Distracted Driver Monitoring with Smartphones: A Preliminary Literature Review

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Abstract—**Distracted driving is known to be one of the leading causes of vehicle accidents. With the increase in the number of sensors available within vehicles, there exists an abundance of data for monitoring driver behaviour, which, however, have so far only been comparable across vehicle manufacturers to a limited extent due to proprietary solutions. A special role in distraction is played by the smartphone, which is repeatedly a source of distraction for drivers through calls and messages. However, the smartphone can be used for driver behaviour monitoring (like driver distraction detection) too, as current developments show. As vehicle manufacturer-independent device, which is usually equipped with adequate sensor technology, smartphones can provide significant advantages, however, an overview of such approaches is missing so far. Thus, this work carries out an author-centric literature review of 16 research papers to illustrate the opportunities in using smartphones to detect driver distraction.**

I. INTRODUCTION AND MOTIVATION

A. Driver distraction

Driving a vehicle is a cognitively demanding task and driver distraction and, more generally, driver inattention has been a major problem for many years, as both significantly increase the risk of accidents (cf. e.g., [1]–[4]).

Driver distraction is the 'diversion of attention away from activities for safe driving toward a competing activity' [5] and 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' [6]. Drivers may increasingly shift their attention from their driving task to non-driving related secondary tasks by e.g., taking their hands (manual distraction), eyes (visual distraction), and/or mind (cognitive distraction) off driving (cf. e.g., [7]–[9]).

Driver distraction through secondary tasks, i.e. phone usage, is one of the major causes of road accidents (cf. e.g., [10]–[13]), while the avoidance of road accidents has ever been a driving force to technological advances. Consequently, the detection of driver distraction has become a popular research topic (cf. e.g [14]–[16]), and vehicle manufacturers will increasingly implement proprietary distraction detection systems to prevent accidents (cf. e.g., [17], [18]) in quantified cars / vehicles [19]–[21]. As modern vehicles have become computers on wheels equipped with a plethora of sensors (

[22], [23]), distraction detection systems can integrate the data generated by vehicles during operation (c.f. [22], [24], [25] and infer certain types of distraction. However, distraction detection systems can also be based on additional hardware and software that is installed in vehicles, such as smartphones.

B. Smartphone-based distraction detection

As the smartphone penetration continues to grow rapidly, the number of messages received (via email, instant messaging, etc.) is also steadily increasing. According to the Pew Internet survey [26] the share of Americans owning a smartphone has grown to 81% in 2019. As smartphones are increasingly used while driving, smartphone-based distractions have become a major problem ([12], [27]). This has even exacerbated the case of phone-based distraction, as smartphones offer more communication options than traditional mobile phones.

Studies show that people may check their smartphones about 6 times per hour to see if they have received any new messages. And many people also do this while driving their vehicles, and not just when waiting at the traffic lights. Interestingly, many phone-based distraction detection applications only register whether people are actively answering a phone call or using a messenger app, but not whether they are just checking their phone status. An increasing usage of smartphones while driving was evident in [28] not only phoning but using apps and texting.

Since not only the adoption but also the computing power of smartphones has increased significantly and modern smartphones also allow the deployment of machine learning approaches, the authors assume that a number of studies have been published in recent years that use smartphones as systems for detecting driver distractions. Both smartphone-based data analytics and building data-driven context-aware systems on smartphones have gained increasing attention in recent years [29].

The aim of this paper is to review published peer-reviewed scientific work on driver distraction using smartphones to detect inattentive and distracted driving or related aspects. While there have been several literature reviews been published on drivers distraction in general (cf. e.g. [2], [5], [30]) and driver distraction monitoring approaches (c.f. e.g., [3]), none of them has exclusively focused on smartphone-based

driver distraction. Therefore, the authors (due to the rather small number of selected papers) perform an author-centric literature review following established guidelines on how to conduct a literature review (cf. e.g., [31]–[33]) to shed light on previously published smartphone-driven distraction studies and compile the state of the art on this subject. After this introduction and motivation, Section 2 presents the research method used, an author-centric literature review. Section 3 contains a description of the sample and an introduction to each of the papers studied, focusing on the aim of the work and the approach chosen, the detection method chosen and the smartphone sensors used, as well as some concrete results obtained. Section 4 provides a discussion of the results and section 5 concludes the paper.

II. RESEARCH METHOD: LITERATURE REVIEW

A literature review is a valuable research method to providing a theoretical background for subsequent research [33] by summarising prior research and critically examine their contributions [31]. The need to conduct a literature review became apparent as the authors could not identify any review paper that focused exclusively on smartphone-based driver distraction detection. An author-centric literature review was chosen that essentially presents a summary and contribution of the relevant articles.

The literature review was guided by the following research questions (RQs):

- RQ1: What smartphone-based approaches for driver distraction detection have been published in the last ten years?
- RQ2: What smartphone sensors and detection methods have been used?
- RQ2: What tangible results have been achieved by using smartphone-based detection approaches?

Two researchers first developed the keyword string in three iterations, which should not be too specific and not too generic. After each iteration, both authors applied the string to several scientific databases and scanned the results. Based on the scan, they tried to further improve the keyword string to get the most promising search results.

Once the keyword string was determined, the three scientific databases IEEE Xplore, Scopus and Web of Science were selected (scoping phase). The search results were imported into a Mendeley group, and metadata of the papers was completed when needed. The 78 papers were then imported into Rayyan QCRI [34], and blindly provided to the two researchers for analysis. In the selecting phase, the researchers each analysed all 78 papers, categorising them as "include", "exclude", and "maybe", and adding notes and labels. Through three rounds of joint iteration, the researchers ultimately settled on 16 papers: [35]–[50].

In the selecting step, a category for comparing the papers was already found: The approaches described in the papers used either one, two, or three different types of smartphone data, e.g.:

- the smartphone camera (front and/or rear camera) to collect images or videos,
- data from a GNSS (global navigation satellite system, often the US-developed Global Positioning System is used) to collect position data or to calculate vehicle speed,
- data from the inertial measurement unit (IMU) of the smartphone, which usually includes an accelerometer, a gyroscope, and in some cases a magnetometer,
- the smartphones microphone to collect sound data, and
- different types of radio signals from the smartphone, e.g. WiFi signals or the radio signal connection between the smartphone and the base station/base transceivers.

A. Scoping

This step includes searching within a set of scientific databases as sources of information, namely: ACM, IEEE Xplore, Scopus and Web of Science (WoS). The scientific databases and the search string were revised and agreed among the authors based on the quality of results obtained. The keyword search string used across the databases is: *("*phone" AND ("sensor?" OR "data") AND ("driver distraction" OR "driving distraction" OR "distracted driving") AND ("detect*") AND NOT ("simulat*"))"*. The search was performed on Feb-18 2021. The search string was used on the title, abstract and keywords (hence, i.e. ACM digital library could not be used, as it does not provide this title, abstract and keyword search). We restricted the search to include papers from the last 10 years (2011-2021) due to the huge growth smartphones have had in the last decade and the changes in the automotive domain due to digitalisation. In Scopus the search excluded all other subject areas (i.e. Medicine) except Engineering, Computer Science and Social Sciences. In WoS all the databases were used.

B. Selecting

Selecting papers from the scoping step is a method to identify the most relevant publications to the RQs. The researchers carried out this step independently and with a blind process. After the blind process the differences were discussed until an agreement was reached. As illustrated in Table II, 78 papers (60 of them unique) were the input for the analysis, while the researchers agreed to use 20 of them (16 unique) for further analysis, using inclusion/exclusion criteria.

TABLE I. OVERVIEW OF PAPERS FROM IEEE, SCOPUS, AND WEB OF SCIENCE USED IN THE SCOPING AND SELECTION STEPS

Database	Scoping step	Selecting step
IEEE	14	3
Scopus	16	7
Web of Science	48	10
In total	78 (60 unique)	20 (16 unique)

The following inclusion/exclusion criteria were agreed:
1) Exclude results that are handbooks, PhD thesis, patents, or only an abstract.

2) Exclude results that are citations, conference proceedings (e.g. full conference proceedings, introductory texts of conference tracks and similar).
3) Exclude duplicates.
4) Exclude results that do not use smartphone data or phone data.

In particular, two researchers blindly looked at the 78 papers using the online-tool Rayyan QCRI in an initial analysis phase. The results of the initial analysis of the two researchers were contrasted and discussed. At first glance, the results of the two researchers differed stronger than expected (see column "Initial analysis" in Table II; in total 19% conflicts). However, through two rounds of joint iteration, the researchers ultimately agreed and settled on 16 papers. In Iteration 1, the papers categorised as "maybe" were discussed jointly. Thereby, a clarification of detailed criteria for papers in the boundary has been made (i.e., include papers utilising WiFi/Radio signal strengths from smartphones), as well as a clarification on duplicates, where one researcher included the first entry, while the other researcher included the second entry of the duplicate. In the second iteration, the 15 remaining conflicts (where one researcher wanted to include it, while the other researcher wanted to exclude it) were resolved, by jointly scanning and discussing the papers one more time.

However, in the subsequent phase (Iteration 3), when all papers were analysed in detail, the authors noticed that two papers did not use smartphone sensors at all, although at first glance it looked like they did. In particular, Kim et al. [51] mention a "resource sharing device" device and name the a driver's mobile phone as example several times, however, they used a Raspberry Pi to collect camera images as input for a driver monitoring system, but state that they plan to "verify the proposed system with a real device in the vehicle, such as the driver's mobile phone" in the future. Saeed et al. [52] detect risky behaviour through differentiable patterns in received WiFi signals-patterns in a classification system and drowsy and inattentive driving is classified into four main gestures that reflect unsafe driving. These gestures include: (a) Yawning, (b) Head Jerks, (c) Sideways motion, and (d) Smart-phone usage. As a result, they found a representative received CSI waveform corresponding to smartphone-usage (which involves several different movements: pick-up, move to front of face, look at phone, put back, hands back at steering wheel). However, it turned out, that the WiFi signal used is not from the smartphone. Consequently, both papers have been excluded in Iteration 3.

After the selecting step, 16 unique papers have remained. Table I shows, that among them are representatives of all three databases used. Two of the 16 unique papers can be found in two of the databases (Shabeer & Wahidabanu, 2012 [44] is in the result lists of Scopus and WoS, and Paruchuri & Kumar [41] is in the result lists of WoS and IEEE), while one (Song et al., 2016 [46]) is present in all three database result lists, as illustrated in Fig. 1.

TABLE II. STATISTICS OF THE SELECTING STEPS OF PAPERS

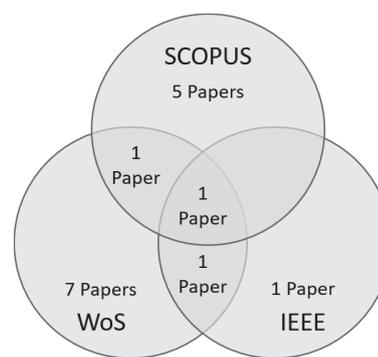| Resea-rcher	Initial analysis	Iteration 1	Iteration 2	Iteration 3
1	Incl.: 17 Excl.: 52 Maybe: 9	Incl.: 20 Excl.: 58	Incl.: 18 Excl.: 60	Incl.: 16 Excl.: 62
2	Incl.: 11 Excl.: 65 Maybe: 2	Incl.: 11 Excl.: 67	Incl.: 18 Excl.: 60	Incl.: 16 Excl.: 62

Fig. 1. Selected Papers and the database where we retrieved them

C. Review sample description

Our review sample consists of 16 unique papers. It includes six studies from journals, specifically the journals *Advances in Intelligent Systems and Computing*, *Journal of Advanced Transportation*, *Procedia Engineering*, *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, *Safety Science*, *Sensors (Switzerland)*, one study from the book series *Lecture Notes in Electrical Engineering*, and nine studies from conferences, as illustrated in Table III, which shows a spread in the venues where the relevant papers are found and that no dedicated venue to host the research topic was found.

III. REVIEW RESULTS

In the following, first, the content of the 16 selected papers is described in an author-centric way and in alphabetical order, to answer RQ1-RQ3. In particular, the following points are addressed: Type of application, smartphone sensors used, methods used and tangible results of the application. Second, the papers are classified in a table illustrating which data they use from the smartphone.

Ahn et al. [35] present a system, capable of classifying the smartphone wearer into "driver" or "passenger", by classifying if he/she is sitting left or right (left–right classifier - LRC), front or rear (front–rear classifier - FRC), and if they have entered a vehicle (in-vehicle classifier - IVC). Thereby, it is "utilizing the inconsistency between gyroscope and magnetometer dynamics and the interplay between electromagnetic field emissions and engine startup vibrations." As their method, they use the smartphones' IMU data in a Bayesian classifier. They claim to identify the driver's smartphone with 89.1% accuracy.

TABLE III. SUMMARY OF VENUES THAT THE PAPERS WERE
PUBLISHED

List of Journals and Conferences	No. of papers
Advances in Intelligent Systems and Computing	1
Journal of Advanced Transportation	1
Procedia Engineering	1
Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies	1
Safety Science	1
Sensors (Switzerland)	1
Lecture Notes in Electrical Engineering	1
Conference on Human Factors in Computing Systems	1
International Conference on Neural Computation, Fuzzy Systems and Knowledge Discovery	1
International Conference on Transportation Information and Safety	1
International ACM Conference on Automotive User Interfaces and Interactive Vehicular Applications	1
International Conference on Computing, Networking and Communications	1
International Conference on Advanced Information Networking and Applications	1
International Conference on Orange Technologies	1
IEEE International Conference on Systems, Man, and Cybernetics	1
IEEE International Conference on Computer Communications	1
Total	16

However, the solution is limited, as the smartphone "should remain static while an engine is being turned on".

Eraqi et al. [36] aim to detect ten types of driver distractions from images showing the driver. They use (in one phase) the rear camera of a fixed smartphone to collect RGB images, in order to extract the following classes with convolutional neural networks (CNNs): safe driving, phone right, phone left, text right, text left, adjusting radio, drinking, hair or makeup, reaching behind, and talking to passenger. Thereby, they run a face detector, a hand detector, and a skin segmenter against each frame. As results, first they present a new public dataset, and second their driver distraction detection solution performs with an accuracy of 90%.

Janveja et al. [37] present a smartphone-based system to detect driver fatigue (based on eye blinks and yawn frequency) and driver distraction (based on mirror scanning behavior) under low-light conditions. In detail, two approaches are presented, while in the first, a thermal image from the smartphones RGB camera is synthesised with Generative Adversarial Network, and in the second, a low-cost near-IR (NIR) LED is attached to the smartphone, to improve driver monitoring under low-light conditions. For distraction detection, statistics are calculated if the driver is scanning his/her mirrors at least once every 10 seconds continuously during the drive. A comparison of the two approaches reveals that, "results from NIR imagery outperforms synthesized thermal images across all detectors (face detection, facial landmarks, fatigue and distraction)." As a result, they mention a 93.8% accuracy in detecting driver distraction using the second approach, the NIR LED setup.

Kapoor et al. [38] designed a system capable of detecting distracting tasks, by the classification of driver images through pre-trained Convolutional Neural Network (CNN) model(s). Driver images of the "custom dataset" are taken from the smartphone camera, and the CNN models can even run within the constraints of an Android smartphone. Thus, "the system is designed to distinguish the state of the driver in real-time using only an Android phone (mounted on vehicle dashboard) without any need of additional hardware or instruments in the vehicle." In case of a detected distraction, an alert is generated with a beep sound. The ten classes of distraction are taken from the State Farm Distracted Driver dataset, which is used for fine-tuning of the CNN models. Finally, they state an accuracy between 98-100% for four classes (e.g. calling or texting on mobile), if they fine-tune with public datasets.

Khurana & Goel [39] detect phone usage by drivers using on-device cameras. Thereby, they present a software-based solution that uses smartphone camera images to observe the vehicle's interior geometry and detect the phone's position and orientation. For model training, they used continuous video recording to obtain a large dataset of images. In addition, they use IMU sensors (accelerometer and gyroscope) to detect if the phone is docked, however, this is not described in detail. The authors' system is able to distinguish between driver and passenger use of the phone. The authors train Random Forest Classifiers on data collected in 16 different cars from 33 different drivers and claim to have achieved an overall detection accuracy of about 90 % to distinguish between the driver and passenger. Thereby, the phones can be held by the persons or mounted in a docking station. However, it is not possible to collect data for the phone in the in-hand position in real-time.

Mantouka et al. [40] use data collected from smartphone sensors to identify unsafe driving styles based on a two-stage K-means clustering approach and use information on the occurrence of harsh events, acceleration profiles, mobile phone use and speeding. Trips where the driver used the smartphone are classified as distracted trips. Variables used are harsh acceleration and hard brakes per km, a smoothness indicator, the standard deviation of acceleration, the percent of mobile phone use and the percent of speeding. In the first clustering, the authors separate aggressive from non-aggressive trips, while in the second clustering they distinguish normal trips from unsafe trips. Finally, the trips were categorised into six groups: aggressive trips (aggressive trips, distracted trips, risky trips) and non-aggressive trips (similar: safe trips, distracted trips, risky trips). The authors claim that 75% of the 10,000 recorded trips (from 129 drivers) did not have aggressive features, and in just 8% of the trips the driver was factually distracted.

Paruchuri & Kumar [41] present how the smartphone camera can be used to provide context and/or position of the smartphone. The paper is focusing on distinguishing the driver from the passengers, by comparing images from the smartphone camera to reference images. In particular, they compare the angle difference of reference objects (e.g. ventilation grille), and calculate the distance between images, to locate the phone position. As a result, unfortunately 15 out of 38 images were registered incorrectly.

Punay et al. [42] present a summary of the "unDivided"

mobile application which utilises GPS data to calculate the vehicle speed and warns when certain speed limits are exceeded. The application auto-starts when driving is detected (speed of human running/walking is exceeded). When driving is detected, the application automatically turns down and answers back with messages when the driver receives calls or messages, while it allows emergency calls to go through, to keep distraction to a necessary minimum. In addition, it tracks the users' location, provides navigation features, and implements e-Call functionalities. However, no evaluation is available, as the system seems to be in a prototypical state.

Qi et al. [43] present a human activity detection system for two areas, inside the vehicle based on audio information (chatting, silence, etc.) and context information (clear or crowded traffic) for areas outside the vehicle which is derived from IMU-based vehicle dynamics detection (brakes, lane changes, turns, and stops). Inside the vehicle, a microphone is used to record audios, and infer human activities. For context information, they used their (IMU- & GPS-based) activity detection methods with a Convolutional Neural Network-based model to derive a data fusion model (including OBD-II data) for activity detection. They report 90% detection accuracy for 7 different activities by combing data from multiple sensors.

Shabeer & Wahidabanu [44] detect incoming or outgoing phone calls while driving, using an antenna located on the top of driver seat for detecting when the driver uses its mobile phone. Thereby, a GSM signal connection between the smartphone and other entities of the GSM Network Architecture (e.g. mobile switching centers, and base stations with associated base transceivers) is detected. If a call is detected, a low range mobile jammer is used to prevent drivers from receiving base stations signals, with its range covering only the driver seat. However, no evaluation is available, as the system seems to be in a prototypical state.

Singh et al. [45] do not detect driver distraction itself, but develop a system that alerts the driver in case of detected vehicles in the blind spot, thus assists the driver if he/she is distracted. In particular, the developed smartphone-based system monitors the blind spot on the driver side in real-time and alerts the driver about the presence of a vehicle. Using images from the smartphones' front camera, two approaches are explored based on intensity variation and contour matching to detect a vehicle in the blind spot. They state, that their system is able to detect vehicles in the blind spot with an accuracy of 87% in real-time and warn the driver accordingly.

Song et al. [46] detect driver phone calls by using audio and voice recognition, combined with the smartphone's call state. Thereby they use a client-server based system with the smartphones being the clients, which is extended with an unidirectional microphone and placed in front of the driver seat, together with an on-board unit, being the server. They state that the system is able to use driver's voice features to differentiate a driver from other passengers, thus also determine whether the driver is participating in a current phone call or not. In particular, first, they collect driver's audio signals for training, second, transform it into feature vectors by feature extraction, and third, train a speaker model using the driver's feature vectors. The detection system will cut off the phone call if the similarity score is higher than a certain threshold. An evaluation shows, that the system's true positive rate (TPR) is above 98% for three different evaluated passenger positions, over 90% with the impact of noise, 80% if three people are talking, and 67% if four people are talking.

Vasey et al. [47] aim to address the impact of driver emotions such as anger and happiness on driving behavior and driver distraction. Thus, they describe a system to identify a driver's emotional arousal. Thereby, the make use of an Android application as a hub to collect data from driver's physiological and the vehicle's kinematic data. The smartphones' accelerometer, jerk and GPS data, a wearable's chest band sensor to collect the drivers' heart rate and a vehicle's OBD-II connector to read CAN bus data, i.e., accelerator pedal position, steering wheel angle and engine RPM, are used. They mention a machine learning classifier, such as a decision tree, support vector machine (SVM), and neural network will be used to train. Questionnaires are planned to be used to rate the drivers' emotional state and workload. However, the paper presents a concept, and there are no results in it.

Xiao & Feng [48] describe a driver attention detection system based on smartphones with dual cameras. It consists of three modules: the first module is an estimator of gaze direction (pupil location, yaw and pitch angle of eyes, position and size of face detected with the smartphone front camera), the second is a detector of road motion objects, and the third module is an inference engine which integrates the input from the above mentioned two modules and outputs a voice alert to the driver when needed. SVM classifier is used to estimate the gaze area and Lucas-Kanade optical flow is used to detect road motion objects combined with dynamic background compensation. As a result, they state a 93% accuracy for gaze estimation and a 92% overall accuracy.

Xie et al. [49] developed a smartphone sensor-based driver distraction system using GPS and IMU data and an ensemble learning method to detect vehicle shifting and erratic braking for instance. Ensemble learning of four standard classifiers is used namely K-Nearest Neighbor, Logistic Regression, Gaussian Naive Bayes, and Random Forest. They state that their "best performing model can achieve a weighted F1-score of 87% using all signals."

Yaswanth et al. [50] consider a sequence of actions that trigger the identification of smartphone detectors as follows: walking–standing–entering–seated–engine starts. The following detectors are used: Entering direction classifier (EDC), walking and standing detector (WSD), entrance detector (ETD), seated row classifier (SRC), and smartphone position classifier (SPC). SRC checks whether the driver is in the seat or not. SPC distinguishes between three frequent positions used by the user to hold the smartphone: pockets, bags, and hands. The system is using electromagnetic spikes triggered by the actions above and the engine start. In order to save energy, accelerometer and magnetometer readings are used to detect if the driver has finished entering the vehicle, thus other sensors are waked

TABLE IV. LITERATURE SEARCH RESULT: 16 PAPERS AND WHICH OF THE SMARTPHONE DATA THEY USE: CAMERA (CAM), GNSS, IMU, MICROPHONE (MIC), OR RADIO SIGNALS (RAD).

Author(s)	CAM	GNSS	IMU	MIC	RAD
Ahn et al., 2019 [35]			X		
Eraqi et al., 2019 [36]	X				
Janveja et al., 2020 [37]	X				
Kapoor et al., 2020 [38]	X				
Khurana & Goel, 2020 [39]	X				
Mantouka et al., 2019 [40]		X	X		
Paruchuri & Kumar, 2015 [41]	X				
Punay et al., 2018 [42]		X			
Qi et al., 2019 [43]		X	X	X	
Shabeer & Wahidabanu, 2012 [44]					X
Singh et al., 2014 [45]	X				
Song et al., 2016 [46]				X	
Vasey et al., 2018 [47]		X	X		
Xiao & Feng, 2016 [48]	X				
Xie et al., 2019 [49]		X	X		
Yaswanth et al., 2021 [50]			X		X

up. However, the paper presents a concept, and there is no evaluation available.

To provide an overview of the papers and to answer RQ2, Table IV explicitly shows which smartphone sensors were used per paper, using the categories Camera, GNSS (e.g. GPS), IMU (e.g. accelerometer, gyroscope, magnetometer), Microphone, or radio signals (e.g. WiFi).

IV. DISCUSSION

To summarize, this paper provides the results of an author-centric literature review on published smartphone-based distraction approaches. Section I provides an introduction on driver distraction, and smartphone-based distraction detection. Section II describes the method used for the preliminary literature review, where two researchers performed the keyword search, which ultimately lead to 16 papers all authors agreed on. It provides details on the scoping and selecting process, and a description of the review sample. Section III proceeds with an author-centric literature review, providing information on application type, smartphone-sensors used, method and results per paper, and finishes with Table IV, which explicitly shows which smartphone sensors were used per paper. The table demonstrates, that the majority of the selected papers use

the smartphones camera, the GPS (or more general - GNSS) position data or the IMU data (e.g. accelerometer, gyroscope).

The authors want to mention the limitations of the research - the limited number of scientific databases used, and the missing forward and backward search, to detect further articles.

However, there is a significant contribution to theory, as no existing literature review focuses explicitly on the specific topic of smartphone-based driver distraction detection.

The paper also provides a contribution to practice, as the majority of the papers describe concrete systems or system concepts, thus, provides a preliminary overview, however, a share of them provide a concept only and therefore do not provide results yet, which will be further addressed using forward search in future work.

V. CONCLUSION AND FUTURE WORK

Driver distraction is a major cause of road accidents. Smartphone usage can cause such distractions. However, smartphones can also support distraction detection. The paper provides the results of an author-centric literature review on published smartphone-based distraction approaches. The authors have reviewed 16 scientific papers and summarized their application case, smartphone sensor data used, method used, and their results. The research is valuable for providing an overview on published smartphone-data-based approaches. In future work, the search scope will be extended (including forward search, backward search, further scientific databases) and the findings from the literature review will be clustered, to identify research gaps in existing literature.

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