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Driver Distraction Detection Methods: A Literature Review and Framework

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ABSTRACT Driver inattention and distraction are the main causes of road accidents, many of which result in fatalities. To reduce road accidents, the development of information systems to detect driver inattention and distraction is essential. Currently, distraction detection systems for road vehicles are not yet widely available or are limited to specific causes of driver inattention such as driver fatigue. Despite the increasing automation of driving due to the availability of increasingly sophisticated assistance systems, the human driver will continue to play a longer role as supervisor of vehicle automation. With this in mind, we review the published scientific literature on driver distraction detection methods and integrate the identified approaches into a holistic framework that is the main contribution of the paper. Based on published scientific work, our driver distraction detection framework contains a structured summary of reviewed approaches for detecting the three main distraction detection approaches: manual distraction, visual distraction, and cognitive distraction. Our framework visualizes the whole detection information chain from used sensors, measured data, computed data, computed events, inferred behavior, and inferred distraction type. Besides providing a sound summary for researchers interested in distracted driving, we discuss several practical implications for the development of driver distraction detection systems that can also combine different approaches for higher detection quality. We think our research can be useful despite - or even because of - the great developments in automated driving.

INDEX TERMS Automotive applications, automated vehicles, data systems, distraction detection, driver distraction, driver monitoring, driving distraction, intelligent transportation, vehicle driving.

I. INTRODUCTION AND MOTIVATION

Both driver inattention and driver distraction are huge challenges in road traffic, resulting in a high number of accidents and fatalities every year [1]–[3]. For this reason, vehicle manufacturers, suppliers, start-ups, and researchers are devoting more and more resources to better understand and measure the causes of driver distraction and inattention. Thereby, they develop warning and prevention mechanisms for drivers [4] or increase the automation level of the vehicle to avoid dealing with driver distraction in the first place, e.g., with automated driving functionalities [5], [6].

Some modern vehicles above a certain vehicle class and equipment level may already have simple systems that can detect certain types of driver inattention, such as driver fatigue [7], and warn the driver accordingly. Such systems are usually subsumed under the term driver assistance systems, which also includes vehicle automation systems such as adaptive distance keeping or lane keeping [8]. With the increasing automation of the driving function, more and more powerful systems will find their way into vehicles, with the aim of fully automated or autonomous driving [6]. Consequently, there is

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also increasing research and publication on driver distraction detection and related topics.

To increase understanding of driver distraction methods, we present in the paper the results of a scientific literature review to identify existing driver distraction detection methods, carefully analyze them, and extract the information flow for distraction detection. In the process, the identified methods are transferred into a framework for the detection of distracted driving to capture and structure the entire spectrum of distraction detection methods. By explicitly listing methods for detecting different types of driver distraction and integrating them into this detection framework, developers of driver detection systems can build on this basic knowledge in the future.

We see the novelty of our paper twofold: (1) We point out that despite the increasing automation of the vehicle, the human driver will continue to play a role as supervisor of the automation system for a long time, having to take control when initiated by the automation system and therefore needing at least a minimum of attention to keep delay to a minimum. (2) We reviewed the referenced literature on distracted driving detection according to a predefined scheme: Description of sensors used, data measurement, computed information, computed events, inferred driver behavior and inferred distraction detection approaches. By adding this information to a holistic distraction framework (cf. Figure 3), we point out several possible information chains from used sensors data to detected driver distraction types. Therefore, we see our literature review as a significant extension of existing reviews by taking this perspective. A further novelty of the paper is to include modern driver distraction methods into our analysis, non-intrusive ones that are based on fast-growing last years' computer vision technologies and intrusive ones that can be also used for detection of certain types of distractions detection approaches rooted in the psychological domain as well as to validate the results of non-intrusive driver distraction detection methods. In the paper we present a survey that considers and analyzes modern approaches, technologies, and systems as well as framework that shows the main approaches applicable for driver drowsiness detection.

After this introduction in Section 1, Section 2 provides the related background on driver distraction in general and in the context of automated driving to clarify what driver distraction is and how it relates to driver inattention. Next, Section 3 describes the research method used, a systematic literature review, while Section 4 presents the results of the literature review, a detection framework for driver distraction detection methods. Section 5 provides a discussion of the results and highlights the contribution of the paper to science and practice, while Section 6 concludes the paper.

II. BACKGROUND

A. DRIVER DISTRACTION

Driving a vehicle is an extremely complex task. Distraction and more generally driver inattention has been a major concern for road safety professionals and other stakeholders for many years as both increases the risk of an accident considerably. According to NHTSA statistics [9], approximately 25% of police-reported crashes involve some form of driver inattention such as the driver is distracted, fatigued, or otherwise lost in thought [10], [11].

For this very reason, researchers from the mobility and transport domain have been working intensively on both topics for many years. Many researchers have come up with definitions for the term distraction. For instance, Lee *et al.* [3] defined driver distraction as 'the diversion of attention away from activities for safe driving toward a competing activity.' Distraction occurs, when a driver 'is delayed in the recognition of information needed to safely accomplish the driving task, because of some event, activity, object, or person within or outside the vehicle compels or induces the driver's shifting attention away from the driving task' [10]. 'A triggering event induces an attentional shift away from the task' [12]. Regan *et al.* in the paper [13] reveal four key elements in defining driver distraction: i) 'a diversion of attention away from driving', ii) 'attention is diverted towards a competing activity, inside or outside the vehicle, which may or may not be driving-related', iii) 'the competing activity may compel or induce the driver to divert attention toward it', and iv) 'there is an implicit, or explicit, assumption that safe driving is adversely affected'.

An important question is to clarify the relationship between driver inattention and driver distraction. Distraction is only one of several mechanisms of inattention that can result in insufficient attention or even no attention at all for safe driving [12]. Regan *et al.* [13] reviewed existing definitions and taxonomies of driver distraction and driver inattention to more accurately interpret and compare research findings for a given form of driver inattention. According to them, driver inattention means insufficient or no attention to activities critical for safe driving. Forms of driver inattention are Driver Restricted Attention (DRA), Driver Misprioritized Attention (DMA), Driver Neglected Attention (DNA), Driver Cursory Attention (DCA), and Driver Diverted Attention (DDA) – a synonym for driver distraction. According to Regan *et al.* [13], driver distraction is one form of driver inattention. For some researchers, however, driver inattention differs from driver distraction, because the competing activity is missing [3].

Despite distraction is cognitive state of the driver, researchers distinguish several distraction detection approaches such as visual distraction, manual distraction, and cognitive distraction [14]–[16]. Drivers increasingly shift their attention from their driving task to non-driving related secondary tasks by taking their hands (manual distraction), eyes (visual distraction), and/or mind (cognitive distraction) off driving [14]. However, activities can also involve a combination of two, or even a combination of three distraction types (e.g., i – holding a smartphone for reading, ii – looking at the smartphone and texting messages, and iii – thinking about a message to texting), leading to an even higher risk of an accident. Additional types of driving distraction are auditory distraction (caused by acoustic stimuli) and vocal distraction (caused by any kind of vocal utterance) [15]. Cognitive distraction is probably the most difficult type of distraction to assess because it is difficult to observe what a driver's brain (as opposed to hands or eyes) is doing [16]. While also verbal distractions have been reported in the scientific literature, they were not significantly associated with accident responsibility [14].

Several researchers have conducted extensive studies in the domain of driver inattention and distraction: An early overview of related research is provided by Sussman *et al.* in [17], including driver attention processes, safety effects of inattention, their psychological and physiological indices, and works on onboard systems for detecting them. The systems tested include warning systems that monitor steering wheel movements, steering wheel reversal rates, or driver head movements. A review of in-vehicle driver distraction focusing on phone use, given that this device has received huge attention in the driver distraction, is provided by Young and Regan [2]. Both explicitly highlight the impact of devices used in vehicles and especially of mobile phones on driving performance.

Several simulator and field studies have been conducted to explore and better understand these phenomena from a psychological point of view and provide mechanisms to mitigate their consequences: For instance, Klauer *et al.* [18] conducted a comprehensive study on the effects of driver inattention on accident risk, using the data generated within the naturalistic 100-Car on-road study. The results indicate a higher risk when the driver is driving sleepily or performing complex tasks while driving and looking away from the road to scan the driving environment reduces the risk. Horberry *et al.* [12] present the results of a simulator study in which the effects of distraction during the performance of distraction tasks such as operating the vehicle entertainment system and conducting hands-free mobile phone conversations were studied. The paper [12] present the results of a simulator study in which the effects of distraction during the performance of distraction tasks such as operating the vehicle entertainment system and conducting hands-free mobile phone conversations were studied.

B. DRIVER DISTRACTION IN THE CONTEXT OF AUTOMATED DRIVING

The automotive industry worldwide invests enormous sums in the automation of vehicles to make driving safer and more efficient, but also more comfortable. According to the German Association of the Automotive Industry (VDA), the German automotive sector will invest almost 60 billion Euros in electric cars, digitalization, connected, and automated driving over the next three years [19]. The shift towards higher driving automation may suggest that inattention will not be an issue for much longer, but unfortunately this will not be the case in the foreseeable future as fully automated driving is still a long way off. Researchers expect that humans will continue to play a role in automated systems such as vehicles, even at higher levels of vehicle automation (e.g., [20]–[23]).

The maturity of automated driving in terms of vehicle control and rise in the degree of automation can be classified into levels, from no automation, where the human driver is fully responsible for driving, to full automation, where the automation system is fully responsible for driving. Popular taxonomies with detailed definitions of the different levels of vehicle and driving automation have been published by the Germany Federal Highway Research Institute (BASt, www.bast.de), the National Highway Traffic Safety Administration (NHTSA, www.nhtsa.gov), and the Society of Automotive Engineers (SAE, www.sae.org).

The Society of Automotive Engineers [24] provides the most cited taxonomy with detailed definitions for six levels (the so-called *SAE levels*) of driving automation: In Level 0 (no automation) the human driver performs all driving tasks.

In Level 1 (driver assistance) the human driver controls the vehicle, but driving assistance is included to assist the human driver either in steering or in braking/acceleration. In Level 2 (partial automation) the human driver must always remain engaged in the driving task and monitor the environment, but the vehicle has combined automated functions such as automatic acceleration, braking, and steering. In Level 3 (conditional automation), the driver must be ready to take control of the vehicle after prior notice. Under certain circumstances, the automated driving system can perform all aspects of the driving task, but the driver must be ready to take control at any time if requested by the automated driving system. In Level 4 (high automation), the vehicle can perform all driving functions under certain conditions, but the driver can have the option of controlling the vehicle. Under certain conditions, the automated driving system can perform all driving tasks and monitor the environment, taking over the entire driving process. Under these circumstances, the driver does not need to be attentive. In Level 5 (full automation) the vehicle can perform all driving functions under all conditions. The driver can have the option to control the vehicle. The automated driving system can take over the entire driving task under all circumstances. Human occupants are only passengers and never have to be involved in driving. SAE Level 5 vehicle meets the characteristics of a fully autonomous vehicle.

Automated driving at Level 4 and Level 5 has not been technically fulfilled by vehicle manufacturers yet [25]. However, the transition from automation Level 2 to Level 3 alone is perceived as a major challenge and a paradigm shift, especially due to the temporary shift of responsibility from the driver to the vehicle: Level 3 vehicles should be able to operate most of the time in automated mode, but in road or traffic situations that they cannot handle, the driver must quickly take over. This means that the driver must be so attentive while driving to quickly take control if something goes wrong. Suppose a Level 3 vehicle works so well that drivers can distract themselves with music and text messages, for example, while driving on a highway. Would such drivers then be able to take control of the vehicle again, e.g., in front of a construction site that the vehicle cannot handle in automated mode, and would these drivers be able to react quickly enough when the vehicle asks them to hand over?

Automated driving requires the handover between driver and automation system, and this takeover task represents a major vulnerability in the automation system, as situation awareness is reduced and possible breakdowns in communication can arise [26]. It is therefore important to keep drivers 'in the loop', e.g., by providing continuous feedback to them on the system limits and behavior of vehicle automation instead of issuing discrete warnings, to increase the frequency of proactive responses to automation failures and to improve system understanding [27]. A driver who is 'in the loop' has physical control of the vehicle and monitors the driving situation, while a driver who is 'out of the loop' does not have physical control of the vehicle, and does not necessarily monitor the driving situation, or has physical control of the vehicle but does not monitor the driving situation [28]. Reducing the takeover times for drivers engaged in non-driving-related activities poses a challenge for the designers of Human-Machine Interfaces (HMIs).

A central challenge in introducing automated driving is how to reach Level 3, which once seemed like a natural step in the evolution of automated driving technology. However, Level 3 suffers from its division of responsibilities between the automation system and driver. While on Level 2 the human driver is responsible for the entire driving operation regardless of functionality, and on Level 4 the automation system is responsible and the human driver as an occupant plays no role, Level 3 lies between the two: While the automation system is in control of driving, humans are still needed if the system encounters a situation that it cannot handle. This has led some vehicle manufacturers to say that they will skip automation Level 3 altogether and move on to Level 4. While vehicle manufacturers seem to struggle in pursuing the evolutionary mode towards automated driving, other endeavors pursued by Waymo and Uber to deliver commercially viable fleets of fully automated taxis have also not been successful so far [29]. Another attempt to implement Level 3 in practice, at least in the USA, is being made by vehicle manufacturer BMW [30] with the iNEXT model, which has a mode that allows drivers to activate the automated driving system to concentrate on other activities on highways with limited access up to a maximum speed of 85 mph, and only if weather and environmental conditions allow the vehicle sensors to operate without interference.

It therefore remains essential that drivers of automated vehicles continue to concentrate on their driving task if the vehicle is operated in Level 2 or below, while the Level 3 challenge has still to be solved. The advent of autonomous vehicles will give new impetus to driver distraction detection, as the use of vehicle automation features appears to give drivers some scope for distraction. This is another reason why public authorities are imposing more and more regulations on newly registered vehicles to increase road safety and combat driver distraction: for example, the European Commission [31] has adopted a revised General Safety Regulation that requires new mandatory safety features in newly registered vehicles. These include systems to warn of driver drowsiness and distraction (e.g., using camera-based systems).

III. RESEARCH METHOD

A. LITERATURE REVIEW METHOD

In this paper, the researchers use a literature review to identify existing driving distraction detection methods for driver monitoring in the vehicle cabin, analyze them, and extract an information flow for distraction detection. Thereby, the literature review process follows common and established guidelines (based on [32]–[34]) for scientific rigor.

The approach we used to identify the relevant literature included a broad sampling frame that covers a wide range of academic disciplines including computer science, mobility and transport, mathematics, information systems, human factors, and psychology that are interested in the interdisciplinary topic driving distraction focusing on both manual and automated driving. We are especially interested in published scientific works that have published driving distraction approaches and related methods (e.g., for detection of certain human poses). We started our literature review by conducting a keyword search, mainly using Google Scholar using keywords such as "driver distraction", "driver monitoring", or "distraction detection". However, we also searched the references of the identified papers for cited related work and added additional papers to our review sample by applying forward and backward reference searches.

B. REVIEW SAMPLE

We reviewed all papers related to distraction detection presented in the references section and have summarized their sources (peer reviewed journals and conferences) in the Table 1. The table provides an overview of what kind of journals and conference proceedings publish scientific work on driving distraction research (and related topics) and thus contribute to the state of the art of distraction research (we show in the tables only the sources that contains more than one paper from our references section).

IV. RESULTS

A. DRIVER DISTRACTION EVALUATION METHODS

In the scope of our holistic method framework, we consider the following main driver distraction detection approaches: i) manual distraction, ii) visual distraction, and iii) cognitive distraction. Manual distraction manifests in driver actions related to hands and feet (e.g., removing hands from steering wheel or feet from pedals). Visual distraction includes actions related to the driver's loss of visual contact with the road or immediate surroundings (e.g., closing eyes, or not looking ahead on the road).

Cognitive distraction is when the driver thinks about things that have nothing to do with driving (e.g., having conversations, being in high emotions, being stressed,

TABLE 1. Considered paper sources for our literature review.

#	Source	Papers
1	Accident Analysis and Prevention	[12], [13], [14], [35], [36]
2	Transportation Research	[17], [26], [28], [37], [38]
3	Lecture Notes in Computer Science	[8], [39], [40], [41], [42], [43]
4	arXiv	[41], [44], [45], [46]
5	IEEE Transactions on Intelligent Transportation Systems	[7], [25], [47], [48], [49]
6	Applied Ergonomics	[50], [51]
7	SAE	[24], [52]

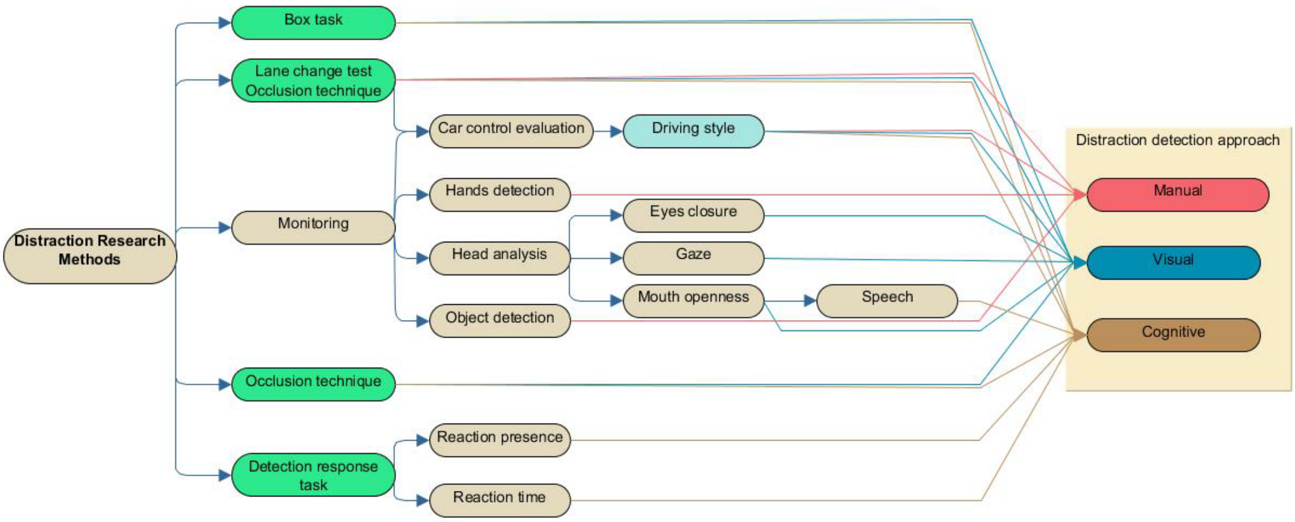

FIGURE 1. Method classification for driver distraction research.

or daydreaming). These three types of driver distractions can occur in isolation from each other, but they can also occur together. The methods reviewed in our paper are used for the analysis of driver distractions according to one or more of these three types.

However, driver distraction can also be of a mixed nature, for example, when the driver rubs his/her eye, this distraction is both visual (because the driver's vision is occluded) and manual (because the driver's hand is not on the steering wheel). Driver behavior in the vehicle cabin is a monitor-able concept.

Driver distractions can also have a severe impact on the driving style. For example, a visually distracted driver may have difficulties in maintaining longitudinal and lateral control of the vehicle. Driving style is another monitor-able concept [53] that may provide the ability to estimate the distraction level indirectly through monitoring a sudden and abnormal change in parameters like speed, acceleration, or position on the road, compared to the usual driver parameters acquired before, which correspond to normal driving situations without distraction. A bad driving style includes speeding, turning from the incorrect lane, inaccurate lane keeping, tailgating, and rough driving. Such rough car behavior can be detected by vehicle and smartphone sensors. Events such as a sudden change in lateral acceleration can be caused by any type of driver distraction, but they can also be intentional.

From our review of the scientific literature, we propose a method classification for driver distraction research (see Fig. 1). Thereby we highlight two classes of methods: methods for distraction research in a laboratory environment (shown in green color) and methods for distraction detection that can be used both in a laboratory as well as in real driving conditions on public roads (shown in brown color). In the scope of the first class of methods, following the experimental setting, drivers are specifically distracted in different situations, or their eyes are covered while the level of distraction is measured in the laboratory environment using a vehicle simulator equipped with additional sensors. In contrast, the second class is aimed at in-vehicle cabin driver monitoring with the goal of actually detecting certain causes of distraction.

There are several techniques that have been developed to assess the degree of driver distraction caused by an engagement in non-driving related secondary tasks [50]. In the following, four of them are explained in more detail. First, the *box task method* is aimed to measure the amount of cognitive load imposed by various distracting tasks [54]. Respective experiments may be conducted in the following way: Participants may use pedals and the steering wheel to control the size and position of a box on a screen. Around this box, there are boundaries that change their size and shape. The main objective of the participant is to keep the controlled box inside the boundaries. To measure the performance of a participant, the system records several intersections of the box with the boundaries and the standard deviation of box size and position from the ideal size and position. During these experiments, in some sessions, participants are not distracted, and in other sessions, participants are also asked to perform some additional secondary tasks, such as talking, or dialing numbers. The drop of measured performance reflects the amount of cognitive load that various additional tasks impose to the driver [50].

It is possible to reverse the box task method to detect driver distractions. If the vehicle has an 'autopilot' function that can keep the lane and the distance to the car driving in front and is switched on but disabled, a standard variation of the steering wheel and pedals positions from the autopilot's proposed steering wheel and pedals positions can be measured to evaluate the driver's level of distraction.

Second, another method used in driving distraction research is the *lane-change test*. The essence of the method is the same, but the main task of participants is not to keep a box in boundaries but to change lanes during driving in a simulated environment. When a lane change sign appears, participants must change the lane as quickly as possible. The standard deviation between the ideal path and the actual path is measured to evaluate the participant's performance [50]. If the car has an autopilot, this method can also be reversed: the standard deviation between the car path and the autopilot's proposed lane change path can be used to measure the driver's distraction level.

Third, occlusion technique [55] is a method to analyze the visual demand of a driver. In the respective experimental setup, the driver wears a special helmet, with a cover that can be moved up and down. When the cover is raised, the driver can see normally. When the cover is down, the driver cannot see anything. The cover occludes the driver's vision most of the time but is periodically raised. The driver is asked to drive as fast as possible in a simulated environment, while still maintaining a safe speed. The dependency between maximal safe speed and the period of moving the cover upwards provides information about the necessary amount of visual information for safe driving.

Fourth, *Detection-Response Task* (DRT) "is a method for assessing the attentional effects of cognitive load in a driving environment. Drivers are presented with a sensory stimulus every 3–5 s, and are asked to respond to it by pressing a button attached to their finger. Response times and hit rates are interpreted as indicators of the attentional effect of cognitive load" [56]. Thereby, sensory stimuli are selected according to the secondary task / system to be evaluated (e.g. visual stimuli for a cockpit) [57]. DRT is simple to implement, rather cheap and a "more reliable detection of the effects of cognitive load compared to self-evaluation questionnaires" [56]. Even development guides exist to build a test-kit on your own using an Arduino [58].

A comparison of the considered methods is shown in Table 2. The main advantage of the *box task* method as well as the *lane-change test* is the possibility to test all approaches to distraction detection considered in the paper. However, the *box task* method is generally unrelated to the driving scene. The driver uses the vehicle controls (pedals and steering wheel), but they only control the box and not a driving scene. In contrast, the *lane-change test* method considers the simulated driving environment, but the driver should only perform one task (lane change control). The method does not consider such tasks as emergency braking, consideration of the driving scene (signs, other participants), etc. Unlike the methods considered so far, the *occlusion technique* allows calculating an important parameter of the possible time when the eyes can be occluded. This may be associated with closed eyes (in case of drowsiness or prolonged blinking) and situations when the driver is not looking at the road (e.g., cell phone use, looking to the right, left), etc. The last considered method is *DRT* that is aimed at driver reaction time measurement. In contrast to other methods it is related to reaction time measurement by asking the driver to implement secondary task. The main disadvantage of the method that it do not take into account the driver scene (e.g., the driver should press the button and the system counts the time from request to response). However, such approaches do not take into account the cognitive approach to distraction detection.

TABLE 2. Pros and cons of driver distraction degree measurement.

Method	Pros	Cons
Box task	All approaches to distraction detection can be tested	Not related to driver scene (box control)
Lane-change test	All approaches to distraction detection can be tested	Only lane change task is considered
Occlusion technique	Calculation of the possible time the eyes can be occluded	Cognitive distraction is not considered
Detection response task	Driver reaction time change is measured	Not measuring the driver scene

The second class of methods we review in our paper is focused on driver distraction detection, while the driver is driving in real conditions. Some of these methods require the driver to react to a stimulus, while other methods rely purely on driver monitoring. Methods based on *driver monitoring* do not require the driver to do anything other than driving.

Thereby, it is possible to detect the presence of distracting objects (cups, phones, bottles, cigarettes) in the vehicle cabin [59]. Also, estimate the drivers hand positions to detect when the driver is removing hands from steering wheel [60].

Authors propose to perform analysis of eye and gaze behavior [51] as well as [38] head movements [44], detect talking [47] and analyze emotions in the driver's voice [39], and to evaluate the driving style [47], [37].

In contrast, methods based on the *reaction to stimulus* require the driver to do some additional actions. For example, the driver may be required to press a button or to say a keyword whenever some stimulus appears. This stimulus can be tactile, visual, or audial. The detection response time is measured and is used to evaluate the driver's vigilance (such systems are widely used in trains worldwide). In some methods, for example in the peripheral detection task method, it is expected that some stimuli will be missed. The frequency of detection misses can also be used to evaluate driver distraction levels [61].

We discuss the methods that can be used for driver distraction detection in more detail in the next section Thereby, we will introduce the relevant sensors, describe how the measured data can be processed, which parameters should be calculated, and what events should be computed to finally infer one or more different types of distraction. Driver distraction detection is about first obtaining and then understanding the behavior of people and objects in the vehicle cabin.

B. DISTRACTION DETECTION

Based on our conducted literature review we propose a comprehensive method framework (see Fig. 2) that discusses different driver monitoring methods capable of inferring three types of distraction, manual, visual, and cognitive distraction.

Driver distraction detection monitoring systems can be described by,

- the set of sensors used,
- the types of distraction that algorithms can detect, and
- the methods used for the fusion of information from different algorithms (that is out of the scope of this review paper).

From the papers reviewed, we present a possible information flow from captured sensor data to the detected driver distraction types. The schema is illustrated in Fig. 2. There are six columns in the framework: ‘‘Sensors’’, ‘‘Measured data’’, ‘‘Computed information’’, ‘‘Metrics and events’’, ‘‘Inferred behavior’’, and ‘‘Distraction type’’. The ‘‘Sensors’’ column contains information about physical devices that capture data about the driver and the vehicle. The ‘‘Collected information’’ column contains nodes, that represent raw, unprocessed data produced by the sensors. The ‘‘Computed information’’ column contains nodes representing measurable observations, computed from measured data. The ‘‘Metrics and events’’ column contains nodes that represent aspects that directly imply driver distraction and can be objectively validated. The ‘‘Inferred behavior’’ column contains assumptions about a real-world situation, that can be interpreted from obtained data. The ‘‘Distraction type’’ column contains the three types of driver distractions that may be inferred by the driver distraction detection system. An example would be an interior camera (sensor), which produces a video / depth map (measured data), which is used to compute the gaze direction (computed information), detects events if the eyes are off the road and detects e.g. a phone (metrics and events), infers manual behavior, e.g. texting (inferred behavior) and thus finds manual distraction (texting) and visual distraction (eyes off road).

Figure 3 includes all the varieties found in the reviewed papers, e.g. 17 different sensors, which act as data sources for distraction detection. The nodes and arrows are colored in accordance with the final destination (light brown nodes have paths to multiple final nodes). Nodes that can be used directly to make a conclusion about the presence of distraction, are highlighted with a bold frame. Driving style evaluation has two major differences from all other nodes: 1) it performs the monitoring of the vehicle, and not the driver and 2) can provide indirect information that the driver is or might be distracted, but no information about whether the distraction is manual, visual, or cognitive. For these reasons, nodes related to driving style evaluation are also shown in distinct color (light blue).

The first column contains sensors that can be used to finally detect the driver’s distraction. Sensors are divided into two categories, intrusive and non-intrusive. Non-intrusive sensors do not distract the driver and are most adequate for large-scale commercial systems, e.g., systems built into series vehicles. Intrusive sensors such as Electroencephalography (EEG) can obtain more accurate data regarding certain causes of driver distraction (e.g., cognitive distraction) as they enable the correct differentiation of human cognitive activities for different tasks. They are more useful for research purposes and to collect ground truth. Intrusiveness thereby refers to the extent to which the sensor could interfere with drivers and affect their ability to drive safely. Ideally, a sensor indicates the level of distraction or the need to focus on the road before the driver feels increased effort or reduced performance [62]. However, for investigating distraction most researchers make use of non-intrusive sensors [63]. Non-intrusive methods are therefore preferred for monitoring the driver, and vision-based systems seem most attractive for both researchers and drivers [64]. Sensor characteristics considered for in-vehicle driving distraction systems, in general, include precision (ability to detect distraction when it occurs), robustness (be insensitive to ambient noise), timeliness (ability to indicate distraction without delay), intrusiveness (does not require overt responses or driver-mounted sensors), and cost (are sensor costs feasible for integration in a production vehicle) [62]. The main use of intrusive sensors comes from the fact that they can help to evaluate the driver’s state of mind and emotions, which is not achievable with non-intrusive sensors. However, some types of intrusive sensors can be very uncomfortable and then also affect the movements and poses of the driver and thus may lead to biased distraction detection results, which should be taken into account when interpreting the obtained results. This property of intrusive sensors shrinks the area of possible applications of some of these such sensors to research purposes only.

Inertial measurement unit, exterior camera, and GPS provide a small amount of information about the driver, but these sensors give a lot of information about the driving style. For instance, the accelerometer allows judging the smoothness of the ride. The exterior camera allows to detect the current car position in the road and current state of the art methods use neural networks to perform it [45], [65]. Such methods allows to estimate the range to the vehicle in front, which can be done using the car detector as well as simple geometric considerations [59]. The lane position allows judging whether the driver is turning from the correct lane. The variance of the position inside the lane allows estimating how well the driver

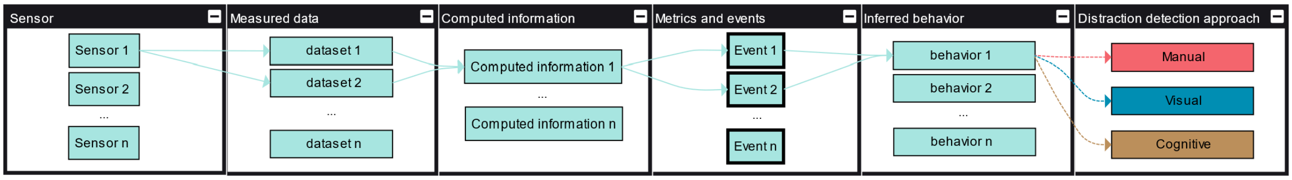

FIGURE 2. **Schema of the distraction detection framework.**

is keeping the lane. When the lane is detected, an instantaneous roadway tangent can be calculated. The difference between the roadway tangent and the vehicle heading is called heading error and can also be used as a driver performance metric [66]. Authors of the paper [67] compared difference between distracted driving and normal driving. The presented approach uses average vehicle speed, lateral acceleration standard deviation (SD), steering wheel input value SD, steering wheel rotation rate SD, lane deviation mean, and lane deviation SD as the identification indicators of distracted driving behavior. Based on proposed characteristics authors propose to train a machine learning model based on logistic regression and Fisher discriminant model and achieve the accuracy of 94.79%.

Another use of the exterior camera is the detection of traffic signs. Any modern image detection technology can be applied to do it, for example, Neural Networks (NNs) with such architectures as YOLOv4 [41], SSD [42], or Faster-RCNN [48]. Traffic sign information can also be obtained from maps. Videos from the exterior camera can be used to perform visual localization and to improve the accuracy of car position estimation (e.g., [49], [68], [69]). Vehicle position (gained through using GPS information) combined with traffic sign information allows to deduce local speed limits, which makes information useful to detect speeding behavior. It is worth mentioning that the current speed of the vehicle should be considered in all distraction detection systems, because if the vehicle is stopped, the determined possible driver distraction is irrelevant.

A steering wheel position sensor can be used to calculate the steering error as the difference between the second-order Taylor series expansion prediction of steering angle and the observed steering angle [52]. This error increases during the cognitive load or when the driver glances off-road [35]. Also, the steering wheel position sensor gives indirect information of the driver's hand behavior. Steering wheel based distraction detection systems have already a comparably long tradition in vehicles.

Interior cameras provide one of the most comprehensive data streams for driver distraction detection. Using only a single frame from the video it is already possible to detect distractions caused by drinking, texting, calling, talking to a passenger, not looking at the road, usage of car multimedia system, reaching behind, adjusting hair or makeup (see [70], [60], [36]), and eyes rubbed [71]. In most cases, NNs are used to detect such types of distractions ([70], [72], [43]). In the paper [73] authors compared performance of such architectures as VGG, AlexNet, GoogleNet and ResNet and achieved the maximum quality with ResNet architecture, with a substantial margin. In the paper [74] authors proposed to extract the features from pre-trained convolutional neural networks VGG-19. The model turned out to be very accurate due to testing with leave-one-driver-out cross validation method.

We compared the mentioned papers in Table 3 based on similarity of used datasets. In some papers authors split considered datasets to train and test data randomly, while in other papers authors divided drivers into train and test groups. Accuracies calculated with these two methods should not be directly compared to each other, because data is highly correlated.

Some distractions can be detected with simpler techniques, such as counting the fraction of pixels darker than the threshold in the mouth area, or calculating eye and mouth aspect ratio [59], [71]. For example, in [60] authors use Support Vector Machine (SVM)-based algorithms to detect eye closure. Head pose is usually estimated using Perspective-N-Points solution combined with the RANdom SAmple Consensus (RANSAC) algorithm, as for example in [59]. Another approach is to use Machine Learning (ML) regression algorithms directly on captured image data as discussed in [44] and [75].

There are many methods to estimate gaze direction using the images of the eyes. Most accurate methods use neural networks (described in [76] and [46]) but for rough gaze direction estimation, it is enough to apply simple computer vision algorithms such as pupil position detection [77].

Depending on the position of the interior camera it is possible to detect the driver's hands position as well as using a hand detection sensor to directly observe when the driver takes the hands off the steering wheel. In case the driver's hands are not fully captured by the camera, their positions can still be indirectly estimated by analyzing the positions of the visible parts of the arms. For example, in [60] authors proposed to use the AdaBoost classifier for this purpose.

Using entire sequences of frames from video, it is also possible to measure such metrics as percentage of eyelid closure (PERCLOS) ([59], [60], [47]), blink duration [71], head off-road time, eyes off-road time ([59], [77]), yawning and nodding ([59], [60], [71]). These metrics are useful to detect driver fatigue and visual distraction.

Other types of cameras can be used for driver monitoring, too: For instance, infra-red cameras can be used to mitigate variation in lighting conditions [43] and feet-looking camera can be used to analyze feet behavior. For example, in [78] authors use a feet looking camera to predict pedal applications even before they happen. Thereby, authors pass

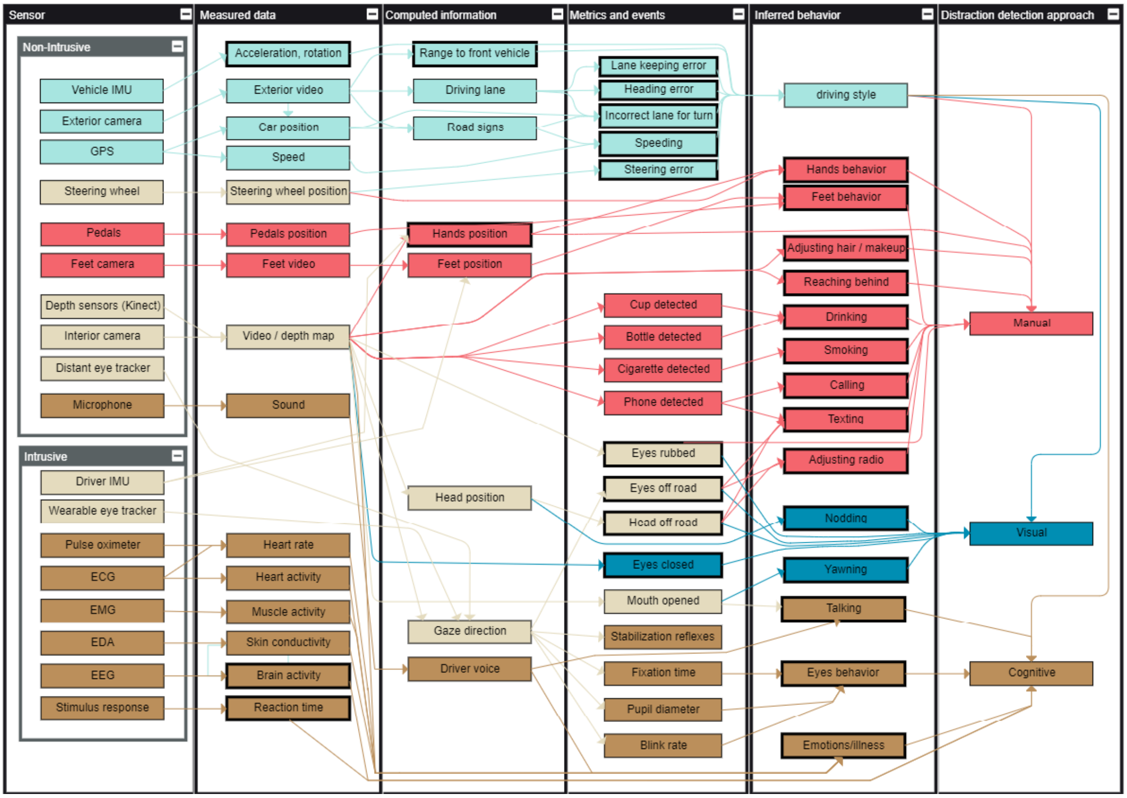

FIGURE 3. **Distraction detection framework.**

features extracted from optical flow to a Hidden Markov Model (HMM) and argue that this might help to predict pedal misapplications such as situations when the driver intended to press one pedal but pressed another pedal.

Specialized eye trackers allow evaluating gaze direction with higher precision than cameras. Eye trackers can be worn on the head or mounted in the vehicle. Both types allow estimating a particular spot, at which the driver is looking, allowing an estimation, how much attention the driver gives to road signs, other vehicles, and pedestrians. It is also possible to evaluate the cognitive load from analyzing the eye behavior. Increased cognitive load leads to lower accuracy of vision stabilization reflexes. In [38] authors used this phenomenon to evaluate the amount of cognitive load. Authors predict such vision stabilization reflexes as vestibulo-ocular reflex and optokinetic response. They calculate the Mean Squared Error (MSE) between gaze direction as predicted by reflex models and actual gaze direction. According to their experiments in case of no additional cognitive load presented, MSE was calculated in the study as 0,00043 and when the driver performed additional cognitive workload, MSE increased to 0,0019.

The authors prove the statistical significance of this difference using the student's t-test, that result in p-value $<0{,}005$. A p-value is a measure of the probability that an observed difference could have occurred just by random chance. This suggests that the increase in this metric can be a reliable indicator of cognitive distraction. The authors used the head-mounted eye tracker EyeSeeCam with a 220 Hz framerate that is an expensive and complex solution. However, looking at the graphs, it seems that a frame rate of 1 Hz, with a discretization of the gaze direction of 1 degree is already sufficient (and significantly cheaper) for their method to be applicable.

In [51] authors analyze how cognitive distractions affect other eyes behavior aspects. They find out that increased cognitive workload leads to increased pupil size (from 25 px to 27 px, with $+/-1$ px std), increased blink rate (from 0.2 to 0.6 blinks/s with 0.05 std) and decreased mean relative fixation time (from 0.9 to 0.75 with 0.07 std).An in-vehicle microphone can be used to detect drowsy voices (for example in [79]–[81]). Researchers have even extract emotions from the captured voices of vehicle drivers [82], [39], [40], [81]. Usually, it is performed by training a machine learning algorithm (e.g., HMM or Recursive NNs (RNNs)) on Mel-Frequency Cepstral Coefficients (MFCC) features, but other features and approaches can also be used. Another useful metric is the voiced/unvoiced ratio [47] that can help to evaluate the driver's fatigue. The microphone also allows to detect the presence of music in the car.

There are papers that are aimed at cognitive issues analysis of the driver (like [83] or [84]) but we did not consider that topic comprehensively in the paper since at the moment there are no non-intrusive way to measure the driver mental condition. Using the intrusive methods are not applicable for the drivers since every time the driver start his/her trip it is uncomfortable to wear some devices.

TABLE 3. Papers that tested different NN architectures.

Paper	Year	Dataset	Architecture	Mean accuracy
[70]	2018	AUC Distracted Driver Dataset (unseen drivers)	VGG-16	0,7613
			ResNet50	0,8169
			InceptionV3	0,9006
		AUC Distracted Driver Dataset random images (mind high correlation with training dataset)	AlexNet	**0,9429**
			InceptionV3	0,9517
			Weighted GA	0,9598
[72]	2018	State Farm random images (mind high correlation with training dataset)	Optimized HRNN	**0,9623**
		State Farm random images (mind high correlation with training dataset)	ResNet+HRNN	0,9172
		AUC Distracted Driver Dataset random images (mind high correlation with training dataset)	Optimized HRNN	**0,9236**
[43]	2019	Own simulated RGB	SqueezeNet	0,8305
			ResNet18	0,9237
			ResNet34	**0,9598**
			ResNet50	0,9443
		Own simulated near infra-red	SqueezeNet	0,7721
			ResNet18	0,9224
			ResNet34	0,9033
			ResNet50	**0,9036**
[73]	2018	Own 10 drivers, in simulator (unseen drivers)	Baseline VGG-16	0,79
			Baseline AlexNet	0,81
			Baseline GoogleNet	0,83
			Baseline ResNet	0,88
			Optimized VGG-16	0,86
			Optimized AlexNet	0,88
			Optimized GoogleNet	0,89
			Optimized ResNet	**0,92**
[74]	2017	Own, 10 drivers, in car (leave-one-driver-out cross-validation)	VGG-19	0,8025

V. DISCUSSION

A. NOVELTY OF OUR RESEARCH

Driver distraction has become a popular topic for research and development during the last years. There are a lot of surveys that have been published related to the topic. In our literature review we analyzed scientific papers published up to the end of 2020 related to distraction detection, propose a classification of the detection methods as well as a distraction detection framework that comprehensively summarizes all information and knowledge related to this crucial topic in transportation research. We see the novelty of our paper in two perspectives: (1) We point out that despite the increasing automation of the vehicle, the human driver will still play a role as supervisor of the automation system for a long time, who has to take control when initiated by the automation system, and therefore needs at least a minimum of attention to keep the delay in cases of take-over maneuvers as low as possible. (2) We reviewed the referenced literature on distracted driving detection according to a predefined scheme: Description of sensors used, data measurement, computed information, computed events, inferred driver behavior and inferred distraction types. By adding this information to a distraction framework (cf. Figure 2), we show several possible information chains from the used sensor data to the detected driver distraction types. Therefore, we see our literature review as a significant extension of existing reviews by taking this perspective. We now compare our performed review results with several other ones that are more similar to our research and highlight the distinguishing features.

Authors of the survey [85] cover such aspects as driver monitoring as drowsiness and distraction. The main focus of the survey is drowsiness, which gives only a small amount of information about driver distraction detection. Furthermore, authors mostly focus on methods, based on the head pose and gaze direction estimation, further narrowing the scope. Furthermore, the methods mentioned in their survey are from 2008-2014. Hence, this survey lacks modern NN-based methods that have been developed las five years. Our survey is substantially more comprehensive, covering many more vision-based methods, as well as methods based on driving style, driver behavior, and driver's voice.

Authors of the survey [86] cover distraction assessment methods in a great detail. However, their focus is dedicated exclusively to distraction assessment methods, while the main focus of our survey is distraction detection methods.

Authors of the survey [87] comprehensively overview papers about different kinds of driver behavior, including fatigue, driving style, aggressive driving, inattentiveness, drunk driving. With such a broad spectrum of driver behavior analysis, the authors provide a much less detailed overview of driver distraction detection systems.

Authors of the survey [88] focused on distraction detection, fatigue detection as well as driving style analysis. Despite the broad spectrum of topics, the authors provide an in-depth overview of methods based on head and eyes behavior, distraction detection based on physiological information such as electroencephalogram (EEG), electrocardiogram (ECG), skin temperature, electrodermal activity (EDA), electromyogram (EMG), and electrooculogram (EOG). The authors describe in detail how visual and cognitive distractions affect driving. They also provide a more high-level overview diagram of interconnections between the research topics driver distraction detection, driver fatigue detection, driving style recognition, driver lateral, longitudinal, and integrated behavior, and driver situational awareness. In our literature review, we put the focus on driver distraction detection systems based on non-intrusive sensors and provided a more in-depth overview of the research papers and methods.

In survey [89] many physiological and physical features are discussed in details, as well machine learning algorithms that are most useful for analysis of such features. Survey was published in 2011, a year before deep convolutional neural networks revolutionized computer vision, and therefore deep learning methods are not covered in that survey. We cover deep learning approaches in our survey and discuss more recent approaches.

B. DISTRACTION IN THE ERA OF AUTOMATED DRIVING

The topic of driving distraction has received a major scientific boost in relation to the increasing level of automation of vehicles. Since drivers can already be assisted more and more in their driving tasks within the system limits, it is to be expected that many drivers will rely on the vehicle to take over the driving task completely and focus their attention on other activities. This is a considerable traffic risk that has already led to accidents with distracted drivers. To counter this, it is expected that vehicle manufacturers will expand their sensor technology not only in terms of a better interpretation of the vehicle environment but also for better interpretation of the vehicle interior to detect possible distractions. With a multi-layered sensor system in the interior, there is considerable potential for detecting distractions at an early stage and warning distracted drivers accordingly. In this respect, our contribution aims to provide a solid basis and an overview of existing methods for the detection of driver distraction.

Paradoxically, distraction detection systems are becoming more important even though the level of vehicle automation is slowly increasing. This is, because vehicle driving will not suddenly happen autonomously, but drivers of automated vehicles will still have to be attentive so that they can take over the controls if necessary. The advent of autonomous vehicles has given new impetus to the development of driver distraction detection systems, as the use of vehicle automation functions appears to provide drivers with some scope for inattention, because, for example, the combined use of lane keeping and distance keeping can give drivers the impression that a vehicle is driving autonomously, and they can misuse these system functionalities to distract themselves with other activities. This over-trust in automation systems combined with driver distraction is one of the main causes of accidents. Vehicle driving does not happen autonomously, but drivers will still have to be attentive in monitoring the vehicle in case automation functions are activated so that they can take over the vehicle controls if necessary. Current automation systems only work within their system limits and must always be monitored by the driver. Although the shift towards more automated driving gives the impression that human driver inattention will not be an issue for much longer, experts disagree. Unfortunately, this will not be the case in the foreseeable future, as fully automated driving is still a long way off. Researchers assume that humans will continue to play a significant role in automated systems such as vehicles, even at higher levels of automation (e.g., [20]–[23]). This fact leads to an increased need for research on the topic of inattentive driver detection.

In the course of increasing vehicle automation, the human driver will increasingly become the operator and supervisor of the automation systems until he or she will no longer be necessary for fully autonomous driving, according to the experts' vision. But until that happens, the driver must carefully monitor the automation system in the vehicle. Thereby, the driver's attention must be ideally divided between monitoring the road and the driving context and monitoring the vehicle automation. This can almost certainly lead to periods of distraction if the driver is too busy monitoring the dashboard and forgets about the road and traffic. But even today, a driver has to monitor the manual vehicle in a certain sense, e.g., whether certain status messages such as "Check Engine Light" in combination with the oil warning light should actually prevent further driving. So even when driving a manual vehicle, the driver is constantly exposed to stimuli or information that can distract him. Therefore, a constant trade-off between conveying important information and reducing vehicle-related sources of distraction must be mastered. In this context, the design of the human-machine interface and the information and warning function of a vehicle play an important role.

We have reviewed the scientific work under the umbrella of distraction detection in the context of the increasing pervasion of automated driving systems. However, we have found that the work we have reviewed does not yet sufficiently address distraction in the context of automated driving and how the information that automated vehicles generate to better understand the environment can finally feed distraction detection systems. The sensors in automated vehicles such as radar or lidar can detect the traffic and environmental context and use this information to enable more advanced context-aware distraction detection systems linking information gained on in-cabin understanding with information gained from a better understanding of the environment. However, distraction in the context of automated driving has so far attracted little attention from the scientific community.

C. LIMITATIONS OF OUR RESEARCH

The limitations of the research presented here are mainly related to our research approach chosen, a structured literature review. We started our review with a keyword search, mainly using Google Scholar, and then also searched the references of relevant papers we identified for other related work. We then added additional papers to our review by applying forward and backward reference searching. However, by doing so, we may have missed some important papers in our literature search and were unable to include them in our work.

However, literature review do not say about exact threshold for particular distraction types. We have found different information for eyes off road, e.g., researchers from the paper [18] say about 2 seconds, researchers from [90] say about 150 feet that vehicle should go, researchers [91] say about 4 seconds in parking area (speed less than 20 km/hour) and 2 seconds if speed is more than 80 km/hour. But for hand position we did not find any threshold information. To give another example, the 15-second rule [92] for driver information systems specifies the recommended maximum time for the driver to perform manual operations in the vehicle with visual displays. Although vehicle designers should make cases for lower task limits, these 15s can be considered an indicator of distracted driving if a driver is engaged in manual vehicle controls such as navigation for longer than 15s. A Level 2 automated vehicle will also warn the driver after 15 seconds, when the driver has taken his or her hands off the steering wheel for the first time.

D. LIMITATIONS OF REVIEW SCOPE

Some of the aspects related to driver distraction are left out of scope of this review. We mention some of them here, without the intention to cover them in comprehensive manner, but to give the reader an awareness of their presence.

There is active research going on related to reduction of driver distraction. For example, authors of the paper [93] show that it is possible to track the driver's visual attention with advanced driver-assistance systems by providing a situated dialog system. They give an example: when person is looking at the building, the system asks him about its color.

Fusion of multiple sources of data is also an important aspect. To maximize distraction detection accuracy in real world applications, systems use all available data from multi-modal sources. In the paper [94] authors introduced deep unsupervised multi-modal fusion network that consists of multi-modal representation learning, multi-scale feature fusion and unsupervised driver distraction detection. This can be called as multi-scale feature fusion approach to aggregate multi-modal features. In the paper [95] authors analyze performance of 21 different machine learning algorithms trained to detect driver distraction based on fusion of physiological data and driving behavior data. On their dataset random forest performs the best. Authors also perform analysis of feature importance, and find, that among driver behavior features the most important are (in ordered decreasing by importance) lane offset standard deviation, speed 90% quantile, speed nonlinearity coefficient, and average absolute value of steering change. In the paper [96] authors test different machine learning and deep learning approaches for fusion of data from physiological sensors (pEDA, HR, BR), thermal camera, eye tracker, video camera, and emotions estimator, and find that gradient boosting and neural networks with STRNet or eLSTM architectures achieve the highest F1 classification score.

VI. CONCLUSION

In this paper, a review of the scientific literature on distracted driving was presented. Reviewed driver distraction approaches were integrated into a comprehensive driver distraction framework with the aim to detect the three main types of distraction: manual distraction, visual distraction, and cognitive distraction. The proposed framework outlines the entire chain of distraction detection from sensor data acquisition to data processing, behavior inference, and distraction type inference. Thereby, this article provides an overview for all researchers interested in both driver distraction research and driver distraction detection systems, which makes the paper also interesting for transportation system practitioners. The framework can stimulate future research endeavors: for example, researchers can use it to better classify their own approaches or even extend their approaches to include additional facets for improved detection of distraction types. We compared our review paper to those of other researchers and find that the holistic driver distraction framework we present summarizes all modern driver distraction methods and takes into account the latest modern computer vision techniques, too.

We would like to mention that drowsiness and distraction are completely different terms. However we consider driver drowsiness in our paper since it influence to such parameters as (reaction time, head angle, eyes not concentrated to the road) that can be captured by our framework and are characteristics of the distraction.

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REFERENCES

[1] R. L. Olson, R. J. Hanowski, J. S. Hickman, and J. Bocanegra, "Driver distraction in commercial vehicle operations," U.S. Dept. Transp., Federal Motor Carrier Saf., Washington, DC, USA, Tech. Rep. FMCSA-RRR-09-042, 2009.

[2] K. Young, M. Regan, and M. Hammer, "Driver distraction: A review of the literature," Monash Univ. Accident Res. Centre, Tech. Rep. 206, 2003. [Online]. Available: https://www.monash.edu/__data/assets/pdf_file/0007/217177/Driver-distraction-a-review-of-the-literature.pdf

[3] J. D. Lee, K. L. Young, and M. A. Regan, "Defining driver distraction," *Driver Distraction, Theory, Effects, Mitigation*, vol. 13, no. 4, pp. 31–40, 2008.

[4] S. L. Gallahan, G. F. Golzar, A. P. Jain, A. E. Samay, T. J. Trerotola, J. G. Weisskopf, and N. Lau, "Detecting and mitigating driver distraction with motion capture technology: Distracted driving warning system," in *Proc. IEEE Syst. Inf. Eng. Design Symp.*, Apr. 2013, pp. 76–81.

[5] M. Cunningham, M. Regan, and K. Imberger, "Understanding driver distraction associated with specific behavioural interactions with in-vehicle and portable technologies," *J. Australas. College Road Saf.*, vol. 28, no. 1, pp. 27–40, 2017.

[6] T. E. Kalayci, E. G. Kalayci, G. Lechner, N. Neuhuber, M. Spitzer, E. Westermeier, and A. Stocker, "Triangulated investigation of trust in automated driving: Challenges and solution approaches for data integration," *J. Ind. Inf. Integr.*, vol. 21, Mar. 2021, Art. no. 100186.
[7] G. Sikander and S. Anwar, "Driver fatigue detection systems: A review," *IEEE Trans. Intell. Transp. Syst.*, vol. 20, no. 6, pp. 2339–2352, Jun. 2019.
[8] N. Neuhuber, G. Lechner, T. E. Kalayci, A. Stocker, and B. Kubicek, *Age-Related Differences in the Interaction with Advanced Driver Assistance Systems—A Field Study* (Lecture Notes in Computer Science), vol. 12212. Cham, Switzerland: Springer, 2020.
[9] *National Highway Traffic Safety Administration Preliminary Statement of Policy Concerning Automated Vehicles*, NHTSA, Washington, DC, USA, 2013.
[10] J. C. Stutts, D. W. Reinfurt, and E. A. Rodgman, "The role of driver distraction in crashes: An analysis of 1995-1999 Crashworthiness data system data," in *Proc. Annu. Assoc. Advancement Automot. Med.*, vol. 45, 2001, pp. 287–301.
[11] K. Hatoyama, M. Nishioka, M. Kitajima, K. Nakahira, and K. Sano, "Perception of time in traffic congestion and drivers' stress," in *Proc. Int. Conf. Transp. Develop.*, Aug. 2019, pp. 165–174.
[12] T. Horberry, J. Anderson, M. A. Regan, T. J. Triggs, and J. Brown, "Driver distraction: The effects of concurrent in-vehicle tasks, road environment complexity and age on driving performance," *Accident Anal. Prevention*, vol. 38, no. 1, pp. 185–191, Jan. 2006.
[13] M. A. Regan, C. Hallett, and C. P. Gordon, "Driver distraction and driver inattention: Definition, relationship and taxonomy," *Accident Anal. Prevention*, vol. 43, no. 5, pp. 1771–1781, Sep. 2011.
[14] M. Née, B. Contrand, L. Orriols, C. Gil-Jardiné, C. Galéra, and E. Lagarde, "Road safety and distraction, results from a responsibility case-control study among a sample of road users interviewed at the emergency room," *Accident Anal. Prevention*, vol. 122, pp. 19–24, Jan. 2019.
[15] J. P. Foley, R. Young, L. Angell, and J. E. Domeyer, "Towards operationalizing driver distraction," Public Policy Center, Univ. Iowa, Iowa City, IA, USA, Tech. Rep., 2013, pp. 57–63.
[16] D. L. Strayer, J. Turrill, J. M. Cooper, J. R. Coleman, N. Medeiros-Ward, and F. Biondi, "Assessing cognitive distraction in the automobile," *Hum. Factors, J. Hum. Factors Ergonom. Soc.*, vol. 57, no. 8, pp. 1300–1324, Dec. 2015.
[17] E. D. Sussman, H. Bishop, B. Madnick, and R. Walter, "Driver inattention and highway safety," *Transp. Res. Rec.*, no. 1047, pp. 40–48, 1985.
[18] S. G. Klauer, T. A. Dingus, V. L. Neale, J. Sudweeks, and D. J. Ramsey, "The impact of driver inattention on near-crash/crash risk: An analysis using the 100-car naturalistic driving study data," Nat. Highway Traffic Saf. Admin., Washington, DC, USA, Tech. Rep., 2006.
[19] A. N. Europe, "German industry to invest 68 billion in electric cars and automation," 2019. [Online]. Available: https://europe.autonews.com/automakers/german-industry-invest-68-billion-electric-cars-and-automation
[20] C. P. Janssen, L. N. Boyle, A. L. Kun, W. Ju, and L. L. Chuang, "A hidden Markov framework to capture human–machine interaction in automated vehicles," *Int. J. Hum.–Comput. Interact.*, vol. 35, no. 11, pp. 947–955, Jul. 2019.
[21] I. Y. Noy, D. Shinar, and W. J. Horrey, "Automated driving: Safety blind spots," *Saf. Sci.*, vol. 102, pp. 68–78, Feb. 2018.
[22] J. D. Lee, C. D. Wickens, Y. Liu, and L. N. Boyle, *Designing for People: An Introduction to Human Factors Engineering*. Scotts Valley, CA, USA: CreateSpace, 2017, p. 659. [Online]. Available: https://www.amazon.com/Designing-People-Introduction-Factors-Engineering/dp/1539808009
[23] P. Stone, R. Brooks, E. Brynjolfsson, R. Calo, O. Etzioni, G. Hager, J. Hirschberg, S. Kalyanakrishnan, E. Kamar, S. Kraus, and K. Leyton-Brown, "Artificial intelligence and life in 2030: The one hundred year study on artificial intelligence," Stanford Univ., Stanford, CA, USA, Tech. Rep., 2016.
[24] "J3016B taxonomy and definitions for terms related to driving automation systems for on-road motor vehicles," SAE Tech. Paper J3016_201806, 2018, p. 35.
[25] L. Claussmann, M. Revilloud, D. Gruyer, and S. Glaser, "A review of motion planning for highway autonomous driving," *IEEE Trans. Intell. Transp. Syst.*, vol. 21, no. 5, pp. 1826–1848, May 2020.
[26] J. R. Clark, N. A. Stanton, and K. M. A. Revell, "Conditionally and highly automated vehicle handover: A study exploring vocal communication between two drivers," *Transp. Res. F, Traffic Psychol. Behav.*, vol. 65, pp. 699–715, Aug. 2019.
[27] B. D. Seppelt and J. D. Lee, "Keeping the driver in the loop: Dynamic feedback to support appropriate use of imperfect vehicle control automation," *Int. J. Hum. Comput. Stud.*, vol. 125, pp. 66–80, May 2019.
[28] N. Merat, A. H. Jamson, F. C. H. Lai, M. Daly, and O. M. J. Carsten, "Transition to manual: Driver behaviour when resuming control from a highly automated vehicle," *Transp. Res. F, Traffic Psychol. Behav.*, vol. 27, pp. 274–282, Nov. 2014.
[29] *BMW Takes Self-Driving to the Next Level*, Autoweek, 2020.
[30] *BMW Group Safety Assessment Report*, BMW, Munich, Germany, 2020.
[31] *Revised General Safety Regulation*, Eur. Commission, Belgium, Luxembourg, 2019.
[32] J. Webster and R. T. Watson, "Analyzing the past to prepare for the future: Writing a literature review," *MIS Quart.*, vol. 26, no. 2, pp. 13–23, 2002.
[33] C. Okoli and K. Schabram, "A guide to conducting a systematic literature review of information systems research," *Sprouts Work. Pap. Inf. Syst.*, vol. 10, no. 26, pp. 1–2, 2010.
[34] F. Rowe, "What literature review is not: Diversity, boundaries and recommendations," *Eur. J. Inf. Syst.*, vol. 23, no. 3, pp. 241–255, 2014.
[35] Y. Liang and J. D. Lee, "Combining cognitive and visual distraction: Less than the sum of its parts," *Accident Anal. Prevention*, vol. 42, no. 3, pp. 881–890, 2010.
[36] L. Li, B. Zhong, C. Hutmacher, Y. Liang, W. J. Horrey, and X. Xu, "Detection of driver manual distraction via image-based hand and ear recognition," *Accident Anal. Prevention*, vol. 137, Mar. 2020, Art. no. 105432.
[37] M. M. Bejani and M. Ghatee, "A context aware system for driving style evaluation by an ensemble learning on smartphone sensors data," *Transp. Res. C, Emerg. Technol.*, vol. 89, pp. 303–320, Apr. 2018.
[38] A. S. Le, T. Suzuki, and H. Aoki, "Evaluating driver cognitive distraction by eye tracking: From simulator to driving," *Transp. Res. Interdiscip. Perspect.*, vol. 4, Mar. 2020, Art. no. 100087.
[39] T. Vogt, E. André, and J. Wagner, *Automatic Recognition of Emotions From Speech: A Review of the Literature and Recommendations for Practical Realisation* (Lecture Notes in Computer Science: Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), vol. 4868. Berlin, Germany: Springer-Verlag, 2008, pp. 75–91.
[40] C. M. Jones and I. M. Jonsson, *Detecting Emotions in Conversations Between Driver and in-Car Information Systems* (Lecture Notes in Computer Science: Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), vol. 3784. Berlin, Germany: Springer-Verlag, 2005, pp. 780–787.
[41] A. Bochkovskiy, C.-Y. Wang, and H.-Y. M. Liao, "YOLOv4: Optimal speed and accuracy of object detection," 2020, *arXiv:2004.10934*. [Online]. Available: http://arxiv.org/abs/2004.10934
[42] W. Liu, D. Anguelov, D. Erhan, C. Szegedy, S. Reed, C.-Y. Fu, and A. C. Berg, *SSD: Single Shot MultiBox Detector* (Lecture Notes in Computer Science: Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), vol. 9905. Cham, Switzerland: Springer, 2015, pp. 21–37.
[43] C. Ou, Q. Zhao, F. Karray, and A. El Khatib, *Design of an End-to-End Dual Mode Driver Distraction Detection System* (Lecture Notes in Computer Science: Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), vol. 11663. Cham, Switzerland: Springer, 2019, pp. 199–207.
[44] A. Berg, M. Oskarsson, and M. O'Connor, "Deep ordinal regression with label diversity," 2020, *arXiv:2006.15864*. [Online]. Available: https://arxiv.org/abs/2006.15864
[45] Y. Ko, Y. Lee, S. Azam, F. Munir, M. Jeon, and W. Pedrycz, "Key points estimation and point instance segmentation approach for lane detection," 2020, *arXiv:2002.06604*. [Online]. Available: http://arxiv.org/abs/2002.06604
[46] C. Palmero, J. Selva, M. Ali Bagheri, and S. Escalera, "Recurrent CNN for 3D gaze estimation using appearance and shape cues," 2018, *arXiv:1805.03064*. [Online]. Available: http://arxiv.org/abs/1805.03064
[47] A. Dasgupta, D. Rahman, and A. Routray, "A smartphone-based drowsiness detection and warning system for automotive drivers," *IEEE Trans. Intell. Transp. Syst.*, vol. 20, no. 11, pp. 4045–4054, Nov. 2019.
[48] S. Ren, K. He, R. Girshick, and J. Sun, "Faster R-CNN: Towards real-time object detection with region proposal networks," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 39, no. 6, pp. 1137–1149, Jun. 2017.
[49] R. Mur-Artal, J. M. M. Montiel, and J. D. Tardos, "ORB-SLAM: A versatile and accurate monocular SLAM system," *IEEE Trans. Robot.*, vol. 31, no. 5, pp. 1147–1163, Oct. 2015.
[50] T. Morgenstern, E. M. Wögerbauer, F. Naujoks, J. F. Krems, and A. Keinath, "Measuring driver distraction–evaluation of the box task method as a tool for assessing in-vehicle system demand," *Appl. Ergonom.*, vol. 88, Oct. 2020, Art. no. 103181.
[51] T. Čegovnik, K. Stojmenova, G. Jakus, and J. Sodnik, "An analysis of the suitability of a low-cost eye tracker for assessing the cognitive load of drivers," *Appl. Ergonom.*, vol. 68, pp. 1–11, Apr. 2018.
[52] O. Nakayama, T. Futami, T. Nakamura, and E. R. Boer, "Development of a steering entropy method for evaluating driver workload," SAE Tech. Paper 1999-01-0892, 1999.

[53] F. Sagberg, G. F. B. Piccinini, and J. Engström, "A review of research on driving styles and road safety," *Hum. Factors*, vol. 57, no. 7, pp. 1248–1275, Nov. 2015.

[54] D. Trommler, T. Morgenstern, E. M. Wögerbauer, F. Naujoks, J. F. Krems, and A. Keinath, "The box task—A method for assessing in-vehicle system demand," *MethodsX*, vol. 8, Jan. 2021, Art. no. 101261.

[55] J. W. Senders, A. B. Kristofferson, W. H. Levison, C. W. Dietrich, and J. L. Ward, "The attentional demand of automobile driving," *Highw. Res. Rec.*, vol. 195, no. 195, pp. 15–33, 1967.

[56] K. Stojmenova and J. Sodnik, "Detection-response task—Uses and limitations," *Sensors*, vol. 18, no. 2, p. 594, Feb. 2018.

[57] J. Engström, P. Larsson, and C. Larsson, "Comparison of static and driving simulator venues for the tactile detection response task," in *Proc. 7th Int. Driv. Symp. Hum. Factors Driv. Assess.*, 2013, pp. 369–375.

[58] *Arduino Detection Response Task DRT*. Accessed: Mar. 26, 2021. [Online]. Available: https://www.mw.tum.de/lfe/downloads/open-source-tools/arduino-drt/

[59] A. Nambi, S. Bannur, I. Mehta, H. Kalra, A. Virmani, V. N. Padmanabhan, R. Bhandari, and B. Raman, "Hams: Driver and driving monitoring using a smartphone," in *Proc. 24th Annu. Int. Conf. Mobile Comput. Netw.*, 2018, pp. 840–842.

[60] C. Craye, A. Rashwan, M. S. Kamel, and F. Karray, "A multi-modal driver fatigue and distraction assessment system," *Int. J. Intell. Transp. Syst. Res.*, vol. 14, no. 3, pp. 173–194, Sep. 2016.

[61] W. Van Winsum, M. Martens, and L. Herland, "The effects of speech versus tactile driver support messages on workload," in *Proc. Enhanced Saf. Vehicles Conf. (ESV)*, 2001.

[62] J. D. Lee, J. Moeckli, T. L. Brown, S. C. Roberts, C. Schwarz, L. Yekhshatyan, E. Nadler, Y. Liang, T. Victor, D. Marshall, and C. Davis, "Distraction detection and mitigation through driver feedback," Nat. Highway Traffic Safety Admin., Washington, DC, USA, Tech. Rep. DOT HS 811 547B, 2013.

[63] L. Marchegiani and I. Posner, "Long-term driving behaviour modelling for driver identification," in *Proc. 21st Int. Conf. Intell. Transp. Syst. (ITSC)*, Nov. 2018, pp. 913–919.

[64] A. Fernández, R. Usamentiaga, J. L. Carús, and R. Casado, "Driver distraction using visual-based sensors and algorithms," *Sensors*, vol. 16, no. 11, pp. 1–44, 2016.

[65] L. Tabelini, R. Berriel, T. M. Paixão, C. Badue, A. F. De Souza, and T. Oliveira-Santos, "Keep your eyes on the lane: Real-time attention-guided lane detection," 2020, *arXiv:2010.12035*. [Online]. Available: https://arxiv.org/abs/2010.12035

[66] J. Greenberg, L. Tijerina, R. Curry, B. Artz, L. Cathey, P. Grant, D. Kochhar, K. Kozak, and M. Blommer, "Evaluation of driver distraction using an event detection paradigm," *J. Transp. Res. Board*, vol. 1843, no. 1, pp. 1–9, 2003.

[67] W. Zhang and H. Zhang, "Research on distracted driving identification of truck drivers based on simulated driving experiment," *IOP Conf., Earth Environ. Sci.*, vol. 638, no. 1, Feb. 2021, Art. no. 012039.

[68] I. Parra, M. A. Sotelo, D. F. Llorca, C. Fernandez, A. Llamazares, N. Hernandez, and I. Garcia, "Visual odometry and map fusion for GPS navigation assistance," in *Proc. IEEE Int. Symp. Ind. Electron.*, Jun. 2011, p. 2011.

[69] Z. Hu and K. Uchimura, "Fusion of vision, GPS and 3D gyro data in solving camera registration problem for direct visual navigation," *Int. J. Res.*, vol. 4, no. 1, pp. 3–12, 2006.

[70] H. M. Eraqi, Y. Abouelnaga, M. H. Saad, and M. N. Moustafa, "Driver distraction identification with an ensemble of convolutional neural networks," *J. Adv. Transp.*, vol. 11, pp. 1–12, Feb. 2019, Art. no. 1805.

[71] R. Manoharan and S. Chandrakala, "Android OpenCV based effective driver fatigue and distraction monitoring system," in *Proc. Int. Conf. Comput. Commun. Technol. (ICCCT)*, Feb. 2015, pp. 262–266.

[72] M. Alotaibi and B. Alotaibi, "Distracted driver classification using deep learning," *Signal, Image Video Process.*, vol. 14, no. 3, pp. 617–624, Apr. 2020.

[73] D. Tran, H. M. Do, W. Sheng, H. Bai, and G. Chowdhary, "Real-time detection of distracted driving based on deep learning," *IET Intell. Transp. Syst.*, vol. 12, no. 10, pp. 1210–1219, Dec. 2018.

[74] A. Koesdwiady, S. M. Bedawi, C. Ou, and F. Karray, *End-to-End Deep Learning for Driver Distraction Recognition* (Lecture Notes in Computer Science: Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), vol. 10317. Cham, Switzerland: Springer, 2017, pp. 11–18.

[75] N. Ruiz, E. Chong, and J. M. Rehg, "Fine-grained head pose estimation without keypoints," in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. Workshops (CVPRW)*, Jun. 2018, pp. 2155–2164.

[76] S. Park, S. D. Mello, P. Molchanov, U. Iqbal, O. Hilliges, and J. Kautz, "Few-shot adaptive gaze estimation," in *Proc. IEEE/CVF Int. Conf. Comput. Vis. (ICCV)*, Oct. 2019, pp. 9367–9376.

[77] L. Alam and M. M. Hoque, "Real-time distraction detection based on Driver's visual features," in *Proc. Int. Conf. Electr., Comput. Commun. Eng. (ECCE)*, Feb. 2019.

[78] C. Tran, A. Doshi, and M. M. Trivedi, "Modeling and prediction of driver behavior by foot gesture analysis," *Comput. Vis. Image Understand.*, vol. 116, no. 3, pp. 435–445, Mar. 2012.

[79] H. P. Greeley, E. Friets, J. P. Wilson, S. Raghavan, J. Picone, and J. Berg, "Detecting fatigue from voice using speech recognition," in *Proc. 6th IEEE Int. Symp. Signal Process. Inf. Technol.*, Aug. 2006, pp. 567–571.

[80] J. Krajewski, U. Trutschel, M. Golz, D. Sommer, and D. Edwards, "Estimating fatigue from predetermined speech samples transmitted by operator communication systems," in *Proc. 5th Int. Driving Symp. Hum. Factors Driver Assessment, Training, Vehicle Design, Driving Assessment*, 2009, pp. 468–474.

[81] L. S. Dhupati, S. Kar, A. Rajaguru, and A. Routray, "A novel drowsiness detection scheme based on speech analysis with validation using simultaneous EEG recordings," in *Proc. IEEE Int. Conf. Autom. Sci. Eng.*, Aug. 2010, pp. 917–921.

[82] A. Tawari and M. Trivedi, "Speech based emotion classification framework for driver assistance system," in *Proc. IEEE Intell. Vehicles Symp.*, Jun. 2010, pp. 174–178.

[83] X. Li, A. Vaezipour, A. Rakotonirainy, S. Demmel, and O. Oviedo-Trespalacios, "Exploring drivers' mental workload and visual demand while using an in-vehicle HMI for eco-safe driving," *Accident Anal. Prevention*, vol. 146, Oct. 2020, Art. no. 105756.

[84] J. Van Dam, S. J. Kass, and L. VanWormer, "The effects of passive mobile phone interaction on situation awareness and driving performance," *J. Transp. Saf. Secur.*, vol. 12, no. 8, pp. 1007–1024, Sep. 2020.

[85] S. Kaplan, M. A. Guvensan, A. G. Yavuz, and Y. Karalurt, "Driver behavior analysis for safe driving: A survey," *IEEE Trans. Intell. Transp. Syst.*, vol. 16, no. 6, pp. 3017–3032, Dec. 2015.

[86] O. Oviedo-Trespalacios, M. M. Haque, M. King, and S. Washington, "Understanding the impacts of mobile phone distraction on driving performance: A systematic review," *Transp. Res. C, Emerg. Technol.*, vol. 72, pp. 360–380, Nov. 2016.

[87] R. Chhabra, S. Verma, and C. R. Krishna, "A survey on driver behavior detection techniques for intelligent transportation systems," in *Proc. 7th Int. Conf. Cloud Comput., Data Sci. Eng. Confluence*, Jan. 2017, pp. 36–41.

[88] M. Q. Khan and S. Lee, "A comprehensive survey of driving monitoring and assistance systems," *Sensors*, vol. 19, no. 11, p. 2574, Jun. 2019.

[89] Y. Dong, Z. Hu, K. Uchimura, and N. Murayama, "Driver inattention monitoring system for intelligent vehicles: A review," *IEEE Trans. Intell. Transp. Syst.*, vol. 12, no. 2, pp. 596–614, Jun. 2011.

[90] K. Kircher and C. Ahlström, "Issues related to the driver distraction detection algorithm AttenD," in *Proc. Int. Conf. Driver Distraction Inattention*, 2009, pp. 1–15.

[91] A. Kashevnik, I. Lashkov, A. Ponomarev, N. Teslya, and A. Gurtov, "Cloud-based driver monitoring system using a smartphone," *IEEE Sensors J.*, vol. 20, no. 12, pp. 6701–6715, Jun. 2020.

[92] P. Green, "The 15-second rule for driver information systems," in *Proc. ITS America 9th Annu. Meeting*, 1999, pp. 1–9.

[93] J. H. L. Hansen, C. Busso, Y. Zheng, and A. Sathyanarayana, "Driver modeling for detection and assessment of driver distraction: Examples from the UTDrive test bed," *IEEE Signal Process. Mag.*, vol. 34, no. 4, pp. 130–142, Jul. 2017.

[94] Y. Zhang, Y. Chen, and C. Gao, "Deep unsupervised multi-modal fusion network for detecting driver distraction," *Neurocomputing*, vol. 421, pp. 26–38, Jan. 2021.

[95] A. D. McDonald, T. K. Ferris, and T. A. Wiener, "Classification of driver distraction: A comprehensive analysis of feature generation, machine learning, and input measures," *Hum. Factors, J. Hum. Factors Ergonom. Soc.*, vol. 62, no. 6, pp. 1019–1035, Sep. 2020.

[96] M. Gjoreski, M. Z. Gams, M. Luštrek, P. Genc, J.-U. Garbas, and T. Hassan, "Machine learning and end-to-end deep learning for monitoring driver distractions from physiological and visual signals," *IEEE Access*, vol. 8, pp. 70590–70603, 2020.