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A review of research on driving distraction based on bibliometrics and co-occurrence: Focus on driving distraction recognition methods

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ABSTRACT

Introduction: The existing selection of driving distraction recognition methods is based on a specific research perspective and does not provide comprehensive information on the entire field of view. *Method:* We conducted a systematic review of previous studies, aiming to come up with appropriate research methods to identify the driver's distraction state. First, this article selects four sets of search keywords related to driving distraction discrimination from five databases (Web of Science, ScienceDirect, Springer Link, IEEE, and TRID) and identifies 1,620 peer-reviewed documents from 2000 to 2020; these 1,620 documents underwent bibliographic analysis and co-occurrence network analysis. The co-occurrence coupling relationship is analyzed from the aspects of time, country, publication, author and keywords. Second, 37 papers published were screened, and the driving distraction recognition methods proposed by these 37 papers were summarized and analyzed. *Results:* The results show that this field has been prevalent since 2013; countries such as the United States, Britain, Germany, Australia, China, and Canada are in the forefront of research in this field, and the cooperation between related countries is relatively close. The cooperation between authors is characterized by aggregation, and the mobile phone as the main keyword is almost connected to other keyword nodes; the recognition model of deep learning algorithm based on video surveillance data sources has become the mainstream hot spot distraction recognition method. The recognition model of machine learning algorithm based on vehicle dynamics data, driver physiology, and eye movement data sources has specific advantages and disadvantages. *Practical Applications:* The results can help people to understand the current situation of driving distraction comprehensively and systematically, provide better theoretical support for researchers to choose the subsequent driving distraction recognition model, and provide research direction for driving distraction recognition in the future.

1. Introduction

The road traffic system is composed of people, motor vehicles, and road environment; motor-vehicle drivers are a weak link in the system, and human factors play a crucial role in about 90% of traffic crashes (Valero Mora, Ballestar Tarin, Tontsch, Pareja Montoro, & Sanchez Garcia, 2012). The driving process is complicated, including multiple aspects such as situational awareness, decision-making, and execution. It is inevitable that sudden abnormal situations such as distraction errors and recognition errors will directly lead to driving risks (Parker, Reason, Manstead, & Stradling, 1995). There are many reasons for driver errors, and distraction is one of the most important. The American Automobile Association Traffic Safety Foundation defines driving distraction status as the driver's attention not being focused on the driving task due to some events, activities, objects, or people inside or outside the car, resulting in a decrease of the driver's reaction ability and failing to deal with dangerous situations or improper behaviors in time (Dewar & Olson, 2002). A survey based on 1,367 drivers found that traffic crashes caused by distracted driving account for 14 to 33 percent of major accidents. (Mcevoy, Stevenson, & Woodward, 2007). Therefore, the recognition of driver's distraction state is of great significance to ensure driver, passenger, pedestrian/cyclist and property safety.

Driving distraction is a temporary shift of driver's attention (Yang, McDonald, & Zheng, 2012). The essence is that the driver's attention shifts from the driver's main task (driving) to thinking about something else. To identify the driver's distracted state in the driving process more accurately and timely, scholars in this field have done much research on identifying data sources, models and so on. Waard et al. collected vehicle dynamics data in

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distracted state, and built a real-time recognition system based on statistics, artificial neural network, and fuzzy logic with a recognition accuracy rate of 89% (Waard, Brookhuis, & Hernandez-Gress, 2001). Masala et al. built a Sanger neural network recognition model by analyzing the video recording monitoring data of the driver's posture and eyes when driving was distracted, and the effective recognition accuracy rate was 92.7% (Masala & Grosso, 2014). Wang et al. conducted a driving distraction test by simulator, collected the electrical signals of the driver's brain, and constructed a support vector machine recognition model based on radial basis function, with a recognition accuracy of 86.2% (Wang, Jung, & Lin, 2015). Le et al. built a multi-scale fast rcnn(MS-FRCNN) recognition model based on deep learning using natural driving data, and the recognition accuracy rate reached 92.4% (Le, Zheng, & Zhu, 2016). Wollmer et al. built a driver's distraction detection model based on LSTM regression neural network by collecting vehicle dynamics and driver's head movement data in the state of driving distraction, and the recognition accuracy rate was 96.6% (Wöllmer, Blaschke, & Schindl, 2011). Dehzangi et al. collected the driver's skin electrical signals through driving distraction test and constructed a convolution neural network distraction recognition model, with an accuracy rate of 93.3% (Dehzangi & Taherisadr, 2018). Therefore, there is a lot of research on driving distraction status recognition by different methods, but there are still many problems and challenges.

Existing driver monitoring mainly focuses on low attention owing to fatigue, fatigue score, short distraction occurrence time, many affected factors and strong delay characteristics, which brings challenges to driver attention monitoring. In current vehicles, the source of distraction faced by drivers continues to exist, and it becomes more difficult to concentrate on driving. Various types of vehicle infotainment systems have developed rapidly. During driving, more and more people use various electronic devices in the car. Drivers are becoming ever more eager to keep in touch with others while driving; this information is the embodiment of modern people's lifestyle changes in driving. The use of in-car entertainment systems, real-time in-vehicle information systems, and smart phones to advance synchronously for multitask operations has significantly increased (Wilson & Stimpson, 1999). Although some literature has analyzed emotional driving behaviors, there is little literature about specific driving distraction behaviors and discussing specific driving distraction recognition methods. Scott-Parker conducts research on young drivers and analyzes literature reviews on emotions and driving behaviors (Scott-Parker, 2017). Yusoff discussed some common measures of disturbing driving and five common methods for measuring driving distraction (Yusoff et al., 2017). In view of all the content mentioned, it can be assumed that reviews on the selection of driving distraction recognition methods have been extensively studied. However, these reviews do not include all research on driving distractions and do not provide a comprehensive understanding of the field. The purpose of driving distraction research is to better detect the state of driving attention deficit. At present, the recognition model constructed by various machine learning algorithms has become the mainstream method of driving distraction recognition. To better reveal the advantages and disadvantages of various recognition methods and their internal relations, it is necessary to conduct an in-depth discussion in this field. The combination of bibliography and co-occurrence network analysis can show more complex cooperation relations in this research field.

However, to the best of our knowledge, there is no literature that uses the co-occurrence network analysis method and literature measurement analysis method to systematically analyze the relationship between driving distraction studies (Gao, Sun, Geng, Wu, & Chen, 2016; Wu et al., 2020). Co-occurrence network distraction is a quantitative analysis method of co-occurrence information in various information carriers, which can reveal the content association of information and the co-occurrence relationship implied by feature items. Bibliometric analysis is a method of quantitatively analyzing all knowledge carriers by using mathematics and statistics. This method combines mathematics, statistics and philology, and can help readers to form a comprehensive knowledge system focusing on quantification. Therefore, this study attempts to fill this gap and provide new ideas when choosing driving distraction recognition methods. Overall, this article aims to provide a reference for future research on driving distraction through bibliography and co-occurrence networks. This paper expects to achieve four goals: (1) evaluate the current system research trends of driving distraction; (2) point out the keywords, countries, academic cooperation between authors and different clusters; (3) identify and sort out the existing literature on driving distraction recognition methods, including the detection targets of the recognition model and recognition methods; and (4) summarize and analyze the current recognition method and provide a theoretical basis for subsequent research. Through the completion of these research objectives, we can achieve a more comprehensive understanding of the breadth and depth of the whole driving distraction research field and have a more in-depth understanding of the most important problem in this field -- the selection of driving distraction recognition methods and future research trends -- and contribute to the development of high-level assisted driving systems and automatic driving systems.

2. Research methods

2.1. Literature retrieval strategy

Reporting criteria is based on systematic reviews and meta-analysis (PRIS-MA) (Page et al., 2020). In April 2020, the author retrieved academic papers related to driving distraction in the five databases of Web of Science, ScienceDirect, Springer Link, IEEE, and TRID. The first three are comprehensive databases, and the journals included in other databases are reputed. The search involves different disciplines such as electric, computer engineering, science and transportation. The search keywords are composed of 4 parts. At least 1 keyword related to each section. The 4 part keywords are: (1) driving, driver, driving age, novice driver, young driver, and driving psychology; (2) vehicles, passenger cars, trucks, electric vehicles and new energy vehicles; (3) road environment, urban roads, rural roads, mountain roads and highways; (4) distraction, factors, psychology, perception, subjectivity and attitude. According to the above keyword combination, the search language is adjusted according to different databases. Some important literature references are also included in the scope of reviewing search.

2.2. Screening criteria

The searched documents were further filtered to make the final documents meet the following conditions: (1) it must be published in a peer-reviewed English journal; (2) the research subject is mainly drivers; (3) there must be empirical data on the driving distraction test. In addition, this article contains only the literature that has quantitative analysis of the factors affecting the recognition of driving distraction, which will help the comprehensive comparative analysis of these documents.

2.3. Information extractions

This article uses the matrix method to extract standardized information tables from the literature being reviewed. The information extracted from each document mainly includes the following: (1) the characteristics of the literature (such as the location, year and author of the study); (2) the attributes of the respondent (such as the sample size, the investigator driving age distribution); (3) environmental factors affecting driving distraction; (4) driving distraction recognition methods and theoretical framework; and (5) main research conclusions of the literature. To ensure the reliability of information extraction, the two authors of this article randomly selected 50 articles from the literature for information extraction and found that the consistency of the extracted information reached 80%, and different information was unified through negotiation. This shows that this article has a high mutual reviewer reliability for the extraction of information in the literature.

2.4. Study collection

According to the above search strategy: 3,726 articles were retrieved from Web of Science, 8,946 articles were retrieved from ScienceDirect, 39,947 articles were retrieved from Springer Link, 1,276 articles were retrieved from IEEE, and 5,981 articles were retrieved from TRID. After removing the duplicates, a total of 59,876 articles were retrieved from these five databases. After manual selection of the title and abstract, 3,607 articles remained, of which 78 were unrelated to the driver and 1,460 were unrelated to driving distraction. Forty-five full texts were not available, and finally 2,024 full text articles were obtained. 246 of the 2,024 full text articles were review articles. Relevant literature in the articles was obtained, 158 non-empirical studies were removed, and 1,620 articles were finally obtained. Eventually, 1,620 available studies were left and satisfied the full criteria in this review, as shown in Fig. 1.

3. Results

3.1. Overview of articles' development trends

Fig. 2 describes the increase in the number of articles (NO) included in this review from 2000 to 2020 after literature search and screening. NO indicates that the number of published articles is increasing with the progress of time. From the perspective of stages, the number of published articles in the first three years is less, which first decreases and then increases from 2004 to 2013, reaches the lowest value in 2009, and increases from 2014 to 2019; however, the number of published articles decreases in the last two years (the literature ends in June 2020). Fig. 2 also describes the changes of annual total cited quantity (TC) and annual average cited frequency per article (ACPP). The figure shows that TC fluctuated up and down before 2013, peaked in 2005, fluctuated greatly before 2009, fluctuated slightly between 2013, and declined year by year after 2014. ACPP showed two peaks in 2002 and 2006, respectively, and then declined slowly from 2009 to 2020.

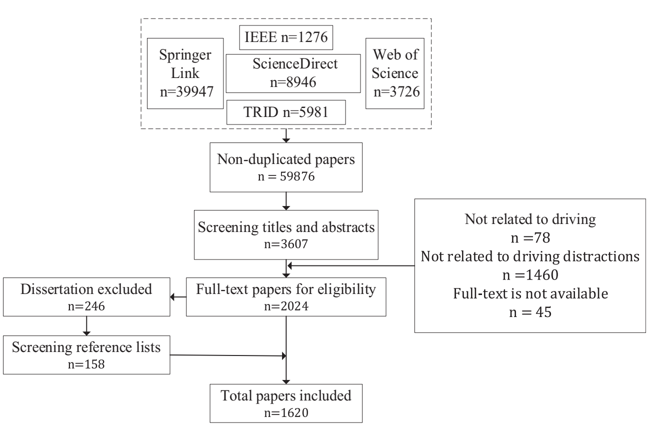

Fig. 1. Flowchart of the systematic review process.

3.2. Academic cooperation of different countries and areas

Promoting academic cooperation in different countries and regions is of great significance, which can promote the discovery of innovative points and the application of solutions.

Fig. 3 counts the number of articles published by various countries from 2000 to 2020. Fig. 3 shows that the United States is the country with the largest number of articles published in this field, which shows the attention and discourse power of the United States in the field of driving distraction. The articles published by U.S. scholars account for 36.5% of the total articles, while those published by British scholars account for 10% of the total number of articles, the articles published by other countries include Australia 8%, Germany 7%, China 7%, Canada 6%, and so forth. The articles published by scholars from the above six countries account for 74.5% of the total articles, while there are 233 countries and regions in the world, which shows that the research in this field is extremely unbalanced in the world at present.

Fig. 4 shows the cooperative relationship between the author's country and region. The thickness of lines and the size of nodes have a positive correlation with the degree of international academic cooperation; the larger the node, the more are the academic achievements, and the thicker the line, the closer is the academic cooperation. Fig. 4 shows that the United States is at the center of the network with the largest node, indicating that the United States is the first echelon of activity in this field internationally. From the line width point of view, the line width between the United States and China, Canada, and Britain is wider, indicating that the academic cooperation between the United States and these three countries is relatively close. From the overall cooperation network layout, the number of nodes is small, and the network is sparse, which means that there are few countries that pay attention to and deeply study this field and academic cooperation and exchange are not close. Therefore, to promote better and faster development in this field, close and in-depth cooperation between countries is indispensable.

3.3. Keyword co-occurrence analysis

Keywords are the concentrated expression of research content in a field. Through the analysis of keywords we can quickly understand the development and current hot spots of research in a field and deepen our understanding of this field.

Fig. 5 shows the keyword co-occurrence network in the driving distraction literature. Node size and line thickness are positively related to the keyword connection; the larger the node, the higher is the frequency of the keyword, and the thicker the line, the closer is the connection between the two topics. Keyword categories are expressed in different colors. Fig. 5 shows that keywords are divided into three categories: the first category is represented by distraction and driving; the second category is represented by driver distraction, driver simulator, and road safety; and the third category is represented by mobile phone and distracted driving. In addition, the secondary task keyword shows that it is mainly studied using the sub-task test at present; keywords such as eye movements and natural driving indicate that research is mainly conducted through eye movement data and natural driving data; mobile phone and cell phone show that there is much research on the influence of distraction in mobile phone driving, but there are still many sources of distraction in the driving process, which should be studied in all directions, in depth, and in a wide field;

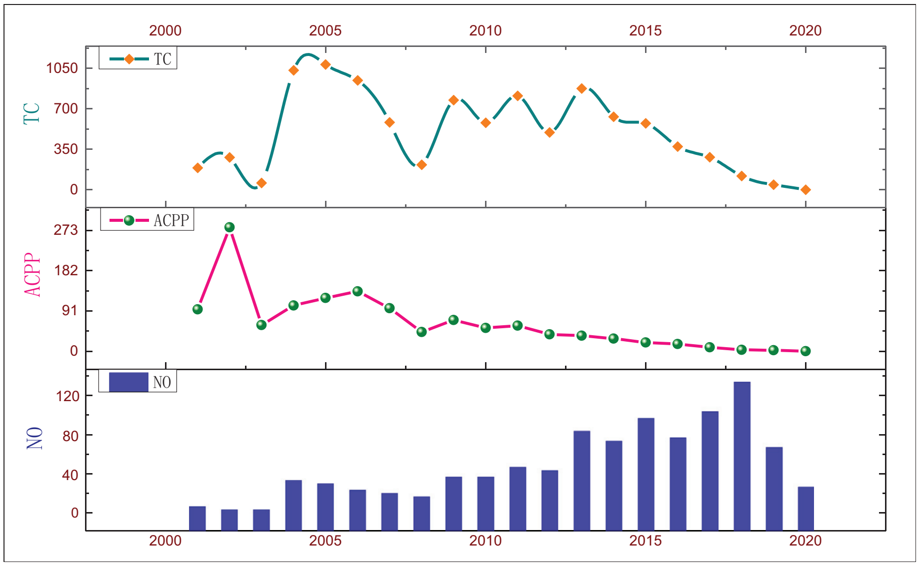

Fig. 2. Literature development trend.

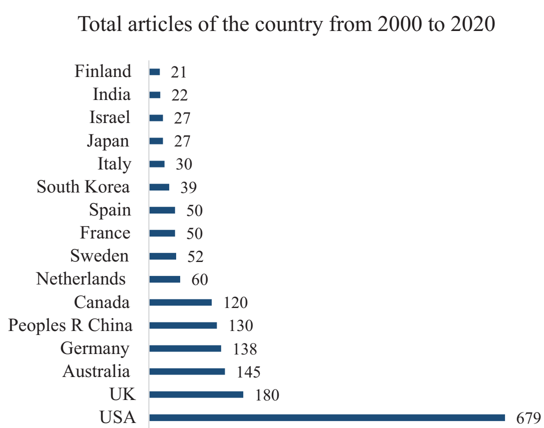

Fig. 3. Total articles of the country from 2000 to 2020.

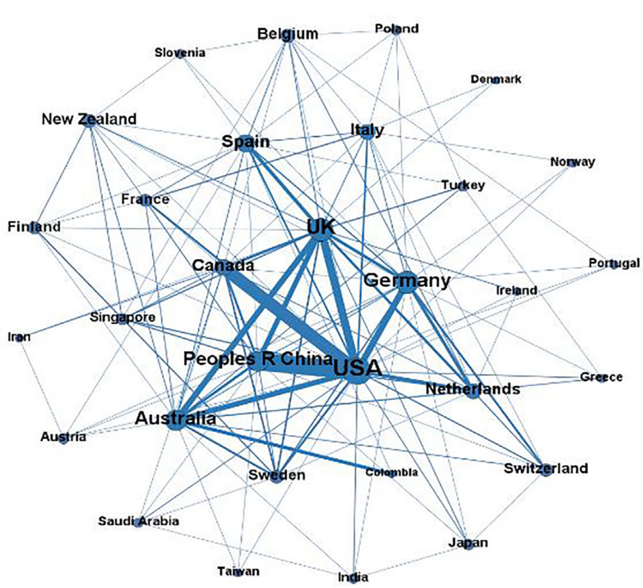

Fig. 4. Academic cooperation between different countries.

keywords such as older drivers and young drivers show the research objects of driving distraction, which are mainly analyzed from the age level, lacking the analysis of factors such as gender and personality. It also includes the research on driving distraction of autonomous vehicles represented by the keyword automated driving, but lacks the research on driving distraction of networked vehicles. To clearly show the meaning of Fig. 5, Table 1 shows the intensity between different keywords.

3.4. Author co-occurrence analysis

Co-occurrence network analysis is not only applied between countries and keywords, but also between authors. Zhao and Strotmann (2011) and Kim, Jeong, and Song (2016) applied the co-occurrence network to authors to analyze influential authors and their associations. Using Bibexcel to draw the relationship diagram and realize the visualization through Gephi, the author analyzes the relevant amount of articles issued by the author and the relationship between the co-authors. Finally, the author co-occurrence analysis showing more than 50 nodes is shown in Fig. 6. The size of the node corresponds to the amount of the post, and the thickness of the line indicates how closely the author cooperates. Color blocks of the same color indicate similarities between them.

To show the collaboration between authors more clearly and classify the research fields of coupling analysis of different color blocks, Fig. 7 expands these co-occurrence analysis graphs of the authors into six clusters. Although the research of each author is diversified, it can be seen from the cooperation between the authors that the authors collaborate in a cluster relationship. The dominant element of cluster1 is methods, the dominant element of cluster2 is driving mind, the dominant element of cluster3 is investment, the dominant element of cluster4 is cognitive distraction assessment, the dominant element of cluster5 is driving visual perception, and the dominant element of cluster6 is driving determinants. Fig. 7 shows that cluster1 with more research is dominated by Lee and Kolodge (2019), Donmez, Boyle, and Lee (2007), Reimer, D'Ambrosio, Coughlin, Kafrissen, and Biederman (2006), Mehler, Reimer, and Coughlin (2012) and so on. To more clearly show the cooperation relationship of the authors in the first category, Table 2 shows the cooperation intensity of the main authors in cluster1. Cluster1 focuses on the choice of methodology, includ-

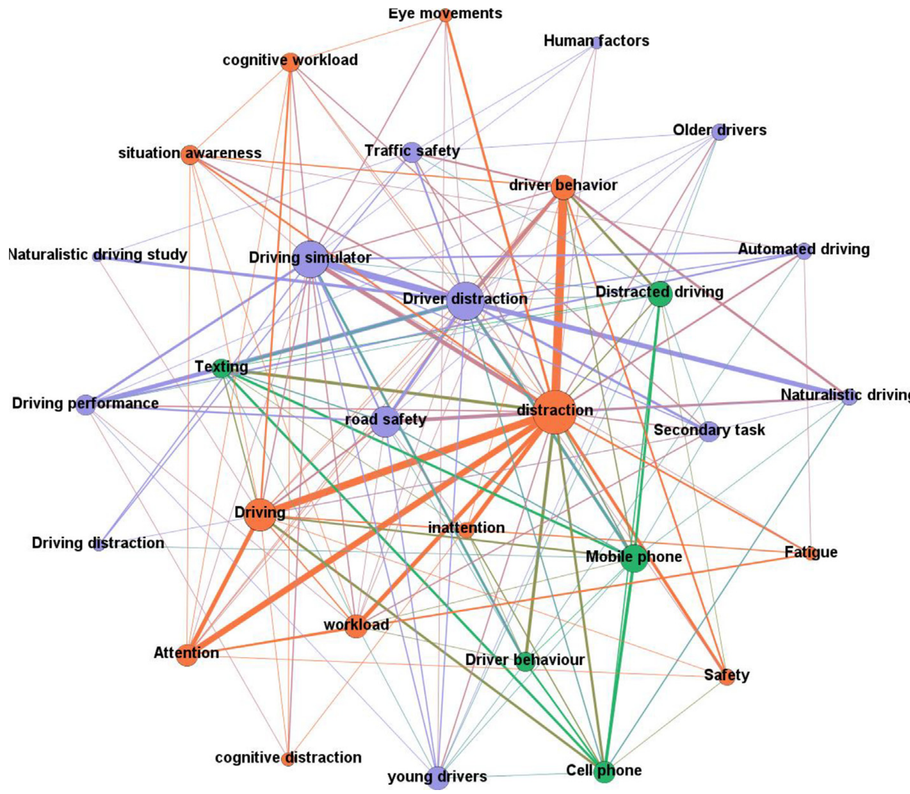

Fig. 5. Keyword co-occurrence network.

Table 1
Co-occurrence strength of the keyword.

Keyword1	Keyword2	Co-occurrence intensity	Keyword1	Keyword2	Co-occurrence intensity
distraction	driver behavior	14	distraction	Driving simulator	7
Driving	distraction	12	Driver distraction	Driving performance	7
Driver distraction	Driving simulator	11	distraction	workload	7
Attention	distraction	10	Driving	Attention	7
Driver distraction	Naturalistic driving	8	distraction	inattention	7

ing the use of eye movement data classification methods to study visual distraction, and the use of tactile detection methods to evaluate the distraction caused by in-car audio and video.

To focus on the study of driving distraction determination methods, 37 research studies were selected; each of these documents is related to the method of driving distraction recognition and is published in peer-reviewed journals. Table 3 provides information selected from 37 research studies. These studies are from 17 peer-reviewed journals in different disciplines such as transportation, biology, and accident analysis. Among them, 14 studies are from transportation-related journals. There are nine studies from journals in the comprehensive field, and three studies from journals in the field of biological health. All articles are published after 2015, and the number increased in the past two years. Table 3 shows that in recent years, the data sources of driving distraction research mainly include vehicle dynamics data, video image data, eye movement data, head and face data, physiological and psychological data, and multidimensional fusion of the above data. Because data acquisition is easy, vehicle dynamics data are most often used, but its recognition accuracy is not high. The recognition method mainly uses traditional machine learning algorithm and deep learning algorithm to build driving distraction recognition model, the recognition accuracy of deep learning model is high, but the real-time performance of the models is poor. Traditional machine learning recognition models represented by support vector machines have better real-time performance although the recognition accuracy is lacking.

3.5. Analysis of factors affecting driving distraction

The analysis of factors that affect driving distraction is the basis of research on driving distraction recognition methods. Different test environments and data types correspond to different recognition methods, and different recognition methods correspond to different recognition accuracy. Therefore, it is necessary to analyze the influencing factors of driving distraction through the study of different detection data types. Table 3 summarizes the influencing factors, recognition methods, and accuracy of driving distraction. Table 3 shows that the research conducted on the recognition of driving distraction is generally carried out from a real car test or a driving simulator test. The specific data detection types can be divided into video images, ECG, SC, EEG, vehicle power and Eye movement data.

With the increasing popularity and wide demand of vehicles, traffic crashes have become one of the most serious problems worldwide, among which driving accidents caused by driver distraction account for a large proportion (Mcevoy et al., 2007). Researchers and scholars are committed to reduce and alleviate

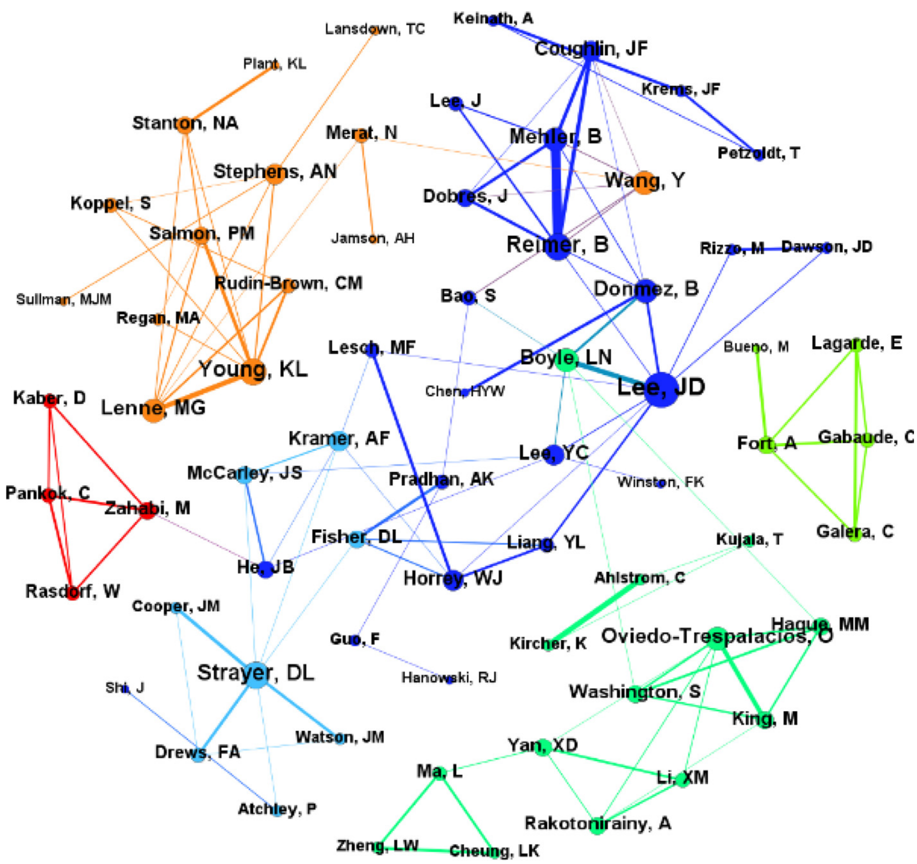

Fig. 6. Author co-occurrence network.

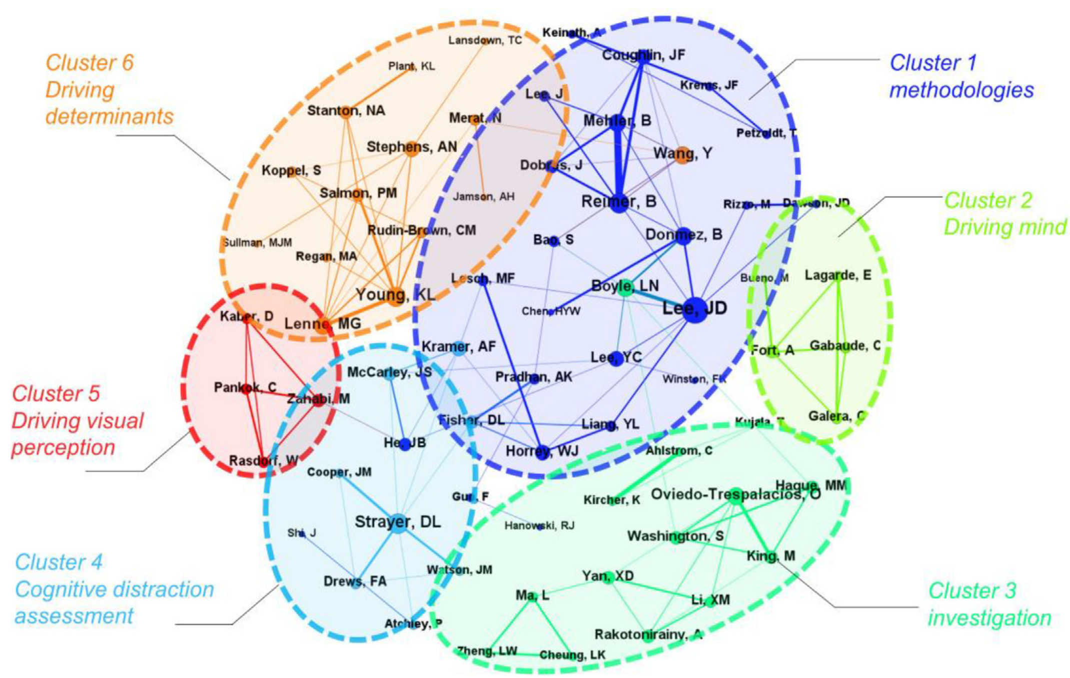

Fig. 7. Author Coupling Analysis Network2.5 Literature overview.

traffic crashes caused by driver distraction. Oviedo-Trespalacios, Afghari, and Haque (2020) developed a comprehensive multivariate ordered model in the Bayesian framework to study the risk compensation behavior of distracted drivers and designed a questionnaire to understand the risk compensation behavior of distracted drivers of mobile phones in Australia to empirically test the multi-ordered model. The results demonstrate that, for the targets corresponding to fixed parameters/fixed thresholds, the

Table 2
Co-occurrence strength of the author.

Author1	Author2	Co-occurrence intensity	Author 1	Author 2	Co-occurrence intensity
Reimer, B	Mehler, B	19	Boyle, LN	Lee, JD	10
Reimer, B	Coughlin, JF	8	Mehler, B	Coughlin, JF	7
Pradhan, AK	Fisher, DL	6	Horrey, WJ	Lesch, MF	6
Donmez, B	Lee, JD	6	Keinath, A	Krems, JF	6
Chen, HYW	Donmez, B	8	Mehler, B	Dobres, J	7
Reimer, B	Dobres,J	6	Dawson, JD	Rizzo, M	6

grouped random parameter/random threshold ordered model has a significantly improved fit, this proves that drivers making different types of risk compensation behaviors are interrelated. Similarly, Zhao, Xu, Ma, Li, and Chen (2019) also used a questionnaire survey method to analyze the characteristics of drivers with a focus on distracted driving behavior and developed a new method to reduce driver errors. Unlike Oviedo-trespalacios O, Zhao X uses a structural equation model (SEM) to grasp the complex relationship between related variables. The model can simultaneously solve the intricate relationship between endogenous variables and exogenous variables. Forty-four participants were recruited to complete the driving distraction test. In the experiment, driving behavior data were collected by driving simulator and driving posture data were collected by questionnaire survey. The conclusion shows that the main factor affecting illegal driving behavior is driving attitude, and the main factor affecting the performance of distracted drivers is the basic characteristics of drivers. In addition, the driver's training level is the most important factor that negatively affects the driver's basic characteristics (factor load = −0.91), and anger at slow driving is the main factor that affects the driver's attitude (factor load = 0.90).

Yang, Guan, Ma, and Li (2019), Atiquzzaman, Qi, and Fries (2018), and Stavrinos (2013) also used the driving simulator to study driving distraction. Yang et al. (2019) installed the electroencephalogram (EEG) detection module on the simulator and compared the model based on EEG features and based on mixed features (combination of driving features and EEG features) to determine the current driving state. Atiquzzaman et al. (2018) are committed to developing algorithms that only use vehicle dynamics data to detect interference tasks involving vision, cognition, and the physical workload. Stavrinos (2013) developed a system to detect inattention by using Electrocardiogram (ECG) and Surface Electromyography (SEMG) signals. This system requires the testers to use telephone and SMS services during driving to detect cognitive and visual inattention during driving. It can be seen by the scholars choosing the type of data collected by the simulation test, except for Chen, Wu, Zhong, Lyu, and Huang (2015) using smart cars to collect vehicle dynamics data. When research is needed on the vehicle dynamics information, most scholars often use simulation tests to collect data. While there is a gap in the authenticity of simulation tests and real car tests, the simulation test is easier to obtain vehicle dynamics test data compared with the actual car test. To ensure the safety of the test, if you want to carry out the real vehicle test, you often need to be equipped with a safety officer (Chen et al., 2015), and the simulation test is safe.

In the real vehicle test, there are also scholars who conduct research on driving distraction based on electrocardiogram (ECG) (Taherisadr, Asnani, Galster, & Dehzangi, 2018) and skin electrical (GSR) (Dehzangi, Sahu, Rajendra, & Taherisadr, 2019). Unlike the instruments used by Yang et al. (2019) to measure electroencephalograms (EEG), which require sensors to be installed on the driver's head, ECG and skin electrical instruments are smaller and can be worn on fingers, so that they can be used in real vehicle tests. Taherisadr et al. (2018) introduced a cepstrum representation of Mel frequency based on ECG and Convolutional Neural Network (CNN) driver distraction detection system. Spectrum cepstrum representation was used as the input of convolutional neural network. Dehzangi et al. (2019) proposed a less invasive wearable physiological sensor (available on smart watches) to quantify the skin conductance (SC) called Galvanic Skin Response (GSR) to characterize and identify natural interference during driving. Use of physiological signals compensates for early and safer distraction detection and has the advantages of low price and low invasiveness.

Depending on the driver's eye movement data, it is a very intuitive indicator to detect driving distraction. When the driver has a driving distraction, the driver's eye movement data often drifts. Topolšek, Areh, and Cvahte (2016) used eye tracking technology to develop a study of the effect of road signs or advertisements on the driver's attention. Xu et al. (2018) collected and analyzed eye movement data of drivers in simulated conflicts at different speeds, selected the peak point of the pupil diameter after wavelet processing, the first point to the left of the peak point and the first point after the peak point, and the construction conflict recognition method (CCFRM) is proposed based on the key point. Eye movement data-based research can more intuitively reflect the connection between driving distractions and roadside visual disturbances than other detection data.

Driving distraction detection based on video images is a more conventional detection method in recent years. Video image detection highlights the authenticity of videos and is often used in real vehicle test. Masood, Rai, Aggarwal, Doja, and Ahmad (2018) detected 22,424 sets of images, and proposed a machine learning model using convolutional neural networks. This model can not only detect distracted drivers but also can analyze the reasons for driving distraction through the images obtained by the camera module installed in the car. Subsequently, Shahverdy, Fathy, Berangi, and Sabokrou (2020) proposed an image deep neural network learning method to analyze five parameters including acceleration, gravity, throttle, speed and revolutions per minute (RPM), and used recursive graph technology to construct a two-dimensional convolutional neural network image based on driving signals. Xing, Lv, and Cao (2020) used a consumer-wide camera (Kinect) to monitor the driver and determine the driving tasks in the actual vehicle, seven common tasks performed by multiple drivers during driving were identified, use of feed-forward neural network (FFNN) was used to identify seven tasks, and finally, it was proven that the FFNN task detector is an effective model that can be used for real-time driver distraction and dangerous behavior recognition.

3.6. Recognition methods and accuracy

Distinct types of driving distraction detection data correspond to different recognition methods, and these different recognition methods correspond to different recognition accuracy. Therefore, it is necessary to analyze the different recognition methods, the

Table 3
Summary of research literature.

Author (year)	Country	Journal	Detection target	Method	Main research conclusion
Oviedo-Trespalacios et al. (2020)	Australia	Analytic Methods in Accident Research	Driving risk compensation behavior	Hierarchical Bayesian multivariate ordered model	Drivers'decisions to make different types of risk compensation are interrelated
Shahverdy et al. (2020)	Iran	Expert Systems with Applications	Acceleration, gravity, throttle, speed and revolutions per minute (RPM)	A two-dimensional convolutional neural network (CNN) on an image constructed from driving signals based on recursive graph technology	A novel and effective deep learning method is proposed for analyzing driver behavior
Xing et al. (2020)	Singapore	Actions for selected chapters	Seven common tasks performed during driving	Random forest and maximum information coefficient method	The average accuracy of the final test results of the seven driving tasks among the participants exceeded 80%
Li, Zhong, Hutmacher, Liang, Horrey, and Xu (2020)	China	Accident Analysis & Prevention	Driving video images	The first module predicts the bounding boxes of the driver's right hand and right ear from RGB images. The second module takes the bounding boxes as input and predicts the type of distraction	For overall distraction detection, it achieved F1-score of 0.74. The whole framework ran at 28 frames per second
Botta et al. (2019)	Italy	Knowledge and Information Systems	vehicle dynamics data and environmental data	single-layer feedforward neural network trained through pseudo-inversion methods	Propose an original approach which benefits from matrix sparsity, showing lower computational times with respect to standard implementations.
Le, Inagami, Hamada, Suzuki, and Aoki (2019)	Japan	Transportation Research Part F: Traffic Psychology and Behaviour	Driver eye tracking data	A model combining VOR and OKR	This model shows greater precision, reduces the effect of optic flow, and works well with changing gaze in the case of involuntary eye movement
Aksjonov, Nedoma, Vodovozov, Petlenkov, and Herrmann (2019)	Czech Republic	IEEE Transactions on Intelligent Transportation Systems	vehicle dynamics data	fuzzy logic and machine learning	The results presented in this research confirm its capability to detect and to precisely measure a level of abnormal driver performance
Chui, Alhalabi, and Liu (2019)	China	Data Technologies and Applications	Head motion coefficient	light computation power algorithm	Distraction detection using a light computation power algorithm is an appropriate direction and further work could be devoted on more scenarios as well as background light intensity and resolution of video frames
Riaz et al. (2019)	Pakistan	Ad Hoc & Sensor Wireless Networks	vehicle dynamics data	HUB-NET technology using an Exploratory Agent-Based Modeling level of a Cognitive Agent-based Computing (CABC) framework	The proposed driver distraction computing methodology and the Driver Distraction Detection Enabled-ADAS outperform simple ADAS
Eraqi, Abouelnaga, Saad, and Moustafa (2019)	Egypt	Journal of Advanced Transportation	face and hand localizations, and skin segmentation	an Ensemble of Convolutional Neural Networks	Propose a deep learning algorithm with 90% accuracy and a simplified version that can achieve 84.64% classification accuracy
Dehzangi et al. (2019)	USA	Smart Health	Galvanic Skin response (GSR) Skin Conductance (SC)	Embedded random forest feature selection and integrated bag classifier	Achieve minimal intrusion and achieve improved accuracy of 92.9% and 93.5%
Louie and Mouloua (2019)	USA	Applied Ergonomics	Working Memory Capacity (WMC)	Working memory diffuser	The weakening effect of distraction on braking response time is partially mediated by WMC
Yang et al. (2019)	China	Accident Analysis &	Electroencephalogram (EEG) characteristics and based on hybrid features (combination of driving	Two EEG analysis techniques (independent component analysis and brain source localization)	The EEG-based model has better performance than the driving data-based model, and the integrated model of

Table 3 (*continued*)

Author (year)	Country	Journal	Detection target	Method	Main research conclusion
		Prevention	features and EEG features)	and two signal processing methods (power spectrum analysis and wavelet analysis)	driving features and whole brain region features extracted through wavelet analysis is superior to other types of features. The highest accuracy is 86.27%.
Zhao et al. (2019)	China	Transportation Research Part F: Traffic Psychology and Behavior	Abnormal driving behavior	Structural Equation Model (SEM)	The main factor that affects illegal driving behavior is driving attitude, and the main factor that affects the performance of distracted drivers is basic driver characteristics
Masood et al. (2018)	India	Pattern Recognition Letters	Driving video images	CNN	The proposed model can greatly reduce training time and achieve 99% high detection accuracy on large data sets
Atiquzzaman et al. (2018)	USA	Transportation Research Part F: Traffic Psychology and Behavior	Vehicle dynamics data	Two linear (linear judgment analysis and logistic regression) and two nonlinear models (support vector machine and random forest)	The random forest algorithm has the best performance, it can detect texting and diet interference, and its accuracy is 85.38% and 81.26%, respectively
Aksjonov, Nedoma, Vodovozov, Petlenkov, and Herrmann (2018)	Czech Republic	IFAC-Papers Online	Changes in curvature and speed	Artificial neural network and adaptive neuro-fuzzy inference system	Although the prediction accuracy of the model depends on the algorithm specifications, compared with the adaptive neuro-fuzzy inference system, the artificial neural network is slightly more accurate in predicting driver performance
Taherisadr et al. (2018)	USA	Smart Health	Electrocardiogram (ECG)	Mel frequency cepstrum representation and convolutional neural network (CNN)	The proposed algorithm can achieve obvious classification accuracy between various topics
Ma, Hu, Chan, Qi, and Fan (2018)	China	Transportation Research Part D: Transport and Environment	Driving distance and vehicle speed	Forecasting model of driving task demand	Driving a vehicle is a multilevel task composed of various driving tasks and secondary tasks. The driver must assign attention to the task requirements in order to drive safely
Xu et al. (2018)	China	Accident Analysis & Prevention	Driver eye tracking data	construction conflict recognition method	The key points based on eye movements are proposed, the construction conflict period and the construction conflict are found, and a fast and effective identification method is proposed.
Duy, Ha, Sheng, Bai, & Chowdhary (2018)	USA	IET Intelligent Transport Systems	Driving video images	Four deep convolutional neural networks including VGG-16, AlexNet, GoogleNet, and residual network	GoogleNet is the best model out of the four for distraction detection in the driving simulator testbed
Son and Park (2018)	South Korea	International Journal of Automotive Technology	vehicle dynamics data	Radial Basis Probabilistic Neural Networks	The best performing model could detect distraction with an average accuracy of 78.0%
Ali and Hassan (2018)	Pakistan	KSII Transactions on Internet and Information Systems	Driver facial data	Active Shape Model (ASM) and Boosted Regression with Markov Networks (BoRMaN)	The approach that uses the novel ideas of motion vectors and interpolation outperforms other approaches in detection of driver's head rotation. We are able to achieve a percentage accuracy of 98.45 using Neural Network.
Li, Bao, Kolmanovsky and Yin (2018)	China	IEEE Transactions on Intelligent Transportation Systems	Vehicle dynamics data	Nonlinear autoregressive exogenous (NARX) driving model	Steering entropy and mean absolute speed prediction error from the NARX model are selected
Dehzangi, Rajendra, and	USA	Sensors	Skin electrical (GSR)	support vector machine recursive feature elimination	Demonstrated cross-validation accuracy of 94.81% using all the features and the accuracy of 93.01% using reduced

(*continued on next page*)

Table 3 (*continued*)

Author (year)	Country	Journal	Detection target	Method	Main research conclusion
Taherisadr (2018)					feature space
Choudhary and Velaga (2017)	India	Transportation Research Part F: Traffic Psychology and Behavior	Standard deviation of lane positioning, number of lane deviations, mean and standard deviation of lateral acceleration, mean and standard deviation of steering wheel angle and steering reversal rate	Repeated measurement ANOVA test	10° SRR can be provided in smart vehicle equipment to detect interference and alert the driver of its decentralized state
Savolainen (2016)	USA	Accident Analysis & Prevention	Vehicle speed and travel time	Random parameters and latent logit model	The goodness of fit between the random parameter model and the latent class model is very similar. While the random parameter model can use the standard to directly compare the statistical test with the merged logit model, you can choose between random parameters and latent parameters to a large extent depends on theoretical considerations
Topolšek et al. (2016)	Slovenia	Transportation Research Part F: Traffic Psychology and Behavior	Driver eye tracking data	Eye tracking technology	The age of the driver is independent of the number of roadside objects detected
Liao et al. (2016)	China	IEEE Transactions on Intelligent Transportation Systems	Vehicle dynamics and driver eye movement data	The support vector machine (SVM) recursive feature elimination algorithm	the classifier based on the fusion of driving performance and eye movement yields the best correct rate and F-measure
Liu, Yang, Huang, Yeo, and Lin (2016)	China	IEEE Transactions on Intelligent Transportation Systems	Dri'er's facial and eye movement data	Laplacian support vector machine and semi-supervised extreme learning machine	Semi-Supervised Machine Learning can enhance the efficiency of model development in terms of time and cost.
Chen et al. (2015)	China	Accident Analysis & Prevention	Standard deviation of acceleration rate (SDA) and standard deviation of yaw angular acceleration (SDY)	Wilcoxon rank sum test and double time window method	The optimized "parent window" and "child window" are 55 s and 6 s, respectively. The research results can be used to develop driver assistance systems
Sahayadhas et al. (2015)	India	Expert Systems with Applications	Electrocardiogram (ECG) and electromyography (EMG)	K-Nearest Neighbor (KNN)	The best combination of the features of ECG and EMG signals, the classification accuracy is 96%
Stavrinos (2013)	USA	Accident Analysis & Prevention	Speed fluctuation and lane change times	Repeated measurement multivariate variance analysis and generalized estimation equation Poisson model	Distracted driving will lead to traffic safety and traffic flow reduction, which will have a negative impact on traffic operation
Klauer (2014)	USA	New England journal of medicine	Vehicle dynamics data and video image data	Logistic regression analysis of mixed effects	With the execution of many secondary tasks, including texting and calling mobile phones, the risk of novice drivers crashing or approaching a crash will increase
Hickman and Hanowski (2012))	USA	Traffic injury prevention	Natural driving data	Advantage ratio analysis	Mobile phone use should not be regarded as a binary variable (yes/no), and the risks of different mobile phone subtasks are different
Foss and Goodwin (2014)	USA	Journal of Adolescent Health	Natural driving data (vehicle motion, video, audio)	Cluster analysis, variance analysis, univariate logistic regression estimation	The common assumption of adolescent drivers' distraction is only partially supported by in-car measurements, and the relationship between passengers and distraction seems to be more complicated than previously realized

Table 4
Influencing factors of driving distraction, recognition method and accuracy.

Author (year)	Participants	Test environment		Detection data type						Method	Accuracy
		Real car	Simulation	Video images	ECG	SC	EEG	Vehicle power	Eye movement data		
Shahverdy et al. (2020)	3	✓		✓						CNN	99.76%
Xing et al. (2020)	5	✓		✓						Random forest	>80%
Li et al. (2020)	20		✓	✓						CNN	92%
Aksjonov et al. (2019)	18		✓					✓		(ED) and (FZ)	＞90%
Eraqi et al. (2019)	44	✓		✓						CNN	98%
Dehzangi et al. (2019)	15	✓				✓				Random forest	93.50%
Yang et al. (2019)	52		✓				✓	✓		wavelet analysis	86.27%
Masood et al. (2018)	22,424	✓		✓						CNN	99%
Atiquzzaman et al. (2018)	35		✓					✓		Random forest	85.38%
Taherisadr et al. (2018)	10	✓			✓					CNN	95.51%
Duy et al. (2018)	2,000		✓	✓						CNN	92%
Son and Park, 2018)	15	✓						✓		RBPNN	78.0%
Ali and Hassan (2018)	4	✓		✓						Active Shape Model (ASM)	98.45%
Li et al. (2018))	10	✓						✓		SVM	95
Dehzangi et al. (2018)	10	✓				✓				SVM-RFE	93.01%
Liao et al. (2016)	27		✓					✓	✓	SVM-RFE	95.8%
Liu et al. (2016)	41	✓							✓	SVM	97.2%

resulting accuracy, and aggregate the distraction recognition method. Its accuracy is shown in Table 4.

Convolutional neural network (CNN) is a commonly used driving distraction recognition method in recent years, and the accuracy of using CNN to identify driving distraction can reach more than 95%, which is the highest accuracy recognition method in the summarized literature. Taherisadr et al. (2018) convened 10 testers to participate in the test, selected electrocardiogram (ECG) as the recognition factor, and adopted a cepstrum representation of Mel frequency based on ECG and Convolutional Neural Network (CNN) driver distraction detection system. The structure of the deep CNN can automatically learn the reliable recognition patterns in two-dimensional spatio-temporal spectral space as features, thereby replacing the traditional hand-made features when processing the recorded time series data sets, and the final recognition accuracy reaches 95.51%. Masood et al. (2018) selected 22,424 groups of video images for research, and proposed a machine learning model using convolutional neural networks. This model can not only detect distracted drivers, but also determine the reason of distraction by camera module installed in the car. The image obtained within the camera module determined the cause of its distraction. By learning spatial features from images, CNN can further examine them through a fully connected neural network, with a detection accuracy rate of 99%. Shahverdy et al. (2020) selected three drivers to participate in the actual car test, and used a two-dimensional convolutional neural network (CNN) on the image constructed from the driving signal based on the recursive graph technology to conduct research, the final recognition accuracy rate reached 99.76%. Through the research of these scholars, we can see that when CNN is applied to the video image detection driving distraction technology, its recognition accuracy is very high, and the data detection device has no contact load with the driver. When CNN is applied to the electroencephalogram (ECG) detection of driving distraction technology, the recognition accuracy is also very high. However, when CNN is used for video image detection to identify driving distraction, the problem of recognizing the distraction delay occurs, and especially when using video images with high accuracy, it is easy to lead to leakage of driving privacy, which provides obstacles for the widespread application of CNN.

Similar to CNN, Random Forest is also a commonly used driving distraction recognition method in recent year. Xing et al. (2020) used the Random Forest method to detect driving distraction in video images and selected five drivers to test seven common tasks during driving, and the average accuracy of the final detection results exceeded 80%. It also applies to video image detection for driving distraction. Random Forest method is lower in accuracy, but the Random Forest method overcomes the problem of CNN method recognition delay, and it has good real-time performance while retaining the advantages of video image detection without contacting with the driver. Also from the point of view of contactless drivers, to solve most real-life interference tasks, as well as the problem that eye, head or face tracking data is difficult to obtain in real time, Atiquzzaman et al. (2018) selected 35 drivers to conduct a real car test and used vehicle dynamics data to determine driving distraction. In this article, Atiquzzaman compares the performance of two linear (linear recognition analysis and logistic regression) and two nonlinear models (Support Vector Machine and Random Forest), and derives the Random Forest algorithm to measure the driving score in car dynamics. The conclusion of the best performance of the heart feature is that when Random Forest is used to detect the two driving distractions of texting and diet interference, the accuracy is 85.38% and 81.26%. Although the accuracy rate is lower than other methods, this detection method has no contact with the driver, and has low cost and strong practicality. It provides useful guidance for car manufacturers who integrate the distraction detection system into their vehicles. Dehzangi et al. (2019) also proposed a less invasive wearable physiological sensor (which can be used on smart watches) from the perspective of reducing body load. It quantifies Galvanic Skin Response (GSR) and Skin Conductance (SC) to characterize and identify interference during natural driving. The embedded Random Forest feature selection and integrated bag classifier only use 10-D and 15-D feature space to achieve 92.9% and 93.5% accuracy, respectively. Although the method proposed by Dehzangi has a load contact with the driver, this physiological sensor has a small load and can provide high-accuracy recognition.

Some scholars have adopted other recognition methods to detect driving distraction. Sahayadhas, Sundaraj, Murugappan, and Palaniappan (2015) selected 15 drivers for driving simulation and used KNN to develop a system that can detect inattention using ECG and SEMG signals. The results indicate that the overall maximum accuracy of the bispectrum feature on the ECG and EMG signals is 98.12% and 90.97%. Sahayadhas, Sundaraj, Murugappan, and Palaniappan (2015) used k-fold verification on the basis of their own research, and the overall maximum accuracy of bespectacled features on ECG and EMG signals was 96.75% and 92.31%. Sahayadhas also uses principal component analysis to fuse features of ECG and EMG signals, improving classification accuracy to 96%. Although this method has achieved good accuracy, the detection and acquisition of electrocardiogram (ECG) and surface electromyography (SEMG) signals have a heavy load on the driver. Yang et al. (2019) selected 52 drivers for simulated driving tests, based on EEG features and based on mixed features (a combination of driving features and EEG features) model, using two EEG analysis techniques (independent component analysis and brain source location), two signal processing methods (power spectrum analysis and wavelet analysis) to extract 12 kinds of EEG features and driving state prediction. The driving performance, EEG features and mixed features are evaluated and compared. The results show that the EEG-based model has better performance than the driving data-based model (accuracy rates are 83.84% and 71.59%, respectively). This method is based on mixed features for comparison, which has better recognition characteristics than single feature. However, the accuracy is lower than the other methods discussed, and there is load contact with the driver.

4. Discussion

4.1. Development of publications, countries and authors

Fig. 2 shows in detail the overall development trend of publications. The figure reveals that the growth of NO is substantial and has been very high since 2013, which is inseparable from the rapid development of using mobile phones and vehicle-mounted functions while driving. The keyword co-occurrence graph in Fig. 5 reflects this very well. In Fig. 5, the mobile phone is almost connected to other keyword nodes. In the statistics of the number of countries published in Fig. 3, the United States, Britain, Germany, Australia, China, and Canada are the top countries in terms of volume of documents. Interestingly, in the co-occurrence chart of countries in Fig. 4, these countries are also the countries with the closest cooperation. This shows that international academic cooperative research has a positive effect on article output, and academic research can promote the professional knowledge of different scholars, leading to more ideas and innovations. Fig. 6 shows the cooperation network between different authors. There is an aggregation feature in the cooperation between the authors, and there is a connection between the author's research field and the cooperation between the authors. Fig. 7 reveals the research directions that are more focused on when scholars collaborate, and focuses on the analysis of the methodology.

4.2. Summary of advantages and disadvantages of driving distraction recognition method

Research on driving distraction has different types of detection data, different recognition methods, and corresponding different recognition accuracy.

Detecting driving distraction based on surveillance video images has no contact burden on the driver. It has a high accuracy rate, but is prone to leakage of driving privacy, and the cost is relatively high. In the driving distraction detection method based on surveillance video images, CNN has higher accuracy than Random Forest, but Random Forest is better than CNN in real time.

The detection of distraction based on Electrocardiogram (ECG) and Galvanic Skin Response (GSR) has less burden on driver contact, and the overall accuracy is higher. However, these methods have the problem that the data are difficult to obtain in real time. The driving distraction detection method based on ECG and GSR is similar to that based on surveillance video images.

The detection of driving distraction based on automobile dynamics has no contact burden on the driver, the data are easily available and the cost is low, but the overall accuracy is low. The accuracy of power spectrum analysis, wavelet analysis, and random forest conversion used in the driving distraction detection method developed by automobile dynamics data is about 80%. Compared with other methods, this method still has room for improvement in accuracy.

Detection of distraction based on eye movement data has no contact burden on the driver, but the data is difficult to obtain in real time, and the cost is high. However, the collected data are the most intuitive.

4.3. The effect of driving fluctuation on driving distraction research

During the literature review, it was found that there were studies related to driving volatility in interconnected and natural driving systems. Driving volatility can be used as a measure of driving distraction behavior, which is of great significance to the study of driving distraction. Kim, Song, Rouphail, Aghdashi, Amaro, and Gonçalves (2016) collected the number of natural driving behaviors for 3 months based on on-board sensors, and studied the correlation between collision tendency and microscopic driving behaviors. Wali, Khattak, and Karnowski (2020) studied the relationship between the severity of collision injury and driving volatility by analyzing the collision event data set in the natural driving database. The results show that the greater driving fluctuation (longitudinal and transverse) increases the possibility of serious collision events. What is important is that the impact of longitudinal deceleration fluctuation is significantly greater than that of longitudinal acceleration fluctuation on collision results. Khattak and Wali (2017) also analyzed vehicle driving data, and captured the state degree of speed change through driving fluctuation, so as to distinguish normal driving from abnormal driving. Shangguan, Fu, Wang, and Luo (2021) put forward a method based on natural driving data, which integrates driving risk status recognition, feature extraction based on rolling time window, real-time driving risk status prediction, and driving risk influencing factor analysis, so as to accurately evaluate and predict real-time driving risk status. Feng, Bao, Sayer, Flannagan, Manser, and Wunderlich (2017) used vehicle sensor data in natural driving to study the variation characteristics of vehicle longitudinal acceleration, so as to identify aggressive drivers and driving behaviors. From the above research, it can be known that by studying driving volatility, abnormal driving behaviors such as normal driving and distraction can be distinguished, and they can also be linked with unsafe results in the real world (such as crash/near-crash). Therefore, we need to strengthen the research on the influence and function of driving volatility on driving distraction.

4.4. Limitations of the study

This article sorts out the literature of driving distraction recognition methods, which is limited by resources and ability, and has the following deficiencies:

(1) When searching for documents, only documents published in English were searched; hence, related documents published in other languages were excluded.
(2) When analyzing the author sharing network, due to the limitation of the database, only the literature data on the Web of Science are collected and analyzed.

(3) The selected driving distraction recognition methods are all based on traditional vehicles, and there also exists the absence of research on autonomous vehicles.
(4) The selected documents in this article focus on the recognition method of driving distraction, and other methods of recognition on abnormal driving behaviors such as road rage and driving fatigue are limited due to space limitations.

4.5. Current research deficiencies and future research trends

From the analysis of the current research situation of driving distraction, it can be seen that the acquisition method of driving distraction detection data is simple, the repeatability of test scenes is high, the research topics are concentrated, the detection data indicators are polarized, and the rationality analysis of detection data selection is less. The main problems existing in the method of driving distraction state recognition include: the types of driving distraction recognition are not comprehensive, the recognition model only recognizes the state, and the comparison between the advantages and disadvantages of the model method is not equal. With the development of artificial intelligence, image recognition technology becomes more mature, and image data analysis and processing will become a hot spot. At the same time, with the further development of technology, video data analysis will become simple and easy. At the same time, we should deeply research using big data forms such as cloud data and car networking data. Because driving distraction is a dangerous driving behavior, and natural driving data set is observed under normal driving behavior, simulation test is still the main data source for a long time, and future scene construction can be combined with holographic projection and VR technology to enhance the realism of tests. At present, the research on driving distraction mainly focuses on mobile phones, which should be decentralized to make the research topics more balanced. The current driving distraction research scenes are all manual driving scenes. With the development of intelligent transportation, there will be a man–machine driving scene for a long time before entering fully automatic unmanned driving. Follow-up research should be done on the influence of driving distraction in semi-automatic driving scenarios, such as the influence of vehicle–road cooperation on driving behavior, the study of task taking-over efficiency in man–machine co-driving, and the human factors analysis of different levels of self-driving vehicles with different mixing ratios in road network.

Combined with the characteristics of the selected indexes, a real-time recognition algorithm with better performance is constructed, and a perfect algorithm performance evaluation index is established. At present, the recognition effect of the same recognition model is uneven, which is mainly caused by the difference in the selection of recognition indicators. At present, the evaluation indicators of algorithms often use single indicators such as accuracy. In addition, the real-time requirements for state recognition are increasing day by day. Therefore, it is necessary to establish a complete comprehensive evaluation index of the recognition model, and compare and evaluate the performance of the model. Because the data used in the recognition model are different, and the quality of data plays an important role in the quality of the model, it is not absolutely fair to judge the quality of the recognition model by comparing the accuracy rate, and this problem can be solved by establishing a special model verification database. With the development of artificial intelligence, the construction of recognition model by deep learning has become a research hotspot in recent years, and will keep this trend in the future.

5. Conclusion

This research combines quantitative metrology and co-occurrence network analysis for the first time to carry out quantitative analysis of driving distraction literature in terms of time, country, publication, author, and keywords. It also analyzes the publications that study driving distraction recognition methods. This research can help researchers to understand the publication co-occurrence coupling relationship, understand the advantages and disadvantages of recognition methods and indicators, and develop more innovative ideas.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

Aksjonov, A., Nedoma, P., Vodovozov, V., Petlenkov, E., & Herrmann, M. (2018). A novel driver performance model based on machine learning. *IFAC-Papers OnLine, 51*, 267–272.
Aksjonov, A., Nedoma, P., Vodovozov, V., Petlenkov, E., & Herrmann, M. (2019). Detection and evaluation of driver distraction using machine learning and fuzzy logic. *IEEE Transactions on Intelligent Transportation, 20*, 2048–2059.
Ali, S. F., & Hassan, M. T. (2018). Feature based techniques for a driver's distraction detection using supervised learning algorithms based on fixed monocular video camera. *KSII Transactions on Internet and Information Systems, 12*, 3820–3841.
Atiquzzaman, M., Qi, Y., & Fries, R. (2018). Real-time detection of drivers' texting and eating behavior based on vehicle dynamics. *Transportation Research Part F: Traffic Psychology and Behaviour, 58*, 594–604.
Botta, M., Cancelliere, R., Ghignone, L., Tango, F., Gallinari, P., & Luison, C. (2019). Real-time detection of driver distraction: Random projections for pseudo-inversion-based neural training. *Knowledge and Information Systems, 60*, 1549–1564.
Chen, Z., Wu, C., Zhong, M., Lyu, N., & Huang, Z. (2015). Identification of common features of vehicle motion under drowsy/distracted driving: A case study in Wuhan, China. *Accident Analysis & Prevention, 81*, 251–259.
Choudhary, P., & Velaga, N. R. (2017). Analysis of vehicle-based lateral performance measures during distracted driving due to phone use. *Transportation Research Part F: Traffic Psychology and Behaviour, 44*, 120–133.
Chui, K. T., Alhalabi, W., & Liu, R. W. (2019). Head motion coefficient-based algorithm for distracted driving detection. *Data Technologies and Applications, 53*, 171–188.
Dehzangi, O., Rajendra, V., & Taherisadr, M. (2018). Wearable driver distraction identification on-the-road via continuous decomposition of galvanic skin responses. *Sensors-Basel, 18*.
Dehzangi, O., Sahu, V., Rajendra, V., & Taherisadr, M. (2019). GSR-based distracted driving identification using discrete & continuous decomposition and wavelet packet transform. *Smart Health, 14*, 100085.
Dehzangi, O., & Taherisadr, M. (2018). Driver distraction detection using MEL cepstrum representation of galvanic skin responses and convolutional neural networks. In *IEEE. 24th international conference on pattern recognition* (pp. 1481–1486). New York: IEEE.
Dewar, R. E., & Olson, P. L. (2002). Human factors in traffic safety. *Publication of Lawyers & Judges Publishing Company Incorporated*.
Donmez, B., Boyle, L. N., & Lee, J. D. (2007). Safety implications of providing real-time feedback to distracted drivers. *Accident Analysis and Prevention, 39*, 581–590.
Duy, T., Ha, M. D., Sheng, W., Bai, H., & Chowdhary, G. (2018). Real-time detection of distracted driving based on deep learning. *IET Intelligent Transport Systems, 12*, 1210–1219.
Eraqi, H. M., Abouelnaga, Y., Saad, M. H., & Moustafa, M. N. (2019). Driver distraction identification with an ensemble of convolutional neural networks. *Journal of Advanced Transportation*.
Feng, F., Bao, S., Sayer, J. R., Flannagan, C., Manser, M., & Wunderlich, R. (2017). Can vehicle longitudinal jerk be used to identify aggressive drivers? *An examination using naturalistic driving data, Accident Analysis and Prevention, 104*, 125–136.

Foss, R. D., & Goodwin, A. H. (2014). Distracted driver behaviors and distracting conditions among adolescent drivers: Findings from a naturalistic driving study. *Journal of Adolescent Health, 54*(5), S50–S60.
Gao, C., Sun, M., Geng, Y., Wu, R., & Chen, W. (2016). A bibliometric analysis based review on wind power price. *Applied Energy, 182*, 602–612.
Hickman, J. S., & Hanowski, R. J. (2012). An assessment of commercial motor vehicle driver distraction using naturalistic driving data. *Traffic Injury Prevention, 13*(6), 612–619.
Khattak, A. J., & Wali, B. (2017). Analysis of volatility in driving regimes extracted from basic safety messages transmitted between connected vehicles. *Transportation Research Part C: Emerging Technologies, 84*, 48–73.
Kim, S., Song, T. J., Rouphail, N. M., Aghdashi, S., Amaro, A., & Gonçalves, G. (2016). Exploring the association of rear-end crash propensity and micro-scale driver behavior. *Safety Science, 89*, 45–54.
Kim, H. J., Jeong, Y. K., & Song, M. (2016). Content- and proximity-based author co-citation analysis using citation sentences. *Journal of Informetrics, 10*, 954–966.
Klauer, S. G., Guo, F., Simons-Morton, B. G., Ouimet, M. C., Lee, S. E., & Dingus, T. A., Distracted driving and risk of road crashes among novice and experienced drivers, New England Journal of Medicine, 370(1), 54-59.
Le, T. H. N., Zheng, Y. T., & Zhu, C. C., et al. Multiple scale Faster-RCNN approach to driver's cell-phone usage and hands on steering wheel detection. In IEEE. IEEE Conference on Computer Vision and Pattern Recognition Workshops. New York: IEEE, 2016: 46-53.
Le, A. S., Inagami, M., Hamada, H., Suzuki, T., & Aoki, H. (2019). Towards online detection of driver distraction: Eye-movement simulation based on a combination of vestibulo-ocular reflex and optokinetic reflex models. *Transport Research F-Traffic, 65*, 716–729.
Lee, J. D., & Kolodge, K. (2019). Exploring trust in self-driving vehicles through text analysis. *Human Factors the Journal of the Human Factors & Ergonomics Society*. 001872081987267.
Li, Z., Bao, S., Kolmanovsky, I. V., & Yin, X. (2018). Visual-manual distraction detection using driving performance indicators with naturalistic driving data. *IEEE Transactions on Intelligent Transportation, 19*, 2528–2535.
Li, L., Zhong, Jr. B., Hutmacher, C., Liang, Y., Horrey, W.J., Xu, X. (2020). Detection of driver manual distraction via image-based hand and ear recognition, Accident Analysis Prevention, 137.
Liao, Y., Li, S. E., Wang, W., Wang, Y., Li, G., & Cheng, B. (2016). Detection of driver cognitive distraction: A comparison study of stop-controlled intersection and speed-limited highway. *IEEE Transactions on Intelligent Transportation, 17*, 1628–1637.
Liu, T., Yang, Y., Huang, G., Yeo, Y. K., & Lin, Z. (2016). Driver distraction detection using semi-supervised machine learning. *IEEE Transactions on Intelligent Transportation, 17*, 1108–1120.
Louie, J. F., & Mouloua, M. (2019). Predicting distracted driving: The role of individual differences in working memory. *Applied Ergonomics, 74*, 154–161.
Ma, Y., Hu, B., Chan, C., Qi, S., & Fan, L. (2018). Distractions intervention strategies for in-vehicle secondary tasks: An on-road test assessment of driving task demand based on real-time traffic environment. *Transportation Research Part D: Transport and Environment, 63*, 747–754.
Masala, G. L., & Grosso, E. (2014). Real time detection of driver attention: Emerging solutions based on robust iconic classifiers and dictionary of poses. *Transportation Research Part C-emerging Technologies, 49*, 32–42.
Masood, S., Rai, A., Aggarwal, A., Doja, M.N., & Ahmad, M. (2018). Detecting distraction of drivers using Convolutional Neural Network, Pattern Recognition Letter.
Mcevoy, S. P., Stevenson, M. R., & Woodward, M. (2007). The prevalence of, and factors associated with, serious crashes involving a distracting activity. *Accident Analysis & Prevention, 39*, 475–482.
Mehler, B., Reimer, B., & Coughlin, J. F. (2012). Sensitivity of physiological measures for detecting systematic variations in cognitive demand from a working memory task: AN on-road study across three age groups. *Human Factors, 54*, 396–412.
Oviedo-Trespalacios, O., Afghari, A. P., & Haque, M. M. (2020). A hierarchical Bayesian multivariate ordered model of distracted drivers' decision to initiate risk-compensating behaviour. *Analytic Methods in Accident Research, 26*, 100121.
Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T., Mulrow, C. D., et al. (2020). Mapping of reporting guidance for systematic reviews and meta-analyses generated a comprehensive item bank for future reporting guidelines. *Journal of Clinical Epidemiology, 118*, 60–68.
Parker, D., Reason, J., Manstead, A. R., & Stradling, S. (1995). Driving errors, driving violations and accident involvement. *Ergonomics, 38*, 1036–1048.
Reimer, B., D'Ambrosio, L. A., Coughlin, J. F., Kafrissen, M. E., & Biederman, J. (2006). Using self-reported data to assess the validity of driving simulation data. *Behav Res Methods, 38*, 314–324.
Riaz, F., Rathore, M. M., Sharif, T., Sajid, M., Ratyal, N., & Jararweh, Y. (2019). Internet of things based driver distraction detection and assistance system: A novel approach. *Ad Hoc & Sensor Wireless Networks, 44*, 305–337.
Sahayadhas, A., Sundaraj, K., Murugappan, M., & Palaniappan, R. (2015). A physiological measures-based method for detecting inattention in drivers using machine learning approach. *Biocybernetics and Biomedical Engineering, 35*, 198–205.
Sahayadhas, A., Sundaraj, K., Murugappan, M., & Palaniappan, R. (2015). Physiological signal based detection of driver hypovigilance using higher order spectra. *Expert Systems with Applications, 42*, 8669–8677.
Savolainen, P. T. (2016). Examining driver behavior at the onset of yellow in a traffic simulator environment: Comparisons between random parameters and latent class logit models. *Accident Analysis & Prevention, 96*, 300–307.
Scott-Parker, B. (2017). Emotions, behaviour, and the adolescent driver: A literature review. *Transportation Research Part F: Traffic Psychology & Behaviour, 50f*, 1–37.
Shahverdy, M., Fathy, M., Berangi, R., & Sabokrou, M. (2020). Driver behavior detection and classification using deep convolutional neural networks. *Expert Systems with Applications, 149*, 113240.
Shangguan, Q., Fu, T., Wang, J., & Luo, T. (2021). An integrated methodology for real-time driving risk status prediction using naturalistic driving data. *Accident Analysis and Prevention, 156* 106122.
Son, J., & Park, M. (2018). Detection of cognitive and visual distraction using radial basis probabilistic neural networks. *International Journal of Automotive Technology-Korea, 19*, 935–940.
Stavrinos, D. et al. (2013). Impact of distracted driving on safety and traffic flow. *Accident Analysis & Prevention, 61*, 63–70.
Taherisadr, M., Asnani, P., Galster, S., & Dehzangi, O. (2018). ECG-based driver inattention identification during naturalistic driving using Mel-frequency cepstrum 2-D transform and convolutional neural networks. *Smart Health, 9–10*, 50–61.
Topolšek, D., Areh, I., & Cvahte, T. (2016). Examination of driver detection of roadside traffic signs and advertisements using eye tracking. *Transportation Research Part F: Traffic Psychology and Behaviour, 43*, 212–224.
Valero Mora, P. M., Ballestar Tarin, M. L., Tontsch, A., Pareja Montoro, I., & Sanchez Garcia, M. (2012). Effects of manually entering navigator destinations while driving in a simulator. *IET Intelligent Transport Systems, 6*, 397–403.
Waard, D. D., Brookhuis, K. A., & Hernandez-Gress, N. (2001). The feasibility of detecting phone-use related driver distraction. *Vehicle Design, 26*(1), 85–95.
Wali, B., Khattak, A. J., & Karnowski, T. (2020). The relationship between driving volatility in time to collision and crash-injury severity in a naturalistic driving environment. *Analytic Methods in Accident Research, 28* 100136.
Wang, Y. K., Jung, T. P., & Lin, C. T. (2015). EEG-based attention tracking during distracted driving. *IEEE Transactions on Neural Systems & Rehabilitation Engineering, 23*(6), 1085–1094.
Wilson, F. A., & Stimpson, J. P. (1999). Trends in fatalities from distracted driving in the United States to 2008. *American Journal of Public Health, 100*(2010), 2213–2219.
Wöllmer, M., Blaschke, C., Schindl, T., et al. (2011). Online driver distraction detection using long short-term memory[J]. *IEEE Transactions on Intelligent Transportation Systems, 12*(2), 574–582.
Wu, L., Wang, W., Jing, P., Chen, Y., Zhan, F., Shi, Y., et al. (2020). Travel mode choice and their impacts on environment—a literature review based on bibliometric and content analysis, 2000–2018. *Journal of Cleaner Production, 249*, 119391.
Xing, Y., Lv, C., & Cao, D. (2020). *Chapter 5 - Driver behavior recognition in driver intention inference systems, advanced driver intention inference*. Elsevier.
Xu, Y., Li, S., Gao, S., Tan, D., Guo, D., & Wang, Y. (2018). Recognition method of construction conflict based on driver's eye movement. *Accident Analysis & Prevention, 113*, 193–201.
Yang, L., Guan, W., Ma, R., & Li, X. (2019). Comparison among driving state prediction models for car-following condition based on EEG and driving features. *Accident Analysis & Prevention, 133*, 105296.
Yang, Y., McDonald, M., & Zheng, P. (2012). Can drivers' eye movements be used to monitor their performance? A case study. *IET Intelligent Transport Systems, 6*, 444–452.
Yusoff, N. M., Ahmad, R. F., Guillet, C., Malik, A. S., Saad, N. M., & Merienne, F. (2017). Selection of measurement method for detection of driver visual cognitive distraction: A review. *IEEE Access, 5*, 22844–22854.
Zhao, D., & Strotmann, A. (2011). Counting first, last, or all authors in citation analysis: A comprehensive comparison in the highly collaborative stem cell research field. *Journal of the Association for Information Science & Technology, 62*, 654–676.
Zhao, X., Xu, W., Ma, J., Li, H., & Chen, Y. (2019). An analysis of the relationship between driver characteristics and driving safety using structural equation models. *Transportation Research Part F: Traffic Psychology and Behaviour, 62*, 529–545.

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