs and delayed development. So, he did many researchers are attempting to provide other precise monitoring strategies to address these difficulties [4]. From another perspective, and be more specific, the difficulty in recognizing driver behavior stems from three factors: first, different classes of driver action exhibit similarity in the same global context; second, distinctions between categories are primarily reflected in small objects such as cellphones and cigarettes; and third, driver actions of the same category exhibit significant intraclass variation (e.g., the action of smoking and smoking gap) [8]. At the same time, researchers look also, into using multi-stream CNN to handle the challenge of recognizing driving behavior in still photos. where, the designation of multi-stream CNN is expected to have a stronger capability in local feature extraction, and the fusing of multi-scale information will result in higher accuracy in final driving behavior detection [10]. In any pattern recognition challenge, the duties of determining the meaning of the examined image, categorizing the objects, and providing the symbolic meaning or interpretation of the image are critical[76, 77]. So according to some recent research studies on computer vision and assistance driving, anticipating a driver's action a few seconds ahead of time is a difficult task. Where, the driver's head movement, eye gaze monitoring, and spatiotemporal interest points are used to anticipate the driver's behavior [15]. There is a study indicating that nearly all driver behavior observation systems only catch one unusual behavior, and only a handful detect multiple. However, no effective monitoring system exists that can reliably detect all of a driver's unusual behaviors at this time [78, 79].

4. CONCLUSION

This study offers a thorough analysis of the literature on the factors that influence driver behavior using a key factor taxonomy. An inventory of the literature's current techniques for collecting data is one of the study's conclusions. Enhancing understanding of the survey and classifying relevant research endeavors were the goals of this study.

Four categories were used in this study to group the research efforts in this field: framework, reviews, experiments, and other studies on driver behavior. Extensive reading and in-depth study of the evaluated literature yielded vital insights about driver behavior, including issues, motivations, and suggestions. The correlative gaps between the data gathering methods and the variables influencing driver behavior were identified by this investigation. Lastly, by categorizing important components and outlining data gathering methods, the framework this study offers may provide valuable understandings and a distinct image of driver behavior, enabling researchers to identify unmet research needs and opportunities.

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CONFLICTS OF INTEREST

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