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Structural analysis of driver fatigue behavior: A systematic review

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A R T I C L E I N F O

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Individual difference

A B S T R A C T

Fatigue is always accompany with the driving task, which have been extensively investigated for driver monitoring and traffic safety. While many scholars dedicate to the study of fatigue detection methods with higher accuracy, but the basic correlation between detection methods and fatigue cause or prevention receive relatively little attention.

This study systematically reviews the authors' studies of fatigue influential factors, fatigue identification and measurement, and fatigue prediction; and then structurally and comparably describes the research of driver fatigue behavior from the above three components within the literature of interest.

Time-related indicators are usually considered as the main driver fatigue influential factors, and driving environment and vehicle performance are also found to be contributive to driver fatigue. The elastic control of driving time and rest time is an effective measure for the prevention of driver fatigue. Sensitivity analysis can test the correlation between measurements of fatigue identification and fatigue level, and then ensure the performance of measurements. Models that consider time-related factors based on bio-mathematic model theory can be used for real-time fatigue level prediction and characterizing the fatigue dynamics in the planned travel time. Driver individual differences should be considered for the fatigue behavior research as the performance of fatigue detection model and prediction models could vary greatly within drivers from different population.

This review described the structure of driver fatigue behavior studies, and the link between fatigue influential indicators, fatigue identification, prediction. The effect of fatigue identification should be further explored, not just for detection or high accuracy.

1. Introduction

Driving fatigue has been a great threat to transportation as it increases the number of accidents and leads to heavy losses of property (Editorial Department of China Journal of Highway and Transport, 2016). According to the National Highway Traffic Safety Administration (NHTSA), there were 697 deaths due to fatigue driving in 2019 in U.S., accounting for 1.9% of the total number of deaths (United States Department of Transportation. Drowsy driving, 2020). Accidents due to fatigue driving account for 25% freeway accidents in Germany as reported by the German Insurance Association (Wei, 2010). In France, fatigue accidents account for 14.9% and 20.6% of injury accidents and fatal accidents, respectively (Li et al., 2010). According to statistics from the Ministry of Transport of the People's Republic of China, the accident caused by fatigue driving in 2020 accounted for 21% of the total number of road traffic accidents, and the increase rate of fatigue driving accidents rise while the rate of total traffic accidents declined during 2015–2020 (Yearbook of China Transportation &Communications, 2020). The situation becomes even worse with the emerging and rising automotive technology. Fatigue driving and related accidents have received extensive attention globally. In the USA, Gender et al. (2006) and Forsman et al. (2013) found that fatigue driving was a major factor causing road traffic accidents, and it accounted for 10%-20% of total accidents and more than 40% of serious accidents. Klauer et al. (2006) found that the probability of traffic accidents caused by fatigue driving was 4–6 times that of normal driving through naturalistic driving data. In 2010, the proportion of drivers who have experienced fatigue driving reached 11% through the NHTSA's questionnaire of 2000 drivers (Liu and Subramanian, 2009). In Canada, the proportion of drivers who experienced fatigue driving reached 58.6% from the questionnaire of 750 drivers in 2008 (Vanlaar et al., 2008). In China, the proportion of drivers who have experienced fatigue driving reached 50% from the questionnaire of 516 drivers in 2003 (Di, 2010). Fatigue is a more serious issue among truck drivers in China, 64% of trucks has only one

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driver and the proportion of truck drivers with a daily driving time more than 8 h and 12 h accounts for 84% and 40%, respectively (Niu, 2014).

Since the first traffic accident occurred in the US in 1899, fatigue emerges and is related to abnormal/risky driving behavior and accidents. The purpose and significance of fatigue driving research are to reduce accidents caused by fatigue through fatigue relief and fatigue prevention. Many scholars have conducted comprehensive studies on fatigue driving, "Fatigue driving" and "Driver fatigue" were chosen as keywords to search article on the Web of Science. There are 3663 articles from 2012 to 2022 that were searched, and article keywords were analyzed with co-occurrence when the frequency was more than 20 times. The correlation between keywords was described by Cite Space software (Fig. 1), and four clusters were shown in Table 1 from the method of cluster analysis with keywords.

Four clusters can briefly describe driver fatigue research during 2012–2022. It can be summarized as follows, 1) cluster 1: driving performance, it was found that keywords were mainly related to fatigue influential factors like driving time and sleep, etc.; 2) cluster 2: driver fatigue detection system, feature extraction, and detection method are mainly research points; 3) cluster 3: investigating driver fatigue, it belongs to fatigue detection system from subjective indicators like scale, etc.; 4) cluster 4: mental fatigue, it is similar to cluster 1 for the keywords are circadian rhythm and workload, etc. which can affect driver mental state. After cluster analysis, the analysis of the top 10 keywords with strong citation bursts was shown in Fig. 2. It can be found that the algorithm is the research hotspot for a short period of time in the future.

Fatigue influential factors and fatigue identification are the two main directions of driver fatigue research through cluster analysis with keywords. Moreover, the effect of different influential factors and different methods of fatigue identification were explored. The present study aims to review driving fatigue articles based on the authors' studies (summarized in Table 2, which conducted studies of fatigue influential indicators, and fatigue identification).

This study is structured as follows. First, the view was proposed that driver fatigue level was affected by circadian rhythm based on the biological circadian rhythm, the difference of driver behavior features under different circadian rhythm was explored during naturalistic driving and try to find the changing pattern of driver fatigue state (Zhang et al., 2014). Interestingly, we found the SDLP (standard deviation of lateral position) and SRR (steering wheel reversal rate) were affected by fatigue level and circadian rhythm to varying degrees. To further explore the performance of measurements, sensitivity analysis was used to detect the performance of fatigue detection measurements including SDLP and SRR. It was found that the SRR has higher sensitivity and it can be used to detect fatigue level with higher accuracy (Zhang et al., 2016a). The result of Zhang et al. (2016a) aroused our interest in whether the vehicle longitudinal operational measurement can be used to detect the fatigue level. The Time Headway (THW) was chosen as the classical measurement to test the relation with fatigue level and it was found that there has a significant difference between fatigue level and

Table 1
Cluster analysis with keywords.

Cluster		Keywords
1	Driving performance	Risk, driver, time, sleep, fatigue, accident
2	Driver fatigue detection system	Driver fatigue, electroencephalogram (EEG), classification, feature extraction, neural network, fusion
3	Investigating driver fatigue	Sleepiness, driving fatigue, brain network, frequency domain, scale, effective connectivity
4	Mental fatigue	Drowsiness, circadian rhythm, alertness, workload, attention, automated driving

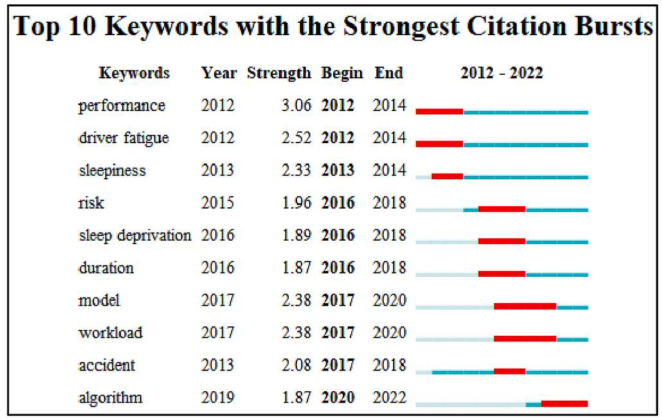

Fig. 2. Top 10 keywords with the strongest citation bursts in 2012–2022 (Keywords with the strongest citation bursts in the scientific article were analyzed and visualized in the keyword's burst map. A line in red stands for the burst detection years. Keywords with red lines extending to the latest year can indicate the research frontiers a short period of time in the future.).

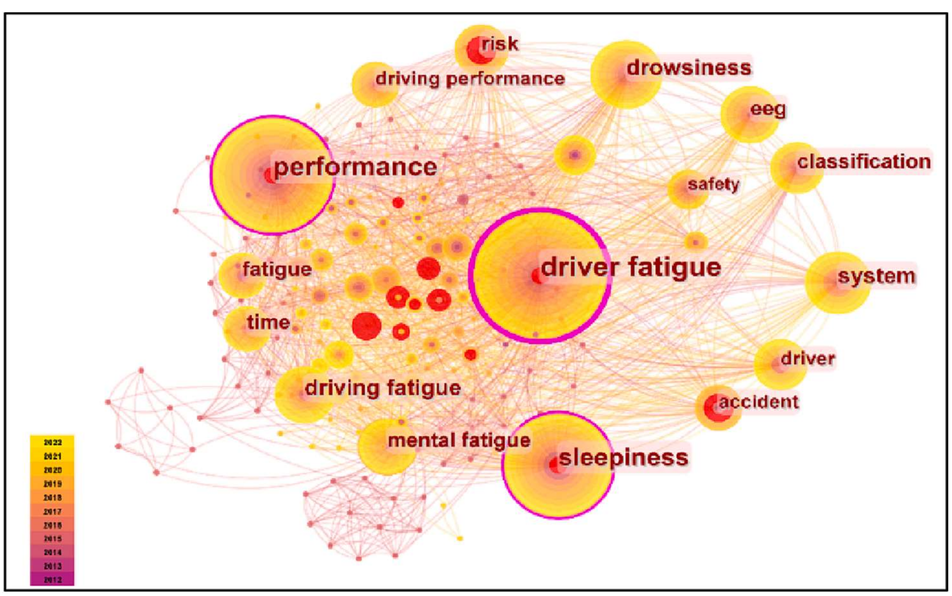

Fig. 1. Keywords analysis between fatigue driving and driver fatigue (Each keyword is represented as a node, and the size of the node typically represents the frequency or importance of the keyword in the literature. The connections between nodes represent the co-occurrence relationships between two keywords, and the thickness or color of the connections reflect the co-occurrence frequency or correlation between the keywords. The color gradient in the heatmap indicates the intensity or strength of the keywords' popularity or research hotspots, wherein a darker color represents that the topic is relatively more extensively studied.).

Table 2
A summary of our studies on driving fatigue.

Study	N	Variables	Key Issues	Hotspot
1. Zhang et al., 2014	15	1 Circadian rhythm (9:00, 13:00, 21:00)2 Driving duration (2 h, 4 h, 6 h)	The change of driver's fatigue level under different circadian rhythms and driving duration	Influential indicator
2. Zhang et al., 2016a	36	1 Indicator value (threshold, time interval)2 Fatigue state (self-report)	Sensitivity of lane position and steering angle measurements to driver fatigue	Fatigue identification and sensitivity analysis of measurements
3. Zhang et al., 2016b	40	1 Car-following scenario (T0, T1, T2, T3)2 Fatigue state (self-report)	The effect of fatigue driving on the car following behavior	
4. Li et al., 2020a	19	1 Fatigue state (self & observer-report)2 Driving scenario (3 sections)	Driver fatigue detection based on BPW feature fusion	
5. Zhang et al., 2020a	34	1 Schedule (sleep time)2 Circadian rhythms (9:00, 14:00, 21:00)	Fatigue prediction considering schedule and circadian rhythm	Fatigue prediction
6. Sun et al., 2021	40	1 Fatigue state (self-report)2 Measurements (SDLP, SRR, etc.)	Optimal measurements for fatigue detection considering driver fingerprinting differences	Individual difference

Note. N = number of drivers. All studies with a real vehicle. All variables were manipulated between subjects.

THW measurements including THW_{mean}, THW_{min}, and THW_{std} (Zhang et al., 2016b). To explore the non-invasive detection method instead of common physiological detection methods like electrocardiogram (ECG), electromyogram (EMG), heart rate variability (HRV), etc. The blood pressure waveform (BPW) was used to build a fatigue detection model and the model has a higher accuracy (Li et al., 2020a). Driver fatigue prediction was proposed based on the bio-mathematic fatigue model and fatigue detection methods, time-related indicators were considered to predict the future trend of driver fatigue level, and then realize the early warning of fatigue (Zhang et al., 2020a). The driver individual difference was underlined for the result in Zhang et al. (2020a) does not correspond to current regulation. Driver individual difference is a difficult point in the field of traffic safety research, the driver fingerprinting was used to represent driver individual features and proposed an optimal measurement method for the calculation of individual driver's best calculation parameters (IDBCPs). It was found that the driver fatigue detection model has a higher accuracy with IDBCPs compared to UCPs (Unified calculation parameters) (Sun et al., 2021). These studies described the structure of driver fatigue research from the loop of "fatigue influential indicators-fatigue identification-fatigue prediction" around the fatigue reduction and prevention, and then tried to explore the relationship between fatigue state and characteristics of driver and vehicle.

The scope of this review reflects the aims of the empirical studies, which centered on the influence indicator and regular pattern of driver fatigue state during naturalistic driving. First, the effect of time-related indicators was discussed which will lead the fatigue level accumulation or reduction. Then, some fatigue identification measurements and methods were summarized, and it was verified that the fatigue detection model could have a higher accuracy when measurements have higher sensitivity. Driver fatigue prediction methods were summarized from two aspects, and it was found that models that consider time-related factors based on bio-mathematic model theory can be used to real-time predict fatigue level and describe the future change of fatigue level with different timelines. Last but not least, driver individual difference need be considered in the fatigue detection model and fatigue prediction model because it will directly affect the accuracy of the model. This review summarized and discussed driving fatigue articles combined with our studies in this field, and the structure of driver fatigue behavior studies was described and the link between fatigue influential indicators, fatigue identification, and prediction was demonstrated.

2. Driver fatigue influential indicators

Driver fatigue is the phenomenon of physical and psychological recession that led to a decrease in reaction level and control efficiency due to monotonous driving or long-term driving (Editorial Department of China Journal of Highway and Transport, 2016). Driver fatigue state is divided into physiological fatigue, drowsiness, and mental fatigue (Hu and Lodewijks, 2020). Physiological fatigue is the power decline caused by repeated or continuous driving activities (Hu and Lodewijks, 2020), such as continuously rotating the steering wheel and frequently replacing the gear. Drowsiness is the subjective sleepiness appetence of the driver and is caused by sleep time (Cori et al., 2021), rest time (Lees et al., 2021), circadian rhythm (Regev et al., 2018). Mental fatigue (Task related fatigue) is the subjective aspiration of the driver to continue driving task, including active task-related fatigue caused by long time driving in a high working load environment and passive task-related fatigue caused by long time monotonous driving (Lees et al., 2021), which is mainly affected by driving time. The fatigue formation mechanisms are different in monotonous driving and long-term driving. Monotonous driving environments are prone to short-term driving fatigue. The reduced unpredictability of road traffic conditions is the main cause of driving fatigue. In monotonous driving environment, drivers perceive the driving task as simple, which leads to insufficient attention and decreased control ability. The reduced unpredictability of road traffic conditions accelerates the accumulation of fatigue, resulting in a shorter formation time. During long-term driving, the cerebral cortex requires inhibitory protection due to the prolonged duration of heightened arousal. Drivers experience fatigue when subjected to high workloads for extended periods of time. This type of fatigue formation takes a longer time. In the process of fatigue formation, the environmental perception ability, situation judgment ability, and vehicle control ability of drivers will decrease to varying degrees and then lead to traffic accidents easily. Through the analysis of fatigue formation mechanism and fatigue state, driver fatigue is mainly affected by driving time, circadian rhythm, sleep time, rest time in the process of driving, and also affected by driving environment and driver individual differences, etc. The circadian rhythm and driving time were selected as representative indicators to analyze the effect on driver fatigue state.

2.1. Effects of circadian rhythm

The 2017 Nobel Prize winner in Physiology or Medicine Jeffrey C. Hall et al (The Nobel Prize in Physiology or Medicine, 2017) proposed the molecular control mechanism of circadian rhythm in the biological world. The increasing circadian rhythm produces an increase in alertness, reaching two peaks each day, mid-morning and evening. Similarly, the decreasing circadian rhythm results in two troughs (Nadirs') that correspond with a post-lunch time and early morning nadir (Fig. 3) (Goble, 2013). It indicated that the study of circadian rhythm is meaningful to driver fatigue research.

To explore the effect of circadian rhythm on driver fatigue state and driving performance, groups with different circadian rhythm were set in Zhang et al. (2014). This study divided 15 drivers into three groups including the morning group (started driving at 09:00), the noon group (started driving at 12:00), and the evening group (started driving at 21:00), drivers were required to complete 6 h naturalistic driving experiment. The Karolinska Sleepiness Scale (KSS) score (recorded every 5 mins) and vehicle operational data including SDLP and SRR were analyzed, and then it was found that the cumulative speed of driver fatigue level in the evening group is faster than morning and noon groups. Driver fatigue level is higher and performance is worse in the afternoon from 14:00–16:00 and at night from 2:00—5:00. It is consistent with the study by Chipman and Jin (2009), who explored the relationship between circadian rhythm and drowsiness through single-vehicle crashes in Ontario (1999–2004), and it was found that driver is easy to sleep and collide at the time of 14:00–16:00 and 2:00–5:00. This rhythm also was verified in Zhang et al. (2020a), the fatigue model shown that the increase of driver fatigue value is faster at the time of 14:00–16:00 and 2:00–5:00 which was built between fatigue value and circadian rhythm through naturalistic driving experiment. Through the above studies, the driver is easy to fatigue at the time 14:00–16:00 and 2:00–5:00, and the driver should have enough rest before driving during this period or keep a positive circadian rhythm during the whole driving process.

2.2. *Effects of driving time*

The driving risk will increase with the accumulation of consecutive driving time. In order to solve the problem of long-time driving, many countries have established clearer laws and regulations for driving time and rest time, but there are differences between these countries (Fig. 4).

All countries pay attention to fatigue driving through the regulation of driving time and rest time. The driving time of commercial or passenger drivers is restrained with detailed regulations including consecutive driving time, consecutive rest time and accumulative driving time, etc. There has a significant difference in regulations like rest time and rest methods between these countries. Among them, the regulation of driving time is more conservative and stricter in China, while the USA is more open to the requirement of driving time, maybe the effect of the geographical environment.

Based on regulation, many scholars have explored the relationship between fatigue and driving time. Ferreira et al. (2019) used driver monitoring system (DMS) to detect alerts caused by fatigue at different driving time period, and then it was found that the longer the driving time, the more the alert caused by the driver. The incidence of driving risk will increase to 40% when driving for more than 14 h (Arnold et al., 1997). The consecutive driving time was extracted to study the driver's change of driving behavior, and then it was found that the driver's driving state will change after 1.39 h of consecutive driving (Hyodo et al., 2017). The calculation of the best driving time threshold through fatigue level causes scholars' thinking. Zhang et al. (2020a) explored the best driving time of drivers at the different initial times including morning, noon and evening combined circadian and driving time. It was found that the threshold of driving time is 2.57 h-3.05 h from the time 14:00 and 2.55 h from the time 21:00. Other studies found the threshold of driving time is 3.82 h (Guo et al., 2011) and 3.92 h (Teng et al., 2013). It can be found that the daytime consecutive driving time of the driver should be controlled at 3 h-4 h and night driving time should be shorter than 2 h through the above studies. It also corresponds to the regulation on driving time in the Law of The People's Republic of China on Road Traffic Safety: daytime driving time limits to 4 h and night driving time limits to 2 h. Driving time and rest time constitute the travel time; it is necessary to find the balance between driving time and rest time. Studies about consecutive driving time and rest time were shown in Table 3, it can provide help for the establishment of national laws and regulations.

The elastic control of the driver's driving time and rest time should be set as an effective measurement for the prevention of driver fatigue. Although countries have regulations on rest time during driving, it is possible that driver fatigue cannot be relieved with invalid rest way and rest duration. It is necessary to explore rest ways which can provide effective rest to relieve driver fatigue.

2.3. *Effects of driver personality*

In addition to the aforementioned factors related to external influences, the driver's personality characteristics are also critical factors (leading to varying driving fatigue performance). The driver's personality characteristics include driver feature (such as age, gender, psychological state, health condition, et al.) and driving feature (such as driving experience, driving style, et al.). In order to explore the relationship between driver fatigue and age, a questionnaire study indicated that younger drivers feel fatigued earlier than older drivers after driving for 3–5 h, the questionnaire also considers driving experience and it was found that drivers with less than 2 years of driving experience are more prone to fatigue (Ren et al., 2007). For further study the effect of driver

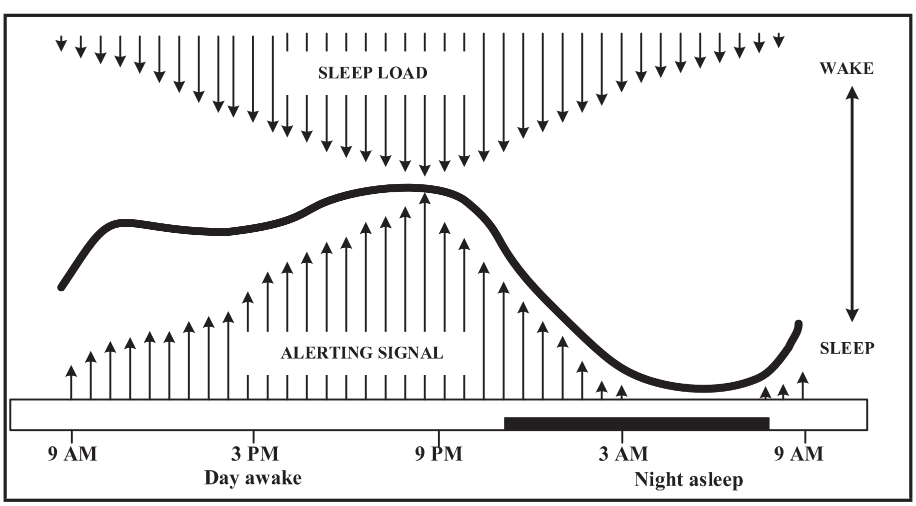

Fig. 3. Circadian rhythm of humans (Goble, 2013).

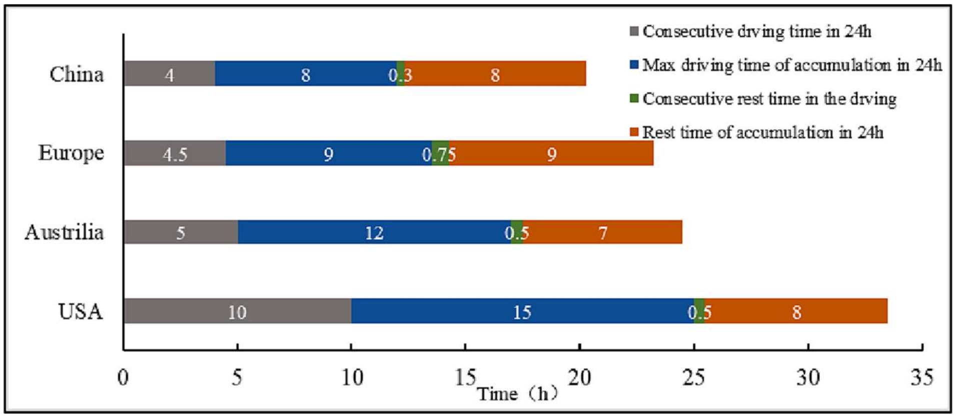

Fig. 4. Regulation of driving time and rest time in the world.

Table 3
Study of continuous driving time and adjust measures.

	Reference	Object	Conclusion
Consecutive driving time	Zhang et al., 2020b	Normal driver	Driving time > 40 min, driver fatigue level > 6
	Arnold et al., 1997	Truck driver	Driving accumulative time > 14 h, risk incident account for 40%
	Hyodo et al., 2017	Normal driver	Driving time > 1.39 h, driving performance will decline
	Guo et al., 2011	Normal driver	Driver's best continuous driving time is 3.82 h
	Teng et al., 2013	Bus driver	Driver's best continuous driving time is 3.92 h
Adjust measures	Ma et al., 2009	Normal driver	Driving time > 3.5 h, then rest time > 30 min
	Jovanis et al., 2012	Truck driver	Drivers can reduce risk (50%) through rest after a long-time driving
	Chen and Xie, 2014	Truck driver	Two rest (30 min) can reduce collision risk in the process of 10 h driving task
	Wang et al., 2017	Normal driver	Male drivers need 24 min and female drivers need 27 min after 4 h of driving

age to fatigue accumulation under different driving duration, Pei et al. (2018) conducted a study by collecting electroencephalogram (EEG) data from drivers of various ages during natural driving. They selected $R_{((\alpha+\theta)/\beta)}$ as fatigue measurement and the results revealed that younger drivers and middle-aged drivers exhibited a relatively slow fatigue accumulation rate within 0–1.5 h compare to older drivers, while within the 1.5–3 h range, younger drivers had the fastest fatigue accumulation rate and middle-aged drivers had the slowest. The optimal driving durations for older, middle-aged, and younger drivers were found to be 60–75 mins, 120–135 mins, and 105–120 mins, respectively. Gender has been proven there has a significant difference in electrocardiogram (ECG) indicators during the recovery period of driver fatigue. Therefore, different rest periods should be set based on gender differences (Wang et al., 2017). For further study the effect of gender to fatigue state, Zeng et al. (2019) studied the impact of fatigue on the autonomic nervous system in drivers of different genders. They extracted 13 heart rate variability (HRV) features to characterize the fatigue state of drivers. The results indicated that only one feature showed a significant difference between males and females during the alert state, while five features exhibited significant differences during the fatigue state. In the fatigue state, drivers experienced increased variability and complexity in their autonomic nervous system (ANS), and there were gender differences. Compared to the awake state, there were more differences in the variability and complexity of the ANS between males and females in the fatigue state. Driving experience has been proved that it has an effect on fatigue, each driver will develop their own driving style with the accumulation of driving experience. In order to study the effect of driving style on fatigue formation, Zhao et al. (2022) conducted a study by collecting electrocardiogram (ECG) signals from drivers to investigate the impact of driving style on driver fatigue characteristics under different driving durations. The research findings indicate that during the 0–80 mins period, aggressive drivers have the fastest fatigue accumulation rate, while cautious drivers have the slowest. During the 80–120 mins period, cautious drivers have the fastest fatigue accumulation rate.

Based on the above review, when analyzing driver fatigue characteristics, it is important to consider not only external factors such as driving duration and circadian rhythm but also the driver's age, driving experience, and other personal factors. This is to avoid inconsistent results in driver fatigue levels due to individual differences in the driver's personality characteristics.

3. Fatigue identification and measurements selection

Driver fatigue is a process of physiological and psychological state change, it is difficult to measure with quantitative physiological indicators like drunk driving, fatigue detection method is always a research hotspot in the field of driver fatigue. The key to fatigue detection methods is how to accurately detect the fatigue state and realize the application of early warning. Many studies have summarized and discussed fatigue detection methods from subjective and objective dimensions, and a general understanding was formed. It was found that the accuracy of driver fatigue detection can be improved combining with machine learning and pattern recognition (Dua et al., 2021; Doudou et al., 2020), which is an effective method for the prevention of road accidents. At the same time, driver fatigue detection technology has been gradually transformed from the field of theoretical research to industrial applications and consistently improved (Pan, 2020; Abdullah et al., 2016).

A variety of fatigue detection methods were used to increase the detection accuracy, and methods were classified by indicators (Dong et al., 2011). Mao et al. (2005) divided driver fatigue detection methods into subjective and objective methods, and the view of information fusion technology can improve the detection accuracy of driving fatigue was proposed. Liu et al. (2019a) divided fatigue detection into direct detection methods including driver physiological signal and behavior features, and indirect detection methods including vehicle operational features. At the same time, it was divided into a multi-information fusion method and a single indicator detection method from the aspect of indicator analysis and model building. Yang et al. (2010) divided fatigue detection methods into four types including method with driving scenarios and environment, method with physiological detection, method with driver behavior detection, and method with multi-information fusion.

At present, the classification of the driver detection method is mainly from two dimensions of "driver" and "vehicle", with the data source of driver facial features, physiological features, and vehicle operational features (Table 4).

Some objective methods of fatigue detection were listed in Table 4, these methods are usually combined with a subjective evaluation scale for the application of fatigue driving research. The fatigue level can be obtained through driver self-report with a questionnaire in the subjective fatigue detection method. Five validated questionnaires were used to subjectively measure fatigue: Karolinska Sleepiness Scale (KSS, 1–9: awake-sleep) (Arsintescu et al., 2019), Stanford Sleepiness Scale (SSS, 1–7: awake-fatigue) (Moore et al., 2019), Epworth Sleepiness Scale (ESS, 0–24: awake-sleep) (Alzehairi et al., 2021), Fatigue Severity Scale (FSS, 9–63: awake-fatigue) (Wong et al., 2020), and Samn-Perelli Fatigue Scale (SPFS, 0–7: awake-fatigue) (Arsintescu et al., 2020). KSS was used to record driver fatigue level in authors' studies (listed in Table 2).

3.1. Measurements of fatigue identification

3.1.1. Lateral measurements of driver fatigue

It can be seen that the source of detection methods is the driver and vehicle from Table 4. The common measurements of vehicle state include steering angle, gas pedal power, brake pedal power, vehicle horizontal angle, and standard deviation of lateral position, etc. (Pan et al., 2019). In the long-time naturalistic driving experiment, vehicle operational data is the main data source to detect driver fatigue state. The standard deviation of lateral position (SDLP) and the steering wheel reversal rate (SRR) are common vehicle lateral performance indicators to detect driver fatigue level (Du et al., 2015). A driving simulator study conducted by Akerstedt et al. (2005) showed that driving home from the night shift was associated with an increased number of incidents (two wheels outside the lane marking, from 2.4 to 7.6 times) and increased later deviation (from 18 to 43 cm). SDLP can reflect the driver's ability of lane keeping because the vehicle will deviate from the lane line frequently when the driver is in a fatigued state. It can be used to evaluate the lane-keeping ability and fatigue state of the driver when the data of lane change was excluded. SRR can reflect drivers' turning stability, and the turning ability and fatigue state of the driver can be evaluated through the duration when the steering angle is greater than the threshold.

Table 4
Classification of the detection method with representative studies.

Reference	Classification	Input feature	Characteristic
Cai et al., 2020	Driver physiological indicators	EEG, ECG, BPW, etc.	Need wear equipment and contact driver directly, higher accuracy and cost, easy to affect driver
	Driver behavior indicators	PERCLOS, Pupil diameter, Blink duration, etc.	Rely on image detection, affected by environment and camera position easily
	Vehicle operational indicators	SDLP, SRR, Gas pedal, etc.	Lower cost, affected by road environment easily
Pan et al., 2019	Intrusive detection with sensor equipment	Physiological signal and vehicle operational data, etc.	Data is accurate, but the collection is difficult
	Non-intrusive detection with pattern recognition, image process	Facial recognition, pose recognition, etc.	Affected by environments, such as light and sunglass
Xu et al., 2019	Vehicle behavior indicator	Velocity, THW, SDLP, etc.	Affected by road and driver habits easily, reliability is low
	Driver behavior and facial expression	PERCLOS, Mouth feature, Pupil, etc.	Higher accuracy, the high requirement for system calculation, affected by light easily
	Driver physiological signal feature	EEG, EOG, ECG, etc.	Contact driver directly and easy to affect driving
…	…	…	…

In Zhang et al. (2014), SDLP and SRR were used to measure driver fatigue level and driving performance, the value of SDLP increases with the increase of fatigue level (KSS score increased from 2 to 8, SDLP increased from 0.38 m to 0.53 m). Driver's lane-keeping ability declined when the fatigue level increased, and the SDLP value of the evening group is greater than the morning group and noon group, which also corresponds to the frequent traffic accident at night. Oppositely, there is no significant difference between the value of SRR and fatigue level.

For further study of the relation between SDLP/SRR and fatigue level, the effect of SDLP and SRR on the accuracy of fatigue detection was explored in Zhang et al. (2016a). The correlation coefficient R was used to represent the sensitivity of SDLP (time interval) and SRR (steering angle threshold). From the result of the analysis, the correlation coefficient of SRR (0.42, 6°threshold) is greater than that of SDLP (0.12/0.11, maximum method/consecutive method). It indicated that the accuracy of SRR is greater than SDLP, and the result of two indicators showed driver ability will decline with the increase of fatigue level, consistent with the conclusion by Yan et al. (2013). The reason for the lower correlation coefficient of SDLP is the driver individual difference, and the driver individual difference was discussed in Sun et al. (2021).

3.1.2. Longitudinal measurements of driver behavior

The daily traffic collision is divided into lateral collision (turning behavior) and longitudinal collision (car following behavior). The sensitivity of SDLP and SRR was discussed in Zhang et al. (2014) and Zhang et al. (2016a) for the analysis of lateral indicators. The normal indicator represents the vehicle's operational state and driver fatigue state of the car following behavior including headway (THW, Time headway/SHW, Space headway) and time-to-collision in the longitudinal collision (Yeung and Wong, 2014). In Zhang et al. (2016b), the value of fatigue level (KSS and PERCLOS) and THW were combined to explore the relation between driver car following behavior and fatigue state. It was found that the value of THW has a decreasing trend with the increase of fatigue level through the analysis of KSS value/PERCLOS value and THW value (THW_{mean}, THW_{std}, THW_{min}).

There has been a decline trend of THW_{mean} with the increase of KSS from Zhang et al. (2016b). When the participants were alert (KSS at level 1), they kept a mean time headway of 2.37 s on average; when the drivers began to feel fatigued (KSS at level 4) during a longer driving duration, the mean time headway decreased to 2.31 s and when drivers felt very fatigued (KSS at level 7 or higher), the mean time headway declined to 2.27 s or 2.24 s. Additionally, THW_{mean} shows a negative correlation with PERCLOS, the mean THW declined from 2.30 s to 2.22 s when the value of PERCLOS was greater than 0.06 (PERCLOS greater than 0.6 correspond to fatigue). These results of studies indicated that the THW will decrease when drivers are in the state of fatigue. Meng and Qu (2012) found that the collision rate will increase with lower THW, and the risk of car following and collision rate will increase when the driver in the fatigue state. THW is an effective indicator to measure the risk state and fatigue level of the driver in the car following behavior.

3.1.3. Physiological measurements of driver behavior

The driver's physiological performance can reflect driver's physical state and it can detect fatigue state effectively. Considering the specific of physiological apparatus, it usually was applied in the driving simulator experiment for safety consideration. Common physiological indicators including EEG (Cui et al., 2022), ECG (Lee et al., 2019), and EMG (Mahmoodi and Nahvi, 2019), etc., EEG was thought as "gold standard" to detect sleep among them (Lin, et al., 2008). However, the fatigue state under driving is different from sleep in the rest state, there still has a distance from the laboratory to the actual application in the fatigue detection area based on EEG signal. To overcome the invasion and discomfort of physiological signal apparatus, the change of human cardiovascular pressure can detect driver fatigue state effectively which is obtained by blood pulse wave (BPW) (Zhang et al., 2007). The linear discriminant analysis was used to extract the power spectrum peak and peak center frequency of BPW and built the driver fatigue state detection model, and it was proved that the indicator can detect fatigue state effectively (Yeung and Wong, 2014). Wang (2012) found that the BPW transmission time and wavelet entropy of BPW signal below 20 Hz can distinguish the state of awake and fatigue effectively, and these indicators can be used as objective indicators to detect driver fatigue. Based on the above studies, BPW features were used to build a fatigue detection model in Li et al. (2020a), the technical route of the detection method was shown in Fig. 5.

In this study, it is a new attempt that the feature of BPW was used to detect driver fatigue. BPW signal data was collected by naturalistic driving experiment and the BPWA method was used to extract feature indicators from the biological signal, and then applied to detect driver fatigue. At the same time, the fatigue scale was used to measure the fatigue level of the data set, and then a BPW feature dataset with fatigue level labels was built for the construction of a driver fatigue detection model. At last, the driver fatigue detection model was built based on the D-S evidence theory. It can be seen that driver fatigue can be dynamically detected through BPW features and the accuracy is 91.8%. This study provided a new method to detect and monitor driver fatigue state, and with a greater application.

Speech feature is also an effective physiological indicator to detect driver fatigue state, driver fatigue state can be detected through rhythm, quality, spectrum and non-linear dynamic etc. However, fatigue detection based on speech features is only applicable to driving scenarios with a standard response, and the speech sample data is rarely (Li et al., 2020b).

The analysis above reviewed driver fatigue detection methods using vehicle motion indicators, both longitudinal and lateral, as well as driver psychophysiological indicators. In comparison to the indirect fatigue representation indicators mentioned earlier, the direct utilization of facial features for fatigue identification in drivers has become the mainstream function of driver monitoring systems in vehicle currently.

3.2. Algorithm of fatigue identification

Traditional machine vision for driver fatigue detection is mainly adopt the method of artificial label characteristics and classifiers, it has disadvantages of slower detection speed and lower accuracy for the method of fatigue judgment mainly through manual feature design and standard detection (Feng et al., 2020). With the successful application of deep learning models represented by Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) in the area of computer vision such as facial organ detection (Sun et al., 2013) and human pose estimation (Toshev and Szegedy, 2014), driver fatigue detection based on visual characteristics deep learning has become a research hot spot in this area. The RNN structure adds the time sequence information to the neural network and then realizes the recognition of the video time sequence image. The CNN can directly enter the original image for convolutional classification without the pre-processing of the image, and the application is more widely. The related studies were shown in Table 5.

In the above studies of driver fatigue detection with visual characteristics deep learning, methods of driver fatigue detection through facial recognition technologies are mainly divided into three types based on the above studies:

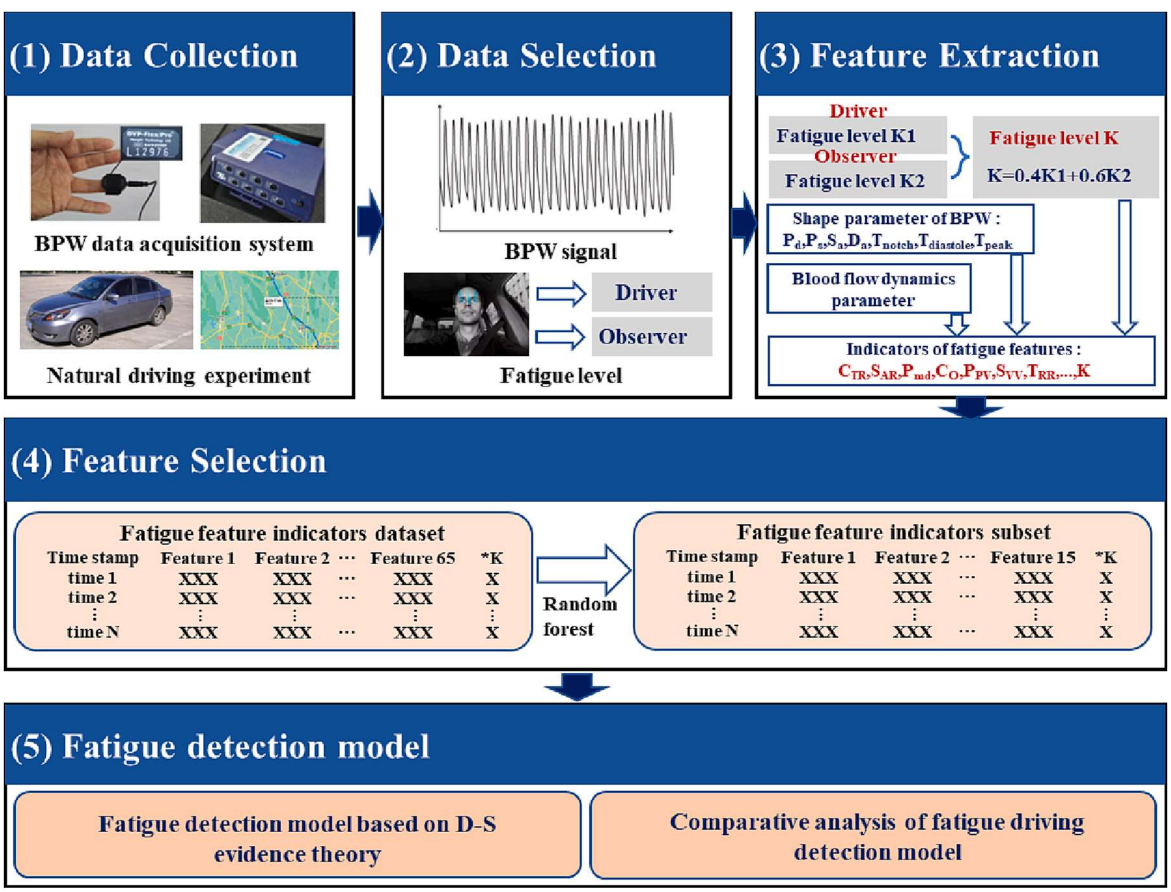

Fig. 5. Fatigue detection process with BPW.

Table 5
Studies of driver fatigue detection algorithm with deep learning.

Reference	Data	Environment				Feature			Method	Accuracy
		B	N	G	S	Eye	Mouth	Head	Algorithm	
Ed-Doughmi and Idrissi, 2019	Dataset	√	√	√	√	√	√	√	LSTM	92.71%
Zheng et al., 2016	Sim	√	√			√			ELM	93.9%
Huang et al., 2022	Dataset					√	√		LSTM&RF-DCM	89.42%
Gu et al., 2018	Dataset	√	√			√	√		MTCNN&MSP	98.86%
Dey et al., 2019	Dataset					√	√	√	SVM	96.4%
Xiao et al., 2019	Sim	√	√	√	√	√			MTCNN&FDR nets	95.83%
Liu et al., 2019b	Dataset	√		√	√	√	√		CNN&MT-CNN	97.06%
Geng et al., 2018	Sim	√	√	√	√	√		√	LSTM&CNN&MT-CNN	94.48%

Note. Sim = Simulation, B = Bareface, N = Night, G = Glass, S = Sunglass.

(1) Machine vision and deep learning algorithms were used to recognize the feature of the limb, position, and other dangerous driving behaviors, including PERCLOS (Gong et al., 2014), blinking frequency (Mandal et al., 2017), facial expression and body features, etc.
(2) Multi-scale homomorphic filtering image enhancement algorithm (Chen, 2017) was used to enhance the images captured in complex environments, the state of the eye and mouth was analyzed by visual position (Li et al., 2010), and then realized the detection of the driver fatigue state and unsafe driving behavior (Xu et al., 2020).
(3) The video temporal semantic information and semantic features were analyzed and extracted through a deep learning algorithm, and then realized the detection of driver fatigue state and unsafe driving behavior (You et al., 2017).

In the process of image processing, there are some problems such as higher system consumption and lower detection efficiency for large images. At the same time, poor image quality and lower quality will be shown when the driver's head posture was covered or unclear. To solve these problems, Li and Bai (2021) proposed a driving fatigue detection algorithm based on the MTCNN-PFLD-LSTM deep learning model, 6 fatigue detection parameters and the weighted cumulative loss function were designed to improve the accuracy and efficiency of driver fatigue detection.

Driving fatigue always exists in the driving process. It is a key issue that how to detect driving fatigue effectively and quickly in the field of scientific research and industrial applications. The following conclusions were obtained based on the summary of existing methods of driving fatigue detection:

(1) Detection of driver fatigue state based on visual characteristics has the advantages of fast, convenient, and high accuracy compared to other detection methods. At present, deep learning was used to improve the accuracy and effectiveness of fatigue state recognition is the main research trend.
(2) It is necessary to choose multi-features for the detection of fatigue state due to it is easy to be affected by the environment. Multi-feature fusion recognition can overcome the disadvantage of low accuracy and poor recognition compared to single-feature recognition. It is a hot spot on how to fuse multi-features of driving behavior.

3.3. *Individual difference analysis of driver fatigue*

In the progress of driver fatigue identification, the detection method affects the performance of the fatigue identification model directly and driver individual difference affects the performance indirectly, but the effect of driver individual difference cannot be ignored in the research of driving behavior (Feng et al., 2012). The classification performance of indicators for driving fatigue is the key to restricting the effect of fatigue recognition, and multiple studies proposed that drivers' fatigue features indicators have individual differences (Ingre et al., 2006; Xu et al., 2014). Ingre et al. (2006) studied the relationship between the subjective fatigue values, blinking time, and lane deviation of the individual in the driving environment, and then found there has significant individual differences in the blink time and lane deviation indicators between the state of awake and fatigue. Xu et al. (2014) thought the individual difference is an important reason to reduce fatigue detection accuracy, Kruskal-Wallis was used to test the consistency of indicators between different drivers and found that there are individual differences such as PERCLOS, cross-line lateral speed, etc. in the state of fatigue. Thiffault and Bergeron (2003) built a relationship between personality characteristics and SDSWM based on hierarchical multiple regression analysis model and found there has a significant difference in SDSWM between drivers with different personality characteristics in the state of fatigue. Furthermore, there are some studies indicating that there has an individual difference in fatigue indicators such as SRR (Zhang et al., 2016a), pupil diameter, and fixation time (Yan, 2017), etc. For eliminating the negative influence of driver individual difference on driver fatigue identification accuracy, scholars have attempted to use measurements of the individual driver to build the identification model with higher accuracy. Chu et al. (2018) built an individual fatigue model based on RBF neural network and SVM through naturalistic driving behavior data, the average accuracy of the model is 85% and some drivers' accuracy reached 90% or more. Xu et al. (2016) built a logit fatigue driving recognition model considering individual features (23 features) which were extracted from simulation driving data, each driver was set a different threshold and found fatigue detection accuracy can be improved considering individual difference through comparison between normal model detection accuracy. In the above studies, they have compared driver's differences using unified calculation parameters (UCPs) instead of considering individual drivers' best calculation parameters (IDBCPs), which restrained contributions of measurements for detecting fatigue. Zhang et al. (2016b) have proposed that one unified parameter value which had a reliable coefficient with the fatigue level could enhance the performance of measurements. Considering UCPs will restrain contributions of measurements for detecting fatigue, it is necessary to explore the best calculation parameter of each driver which made measurements more discriminative for fatigue were various (Liang et al., 2019; Zhang et al., 2016a).

In Sun et al. (2021), the extraction model of optimal fatigue driving measurements of individual drivers, and the validation method of the drowsiness-detection advantages of measurements calculated by IDBCP were described, and the flowchart of measurements extraction was shown in Fig. 6.

First, |Z-statistics| (|Z|) were obtained which represented the fatigue-detection performance of measurements through performing the Wilcoxon test on measurements of the awake state and that of drowsy states, and the fitness function was constructed which can reflect the correspondence between the calculation parameters and measurements' fatigue detection performance. Then, the genetic algorithm (GA) was used to optimize the fitness function and obtain the measurements' IDBCPs. At last, the Wilcoxon test was used to test measurements that were

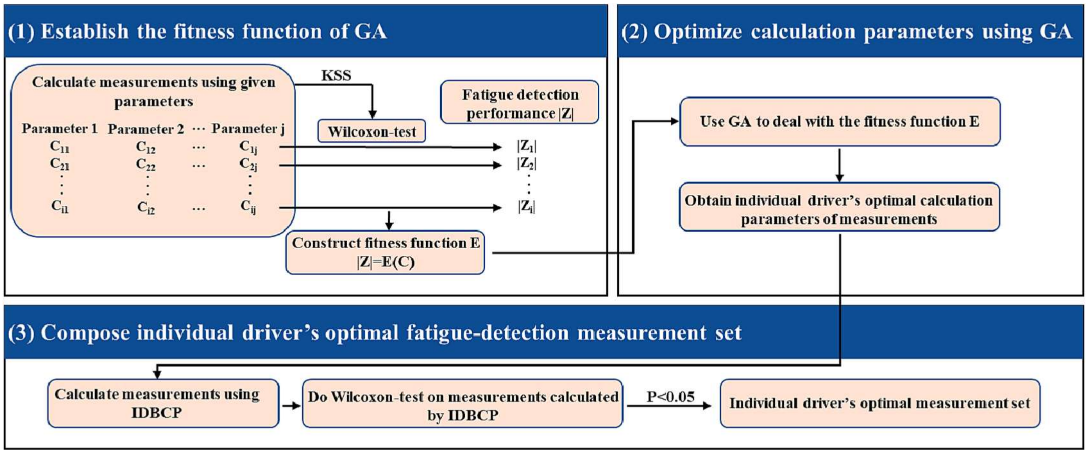

Fig. 6. Extraction model of optimal drowsy driving measurements of individual drivers.

computed by IDBCPs, the measurements whose P value less than 0.05 will be chosen to compose the individual driver's optimal drowsiness-detection measurement set.

The measurement difference between UCPs and IDBCPs was compared, and the result showed that the IDBCPs have higher accuracy to calculate nonintrusive measurements (Table 6).

The average accuracy of fatigue detection using IDBCPs is higher than that of the previous research (Wang and Xu, 2016), and the accuracy of some drivers can reach 93.00%. It is significant that the fatigue of individual drivers can be reliably detected with higher accuracy using nonintrusive measurements calculated by IDBCPs, and the conclusion is the same as Zhang et al. (2016a).

The individual differences among drivers result in different performance of fatigue detection indicators. The personalization of drivers is mainly influenced by their individual characteristics and driving habits. Drivers exhibit different physiological and psychological responses, cognitive abilities, and reaction capacities in different driving environments. Therefore, in order to effectively detect driver fatigue and mitigate the impact of individualized characteristics on fatigue detection models, it is necessary to utilize multiple sensor data to capture fatigue-related indicators of drivers and combining their driving style, habits, and other factors for comprehensive analysis.

4. Driver fatigue level prediction model

Fatigue theoretical models of the sleep and circadian system have been adapted to predict fatigue (Hursh et al., 2017; Calabrese et al., 2017), and the models were divided into the one-step model (predict fatigue directly by using the timing of prior sleep and wake) or two-step model (predict fatigue indirectly by using work schedules to infer an average sleep-wake pattern) (Dawson et al., 2011). Several bio-mathematical fatigue models (BMFM) were proposed to predict

Table 6
Results of fatigue detection across all participants.

		Mean (%)	Standard deviation (%)	Minimum (%)	Maximum (%)
DF_U	Accuracy	**85.25**	2.35	79.4	90.2
	Sensitivity	87.5	2.43	81.33	91.46
	Specificity	84.15	2.54	78.32	89.6
	F1	79.56	3.1	71.76	85.71
DF_I	Accuracy	**91.06**	2.93	81.63	95.97
	Sensitivity	93.39	3.06	83.95	97.78
	Specificity	89.92	3.02	80.49	95.6
	F1	87.38	3.91	75.14	94.51

Note. DF_U = Measurements calculated by UCPs, DF_I = Measurements calculated by IDBSCPs.

fatigue risk based on the neurobiology of sleep/wake regulation and developed with factors such as the range of sleep/wake schedules considered, and the fatigue measures used to fit the model (McCauley et al., 2013; Hursh et al., 2004). The fatigue can be predicted by models through the above scientific article, and then the theory was transferred to the driver fatigue research field. The concept of "driver fatigue prediction" was proposed and developed based on the methods of fatigue detection. Mollicone et al. (2019) developed an analytic approach that predicts driver fatigue based on a biomathematical model and then estimates hard-braking events as a function of predicted fatigue, controlling for time of day to account for systematic variations in exposure. This is reliable that the fatigue prediction was applied to drivers during the whole trip. Many scholars have predicted driver fatigue using different methods (Table 7).

Through the above studies, the existing driver fatigue prediction models can be divided into two categories. One is the driver fatigue level prediction model (DFPM-1) considering driving time/rest time/ circadian rhythm/sleep time based on the bio-mathematical fatigue model considering sleep/circadian rhythm. It can directly describe the relationship between driver fatigue level and time-related factors, and the future change of fatigue level with different timelines. This model is easily affected by driver individual difference, each driver may have an individual prediction model rather than all drivers assessed by one prediction model. The other is the driver fatigue level prediction algorithm framework (DFPM-2) which is used to train and test the multi-feature data based on machine learning/deep learning algorithms. All of the models using new algorithms have shown a positive accuracy with 90% or more, however, the obtained algorithms mostly tend to deal with the subtle driver features rather than analyzing the fatigue value change throughout a given schedule. So, it is not ready to be implemented in real-time fatigue prediction, especially in the case of new samples. This makes such algorithms more suitable for detection rather than for prediction, especially in the naturalistic driving environment.

In the bio-mathematic fatigue model, sleep and circadian rhythm were used to predict human fatigue. This theory was applied to driver fatigue level prediction during driving, and we added driving time and rest time as driving features for the applicability (Zhang et al., 2020a). A new fatigue level prediction model was built based on time-related factors (time of sleep before driving, rest time, circadian rhythm, and consecutive driving time). The real-time fatigue value could be linearly summed to give overall tiredness scores (Koh et al., 2007), and the basic relationship between the four variables is shown in Eq. (1).

$$F(t) = F_{t_d} + F_{t_s} - F_{t_r} + F_{t_c} \quad (1)$$

where, F(t) is the total fatigue value, F_{t_d} is the fatigue value caused by consecutive driving, F_{t_s} is the fatigue value after sleep, F_{t_r} is the fatigue

Table 7
Related studies about driver fatigue prediction.

Reference	Data	Method	Features/Variables		Performance	
			Time series	Multi-feature	Accuracy	Time ahead
Kassem et al., 2021	Dataset	CNN, DFLP framework	×	Eyeblink, mouth yawn, head movement	93.3%	×
Mollicone et al., 2019	NDS	Biomathematical fatigue model, Poisson model	driver sleep/wake timelines	hard-braking events	×	×
Utomo et al., 2019	Dataset	BPNN, LSTM	×	HRV, PERCLOS	>88%	3–5 mins
Zhou et al., 2020	Sim	NARX model	×	PERCLOS, ECG, Breathing data	>97.4%	13.8 s
Zhang et al., 2017	NDS	Linear regression	Task time, rest time, sleep hours, circadian rhythm	×	P = 0.86	×
Tao et al., 2023	Dataset	MDMO algorithm, LSTM	×	Micro expression feature, HR	>91.24%	×
Zhang et al., 2020a	NDS	Linear regression	sleep time, rest time, circadian rhythm, driving time	SDLP	P = 0.98	×
Hajinoroozi et al., 2017	Sim	SPDNet, CNN, DNN	Reaction time	EEG	86.14%	×
Hajinoroozi et al., 2015	Sim	CCNN	Reaction time	EEG	78.3%	×
Lin and Hsiung, 2017	Sim	BPNN	×	HRV	86%	27 mins

Note. DFLP = Driver Fatigue Level Prediction, NDS = Naturalistic driving study, Sim = Simulation, NARX = Nonlinear AutoRegressive eXogenous network, SPD = Symmetric Positive Definite, CCNN = Channel-wise Convolutional Neural Network.

value relieved by rest, and F_{t_c} is the fatigue value caused by circadian rhythms. The raw data of fatigue value comes from KSS.

According to the fatigue level prediction model, the consecutive driving time at a different time can be predicted. Three conditions were predicted: (1) Maximum consecutive driving time is 2.57–3.05 h in the morning group; (2) Maximum consecutive driving time is 2.05 h in the afternoon group; (3) Maximum consecutive driving time is 2.25 h in the night group. At the same time, the driving performance indicator SDLP was used to verify the accuracy (P = 0.98), showing that the model in this study could reflect the drivers' fatigue change trend perfectly. The problem of this model was proposed that the maximum consecutive driving time is shorter than any existing regulation (it was presented in Section 1), and the unified fatigue prediction model lacks consideration of driver individual difference.

To improve the performance of the driver fatigue level prediction model, it is necessary that the driver individual difference need be considered at DFPM-1 and try to combine with other driving features for accuracy. In DFPM-2, the problem of the real-time fatigue prediction during the naturalistic driving environment needs be solved, and then highlight the performance of model prediction rather than detection.

5. Conclusion and future work

The systematic research of driver fatigue behavior was reviewed and it was structured into three components including fatigue influential indicators (What affects driver fatigue), fatigue identification and measurements (How to identify driver fatigue), fatigue prediction (How to predict driver fatigue), combined with our previous studies (Fig. 7). The application and limitation of three components were discussed, and hope to provide help for the realization of fatigue reduction and prevention finally.

The study of driver fatigue influential indicators is originated from the bio-mathematic fatigue model that considering sleep and circadian rhythm as influential indicators. And then the time-related indicators of driving were considered as driver fatigue influential indicators. Sleep hours, driving time, rest time, and circadian rhythm were considered as

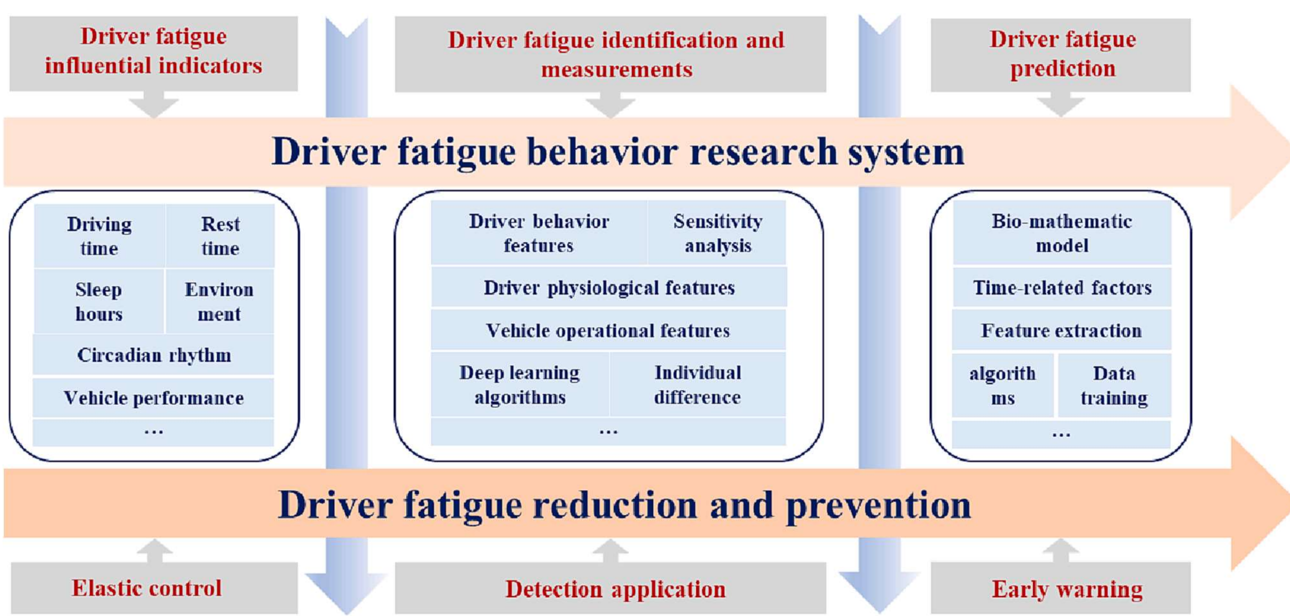

Fig. 7. Structure of driver fatigue behavior research system.

mainly influential indicators that affect driver fatigue level. Countries and scholars pay great attention to the consecutive driving time and consecutive rest time which directly affect driver fatigue level and risk, and a series of systematic research and regulations have been formed. To solve the problem of fatigue accumulation, the elastic control of driver's driving time and rest time is the effective measurement for the prevention of driver fatigue. At the same time, it is meaningful to explore the rest way which can support effective rest to relieve the driver fatigue instead of invalid rest way that cannot relieve fatigue. Various driver fatigue detection methods were proposed based on subjective measurements and objective measurements. The performance of the detection model is determined by measurements which have a correlation with fatigue level. Sensitivity analysis can solve the problem that which measurement has a positive correlation with fatigue level and then ensure the accuracy of detection. However, although single measurement has the best sensitivity, it is not suitable for the current fatigue detection method although. Multi-measurements fusion identification can overcome the disadvantage of low accuracy and poor recognition compared to single measurement identification. And deep learning algorithms can be combined to improve the accuracy. Last but not least, driver individual difference is an important factor that affects the accuracy of fatigue detection. The driver fatigue prediction model is developed from fatigue theoretical models of the sleep and circadian system, and it was divided into DFPM-1 (based on time-related factors) and DFPM-2 (based on feature extraction and recognition) through the summary of present studies. DFPM-1 is easily affected by driver individual differences, so it needs to develop a driver individual fatigue prediction model. DFPM-2 needs to deal with the problem of real-time fatigue prediction during the naturalistic driving environment, and highlight the performance of model prediction rather than detection.

With the development of automobile intelligence, human–machine co-driving has become the main driving mode between drivers and autonomous vehicles. Driver's driving pressure can be relieved while driving tasks are reduced through the automatic driving function, driver fatigue state should be keeping a positive trend under this mode. However, many studies have found that driver fatigue value will be increased faster with human–machine co-driving mode compared to manual driving mode (Merat et al., 2019; Linehan et al., 2019). The phenomenon is not expected by the automatic driving function, and it is urgent to study why this phenomenon happened and what affects it in the future work. First, the difference of fatigue evolution between human–machine co-driving mode and manual driving mode needs to be clarified, and then analyzing the fatigue influential indicators under human–machine co-driving such as auto-driving time, non-driving related tasks (NDRT), trust to autonomous vehicle based on the normal driver fatigue model. Next, fatigue detection and prediction methods need to be studied in human–machine co-driving environments considering the unique scenario characteristics. Finally, it can get theoretical support for driver fatigue prevention measures under the human–machine co-driving environment, and promote the development of automatic driving technology from the perspective of human factors.

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.

Data availability

No data was used for the research described in the article.

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