Available online at www.CivileJournal.org

Civil Engineering Journal

(E-ISSN: 2476-3055; ISSN: 2676-6957)

Vol. 8, No. 12, December, 2022

Review Article

Physiological-based Driver Monitoring Systems: A Scoping Review

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Received 23 August 2022; Revised 04 November 2022; Accepted 12 November 2022; Published 01 December 2022

Abstract

A physiological-based driver monitoring system (DMS) has attracted research interest and has great potential for providing more accurate and reliable monitoring of the driver's state during a driving experience. Many driving monitoring systems are driver behavior-based or vehicle-based. When these non-physiological based DMS are coupled with physiological-based data analysis from electroencephalography (EEG), electrooculography (EOG), electrocardiography (ECG), and electromyography (EMG), the physical and emotional state of the driver may also be assessed. Drivers' wellness can also be monitored, and hence, traffic collisions can be avoided. This paper highlights work that has been published in the past five years related to physiological-based DMS. Specifically, we focused on the physiological indicators applied in DMS design and development. Work utilizing key physiological indicators related to driver identification, driver alertness, driver drowsiness, driver fatigue, and drunk driver is identified and described based on the PRISMA Extension for Scoping Reviews (PRISMA-Sc) Framework. The relationship between selected papers is visualized using keyword co-occurrence. Findings were presented using a narrative review approach based on classifications of DMS. Finally, the challenges of physiological-based DMS are highlighted in the conclusion.

Keywords: Driver Monitoring System; ADAS; Vehicle Safety; Driving Behavior.

1. Introduction

Driving is a complex and challenging task. Drivers must be able to comprehend and adapt to the driving circumstances to decrease traffic accidents. It is vital to monitor the driver's mental and physical state since the driver must always be on alert and keep an eye on his surroundings [1]. It becomes more closely related to automated driving. Therefore, more key players in the automotive industry are interested in driver monitoring systems (DMSs) [2]. DMSs and warning systems have been suggested as standard or optional equipment in vehicles, especially passenger vehicles, driven by the increasing number of road accidents globally [3]. For instance, the earliest driver monitoring systems on the market were systems or tools for recognizing driver fatigueness or drowsiness which may affect their driving abilities. Since then, the DMS market has witnessed notable growth, especially with the increasing number of traffic accidents caused by drivers' lack of alertness. Moreover, future vehicles will be required to include driver monitoring as a fundamental feature, especially vehicles with conditional automation [4]. Drivers may disengage from vehicle control but still need to maintain focus and prepare to re-engage and control the car when necessary.

The study of human physiological characteristics such as heart rate, respiration rate, and heart rate variability [5] and the recent technological advancement of embedded sensors enable the evaluation of drivers' physical and emotional

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http://dx.doi.org/10.28991/CEJ-2022-08-12-020

states [6]. Since physiological signals come from human organs including the brain, eyes, heart, and muscles, they may be utilized to gauge a driver's state of alertness [7]. These signals may be acquired using biosensors such as using electroencephalography (EEG) or Near Infrared Spectroscopy (NIRS) to study brain activity, electrooculography (EOG) to assess ocular activity, electrocardiography (ECG) and blood pressure signals to monitor cardiac activity and electromyography (EMG) signal to record muscle tone of a person [1]. These biosensors are placed in vehicles or attached to drivers as a source of input for driver monitoring systems. They are measurable and may be captured in real-time without the driver's active participation. However, they may be frequently distorted by noise and challenging to be analyzed [8]. Nevertheless, the use of these sensors enables early detection of a lack of alertness in drivers, reducing the likelihood of serious accidents. The three primary components that form the physiological-based DMS overall architecture are signal collection, data processing, and control modules, which include feature extraction and classification methods as shown in Figure 1.

Figure 1. Physiological-based DMS components

The physiological signals may be acquired using wearable or non-wearable sensors where the sensors will transmit the signals for processing. In the data processing stage, main features of the evaluated driver state like fatigue, and drowsiness will be extracted to determine the driver's alertness level. Table 1 lists dry electrode sensors for physiological indicators [9]. If abnormalities are detected, the control module will trigger a warning and notification either visible, audible, or haptic alerts to the driver. Furthermore, the DMS must be built to make optimal use of the radio and sensory components along with intrusive sensors for effective continuous driver monitoring to take place [6].

Table 1. Dry sensors for physiological signals

Physiological indicators	Types of Dry Electrodes for Data Acquisition	
EEG	(i) Mindwave Headset (ii) Flex Sensors (iii) Drypad Sensors	(iv) Imotive Headset (v) Neurosky's Dry Sensors (vi) Quasar Sensor
ECG	(i) Alivecor System and ECG Check (ii) EPI mini (iii) Ambulatory ECG	(iv) Omron (v) Flex Sensor (vi) Drypad Sensors
EMG	(i) NEURONODE (ii) SX230 (iii) Trigno Mini Sensor	(iv) NeuroSky's Dry Sensor (v) Quasar sensors
EOG	(i) NeuroSky's Dry Sensor (ii) Comnoscreen (iii) Google glass	(iv) SMI Eye Tracking Glasses (v) ASL Eye Tracking Glasses
GSR	(i) Empatica wristband (ii) Shimmer 3 (iii) Grove- GSR	
ST	(i) MAXIM302025 (ii) YSI400 Series Temperature Probe	

In this review, we provide a summary of physiologically based driver monitoring systems that have been grouped according to different types of DMS, including driver identity recognition, alertness, fatigue, and drowsiness monitoring, as well as drunk driving, which is different from previous reviews by Guettas et al. [1], Arakawa et al. [10], and Guo et al. [11]. This paper is organized as follows: Section 2 describes the different types of physiological signals that have been used for monitoring drivers' states. Section 3 presents the research method applied in this study. Section 4 presents the classification of physiological-based driver monitoring systems found in the past five years. Section 5 discusses the challenges of implementing the physiological-based driver monitoring system. Finally, Section 6 provides the conclusion of this study.

2. Driver Physiological Signals

2.1. Electrocardiogram (ECG)

The electrocardiogram (ECG), which systematically records fluctuations in heart rate, is used to obtain cardiac signals. Electrocardiogram (ECG)-based physiological metrics include heart rate (HR), heart rate variability (HRV), ECG-derived respiration rate (EDR), and metrics derived from electrodermal activity (EDA) signals [12]. Based on ECG data, the heart rate (HR), also known as inter-beat interval (IBI) which corresponds to the number of heartbeats per unit of time, generally per minute, is another extensively used measure to assess cardiac activity. IBI time changes are referred to generally as Heart Rate Variability (HRV) [5]. Depending on internal and environmental circumstances, HRV data varies across people and over time within individuals [13].

Previous research in studying driver performance has shown that these metrics are related to driver differences in cognition and attention. The instantaneous heart rate varies within a certain range of fluctuation in the normal condition [10]. There are three frequency bands such as very low frequency band (0.003–0.04 Hz), low frequency band (0.04-0.15 Hz), and high frequency band that are provided by the HRV power spectrum analysis derived from R-to-R time series (0.15-0.4 Hz) from period of two to five minutes of recording [5]. The ECG measures cardiac responses recorded from the chest. It gauges how much physical and psychological stress and tiredness the body experiences. Gender and age, along with body posture, temperature, humidity, altitude, emotional state, hormonal condition, medications, and stimulants, have an impact on HRV [14].

The heart rate of an awake participant is substantially closer to the high frequency band. The heart rate begins to slow down and move closer to the low frequency band when a patient begins to feel sleepy. Moreover, analysis of HRV enables classification of various illnesses by measuring autonomic nervous system stress and detecting angina and ischemic heart disease [10]. Since the signals are generally acquired by attaching three or twelve leads to the skin's surface and connecting an electrode to the body, non-invasive ECG recording techniques, such as embedding sensors in the steering wheel, were developed to suit driver applications [1]. Polyurethane electrodes that are flexible and thin were created to enable for continuous in-vehicle heart rate monitoring as well as long-term electrocardiogram (ECG) monitoring while driving [15].

Another study focused on real-time ECG monitoring to mitigate road accidents due to cardiovascular problems such as cardiac arrhythmia and hypoxia. In-vehicle Bluetooth transmission will be used to measure ECG signals from the driver's hand and sent to Android mobile phones or tablets. The signals will be stored in a cloud database so that physicians may access them right away [16].

2.2. Electroencephalogram (EEG)

Drowsiness detection is crucial when performing critical activities like driving duties like operating a crane, running a vehicle. Drowsiness detection techniques based on electroencephalography (EEG) have been proven to be successful [17]. Electroencephalogram (EEG) analysis is a technique used to assess the electrical activity of the human brain and acquire specific information of a person's mental state [18]. The scalp (frontal, temporal, parietal, and occipital) of the subject is used to record EEG signals. Waveforms with frequency bands can be categorized as alpha (8-13 Hz), beta (14-30 Hz), theta (4-7 Hz), gamma (32-100 Hz), and delta (3.5 Hz) bands. Gamma waves indicate conscious awareness, theta waves indicate a profound state of meditation, delta waves indicate deep sleep, and beta waves indicate an attentive state. Alpha waves indicate a calm and detached consciousness [14]. Alpha waves repeatedly occur when our eyes are closed and swiftly vanish when we open them again [19]. According to reports, if the individual is discovered to be sleepy, there will be a considerable increase in the theta frequency band and a drop in the power changes in the alpha frequency band. Additionally, an electrode helmet must be worn on the head to detect the frequencies. It seems obvious that having electrodes attached to the driver's head would be extremely inconvenient, impair their ability to drive, and perhaps even increase the likelihood of an accident occurring.

Nevertheless, EEG behaviour has been widely examined in both simulated and actual driving situations to study driver drowsiness and fatigue [20]. The EEG signals are non-stationary, and the data collecting is quite invasive but very intrusive to drivers [21]. Due to the non-stationary nature of EEG data, techniques like signal modification and sub-band extraction are increasingly being used to automatically discern between awake and asleep states. The majority of these computations take a very lengthy time. For instance, a single-channel EEG-based drowsiness detection approach using analytical and single-feature computation is proposed. The suggested model was tested using the Physio Net Sleep dataset and the Simulated Virtual Driving dataset. In comparison to the previous research, the suggested strategy produces superior outcomes [17].

2.3. Electrooculography (EOG)

EOG is the most frequently used method to automatically identify different phases of sleep [22]. In addition, due to its strong signal-to-noise ratio and distinctive information on eye blinks and other eye movements, EOG is also frequently used to gauge levels of fatigueness [19]. The EOG is a method for measuring eye movement i.e., the electrical potential difference between the cornea and the retina of a human eye which may be used to gauge a driver's degree of attention. When a driver's eye movement is slower compared to the driver's eye movement while awake, it can be assumed that the driver is starting to nod off. This is done by placing disposable electrodes on the outside corners of each eye and a third electrode in the centre of the forehead as a reference [14]. However, the narrow band of the EOG signal, which has a frequency range of 0.5–10 Hz, makes it challenging to extract the EOG signal [22].

2.4. Electromyography (EMG)

The EMG is a diagnostic technique used to evaluate the condition of the nerves and muscles that govern them. The EMG signals amplitude and spectrum analysis have both been utilized as indicators of muscle fatigue where it records signals from the muscles and skin and is connected to muscle contraction. It is regarded as the gold standard for calculating driver muscle fatigue [23]. Muscle fatigue happens when the muscle is unable to exert force and achieve necessary motions, usually when the body is overworked. The EMG device i.e., electrode pads are utilized to find electrical impulses, and examination of the data will show whether the individual has muscular fatigue [21]. Even though this form of measurement is extremely accurate and results in very minimal detection errors, its practical use in a real-time setting is challenging since it is intrusive and requires a complicated setup [14].

2.5. Galvanic Skin Response (GSR) or Electrodermal Activity (EDA)

Pulse oximetry and skin conductance, commonly known as galvanic skin response (GSR) or Electrodermal Activity (EDA), are utilized to collect bio-signals for pre- and post-driving stages in order to identify driver fatigueness [14]. It is used to demonstrate the emotional state or arousal and is easily quantified. However, the emotion triggered is difficult to be determined since emotions like stress and rage produce identical GSR responses. This demonstrates that sympathetic activity and emotional arousal are connected [1].

Plethysmography is the detection of the cardio-vascular pulse wave as it travels through the body where the ambient light reflected from the skin may be changed based on the hemoglobin's absorption spectrum. The circulatory system uses the heart to pump blood, and with each beating, fresh blood flows via blood arteries to all parts of the body. Micro-blushes, which are color fluctuations in the skin that are invisible to the human eye, are produced by this blood circulation [24]. The tonic level of GSR, which refers to the slow-acting parts of electrical activity like the mean level of GSR or gradual ascending and drops with time, is one characteristic that may be obtained from GSR data. The skin conductance level is the most used way to quantify this component. This metric fluctuates because of the overall arousal or emotions variations. Phasic GSR refers to the signal's quickly altering characteristics and measured using the Skin Conductance Responses (SCR) which can be classified as Non-specific SCRs (NS-SCRs) and event-related SCRs (ER-SCRs). NS-SCR collects reactions that happen in the absence of clearly defined triggering stimuli, whereas ER-SCR describes the electrodermal response of drivers to stimuli. The frequency of NS-SCRs, which is typically between one and five per minute at rest and more than 20 per minute at times of high arousal, is one often utilized indicator. Indicators including latency, amplitude, rising time, and half recovery time are typically utilized to describe ER-SCRs. Apart from latency, which must be determined from a time-stamped triggered event, the same indicators may be computed exactly for NS-SCRs [5]. However, GSR's sensitivity to the surrounding temperature is its biggest drawback [1].

2.6. Respiration

The respiratory system is complicated and susceptible to additional psychological factors. Breathing affects both EDA and cardiac activity. Based on the data supplied by breathing transducers, a variety of measurements may be derived, including the breathing rate (BR), which represents the number of breathing cycles per minute. The raw breathing signal may also be used to produce measures of the inspiratory and expiratory volumes and durations, their ratios, and the complexity of the signal (by spectrum analysis). The chest expands because of breathing, and piezoelectric sensors can detect this movement. A phenomenon known as respiratory sinus arrhythmia (RSA) refers to the impact of respiratory cycle on heart rate. Numerous variables, such as exercise level, age, or posture, affect RSA. The key metric is the magnitude of RSA; however, frequency and time domain techniques can also be utilized because they produce comparable outcomes. The respiratory system functions regularly and harmoniously under ideal circumstances while driver's perform various activities in a vehicle, however stressful events can cause disturbances in this system [5].

2.7. Photoplethysmographic (PPG)

PPG is an optical measuring method used to find variations in blood volume in the tissue's microvascular bed [25]. Moreover, since PPG is non-invasive and provides information on cardiac activity by detecting the pulse wave from the finger, earlobe, or toe, it is utilized as an alternative to ECG signals. Information of brain function may also be inferred from PPG signals. It enables driver analysis to be performed based on physiological and psychological factors. However, a light source and a photodetector are necessary for PPG. The photodetector detects minute fluctuations in reflected light intensity linked to perfusion changes in the catchment volume from the light source that lights the tissue [25]. In addition, the HR, HRV, and respiration rates can be more accurately measured on the earlobe. Cardiovascular blood volume pulse and heart rate variability (HRV) are extracted from PPG. PPG has been used to test driver fatigueness [26]. However, it is still less trustworthy than the ECG signal [1]. It requires direct contact from the driver to the detectors and requires at least five minutes to perform the frequency domain analysis which is not reliable for critical assessments [25]. Nonetheless, the measurement of remote PPG (rPPG) is now possible due to developments in the field of contactless heart rate monitoring during the past ten years. rPPG may be monitored by a standard RGB camera and is derived from variations in face color, making it simple to include into physical features for driver tiredness detection. The application of rPPG for driver tiredness identification is currently being relatively under-explored [26].

3. Research Methodology

In this study, previous work from year 2018 to 2022 in this area has been comprehensively mapped, and the study gaps in the field that pertain to tracking driver status to reduce the risk of accidents have been identified. The five steps indicated by Arksey and O'Malley—identifying research questions, finding pertinent studies, choosing studies, charting, compiling, summarizing, and reporting results [27] as shown in Figure 2 were implemented.

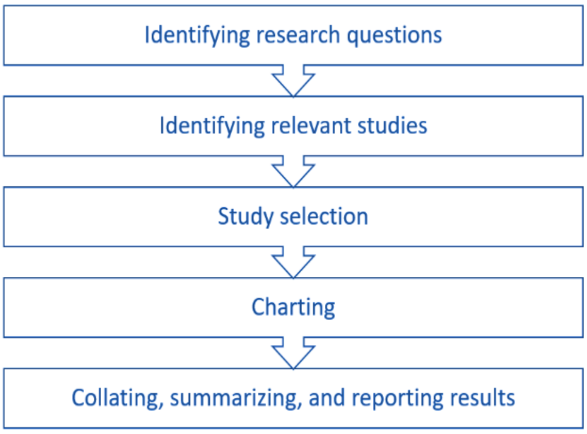

Figure 2. Scoping review processes

Our objectives in conducting a scoping study were to evaluate the scope and breadth of the research activity as well as to identify research gaps in the literature as they are related to psychological-based driver monitoring systems. The following research questions were formulated:

- What are the physiological-based systems or tools proposed to monitor a driver's state in promoting safe road environment in the past five years?
- What are the challenges in monitoring a driver's physiological state in a moving vehicle context?

Potentially relevant studies were identified by adhering to the PRISMA Extension for Scoping Reviews (PRISMA-ScR) framework [28]. This framework allowed for the cautious and thorough analysis of large number of sources to identify and summarize pertinent keywords, main concepts, critical areas, and gaps. We searched the globally acknowledged scholarly database i.e., Science Direct and Scopus from year 2018 until 2022 using search strings listed in Table 2. Boolean logic connectors were used to connect multiple search terms. The main search terms focused on terms commonly used to represent driver monitoring systems (#5). The second group of search terms included keywords related to driver monitoring system categorization (#6). The third group of search terms were related to biosensors and driver monitoring (#7). All journal articles and conference proceedings in computer science and engineering were considered.

Table 2. Search strings

ID	Search Strings
#1	"driver monitoring" OR "driver health" OR "driver state"
#2	"system*" OR "application*" OR "tool*"
#3	"fatigue*" OR "drows*" OR "sleep*" OR "drunk" OR "distract*" OR "alert*" OR "wellness" OR "vigilance" OR "weariness"
#4	"physiological" OR "EEG" OR "ECG" OR "PPG" OR "EMG" OR "HRV" OR "heart rate"
#5	#1 AND #2
#6	#1 AND #3
#7	#1 AND #4

The initial search results from both databases yielded 2,939 articles. The bibliographic citation file (*.ris* file format) was imported into RAYYAN [29] to facilitate collaborative review process among the co-authors. Automatic detection by the software shows 1,862 duplicates and these duplicates have been automatically resolved. The citation information, which includes author and source details, bibliographic data, an abstract, and keywords, is crucial in influencing the screening choices made by the reviewers. The reviewers work in pairs to screen the articles based on the eligibility criteria defined in Table 3. A third reviewer was consulted when both reviewers have contradicting opinions.

Table 3. Eligibility criteria

Inclusion	Exclusion
Articles published in English.	Articles with no clear methodology.
Articles published since 2018.	Articles which members have no access to the full text.
Articles published as original articles, reviews or conference proceedings.	Articles without relevant information to support the research questions.
Articles primarily focused on driver state monitoring	

355 articles were removed from further screening based on titles and abstracts which are not related to physiological-based driver monitoring systems. Next, 208 articles were removed since none of the reviewers have access to the full text, leaving 514 articles for full-text screening. 322 articles do not have relevant information which can provide insights to answer the defined research questions which guides this study. The reviewers thoroughly examined the full texts of all 192 potentially eligible articles to confirm their inclusion. However, 99 articles which do not describe clear methodology were excluded. A total of 93 articles met all the criteria identified. The results of the selection according to the PRISMA flow diagram are shown in Figure 3.

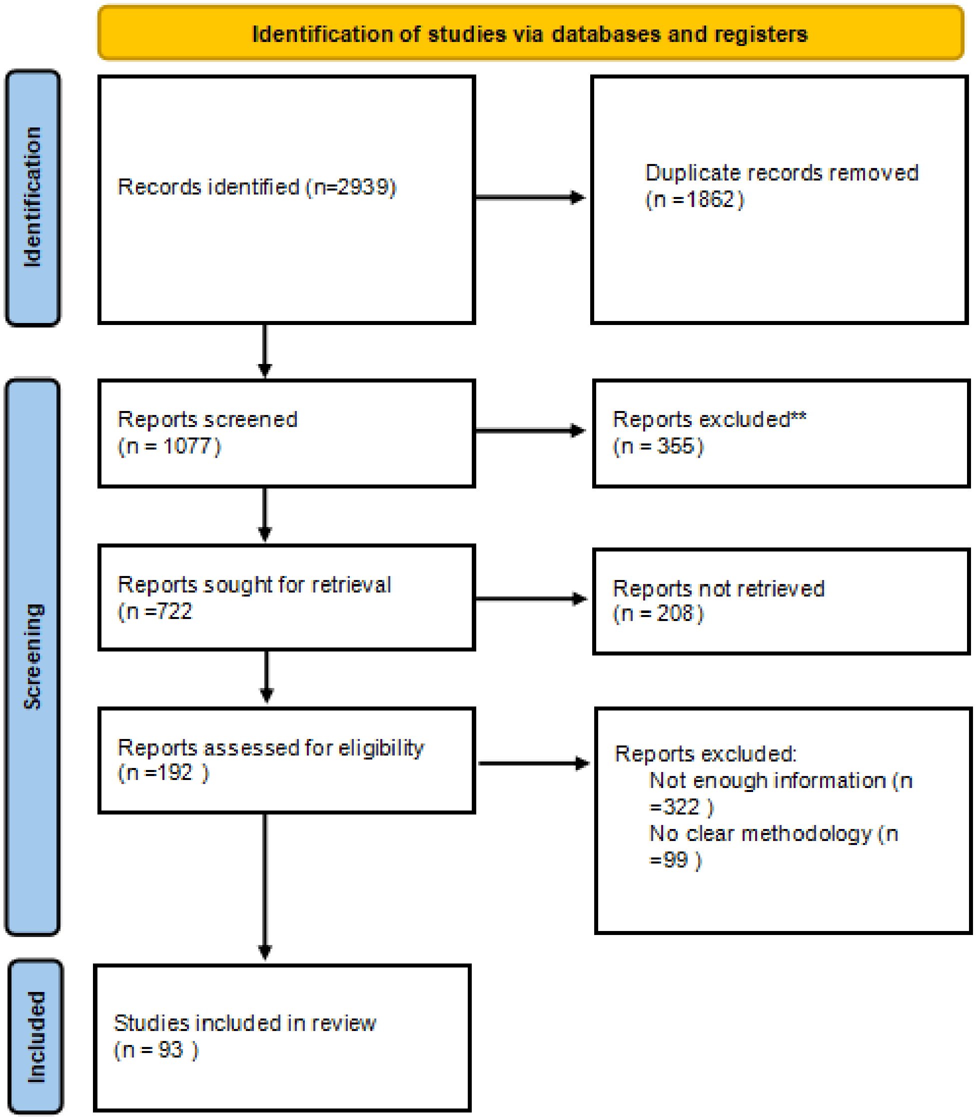

Figure 3. PRISMA-Sc flow diagram

Next, the selected articles were labelled according to the physiological indicators i.e., electroencephalography (EEG), electrooculography (EOG), electrocardiography (ECG), electromyography (EMG), electrocardiogram (ECG) or multi-indicators, and type of driver monitoring system related to driver identification, driver alertness, driver fatigue, drunk driver, or driver emotion. The bibliographic citation file (.ris) of these articles was then exported to a bibliometric analysis software-VOSviewer version 1.6.7 [30].

Keyword occurrence analysis was performed to provide an overview of the research focus from the selected articles. The minimum occurrence of keyword is set to 5 prior to generate the concept map as in Figure 4. In addition, the keywords are visualized as nodes and connected with other keywords which co-occur. The visualization reveals six main themes which are driver monitoring (blue node), automated driving (red node), sleep stages (purple node), heart rate (yellow node), electroencephalography (brown node) and electrocardiography (green node). A narrative review approach was used to summarize information found from selected articles. Finally, the final report was prepared to present the findings and analysis of this study which is suggested to fulfil the research gap in this area

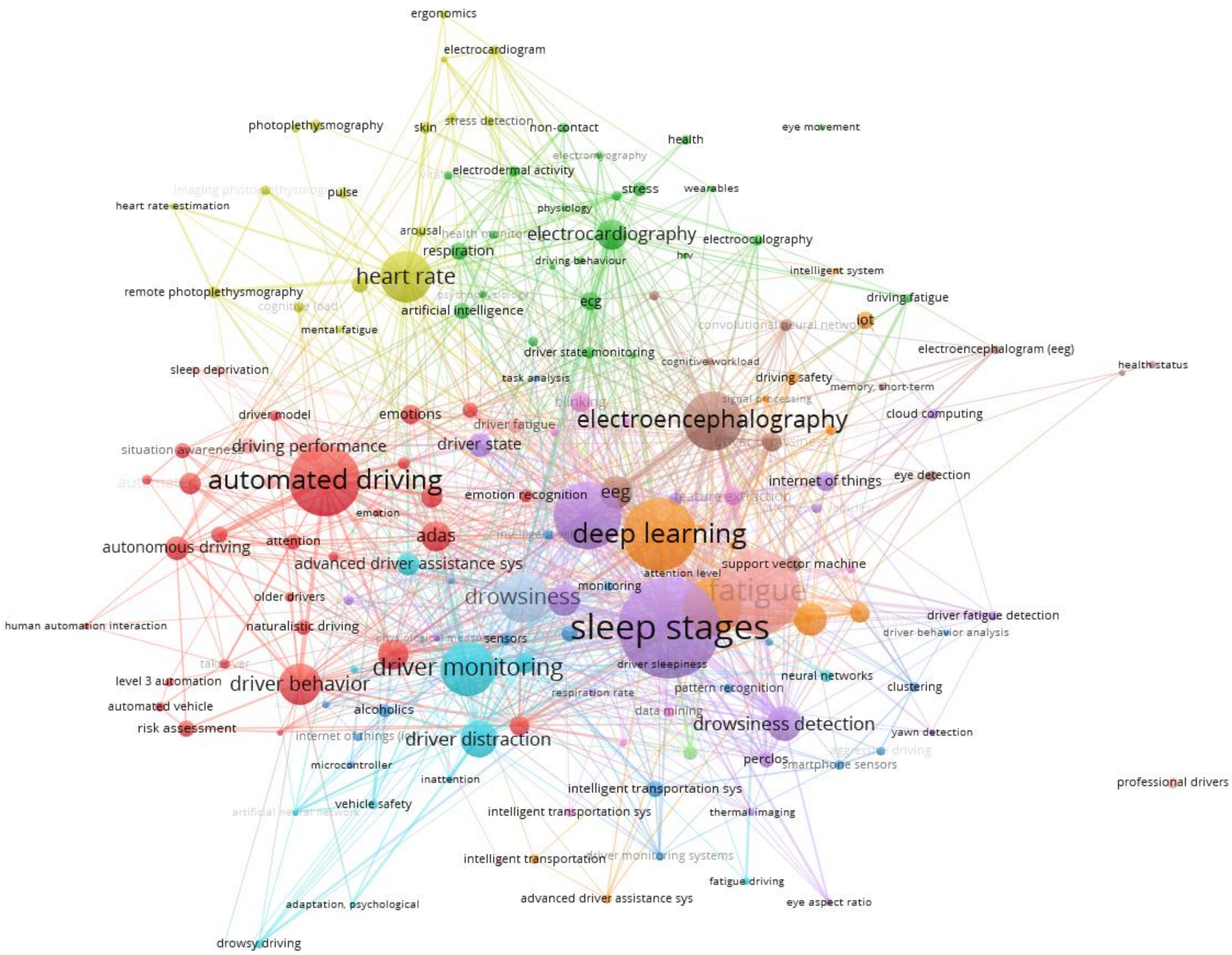

Figure 4. Network Map based on keyword occurrence

4. Findings and Results

The inclusion and exclusion criteria have enabled the categorization process to be conducted in a meticulous manner. However, due to limited space, the narrative review only covers articles within the theme which we selected for presenting related research according to our research objectives.

4.1. Driver Identity Recognition

Driver identity recognition refers to continuously tracking a driver's identity to prevent unauthorized access and behavioral by providing better customized driving assistance through an instructive or non-intrusive approach. It is amongst the most common technologies used in smart automobiles. When a driver is identified in a vehicle using the collected bio-information, the identity recognition technology assists in performing driving tasks. Hence, physiological-based approaches have been proposed by previous researchers. For instance, ECG and electromyography (EMG) were converted into 2D constant Q transform (CQT) for the development of an identification system with a multi-stream convolutional neural network (CNN). Based on experimental data, a single ECG for 2D CQT produces a higher accuracy of driver identification (98.1%) compared to a single EMG which produces an accuracy of 84.4%. Combination of both ECG and EMG signals further improved the accuracy up to 98.9% [31].

A normalized electrocardiogram (ECG) based adaptive threshold filter approach was also presented, which measures the ECG while the subject is sitting, touching a slide, and after the subject has finished exercising. The results of the studies show that the suggested method increased average similarity when compared to results obtained without the normalization step [32].

An identification tool for registered drivers by mapping the fingerprint of each driver was also proposed. The experimental results of false acceptance and rejection rates were relatively low at 4% and 8%, respectively, requiring extensive work to be improved further [33]. Similarly, individual fingerprint mapping was collected, and ten-dimensional features were extracted to identify individual driving patterns. The recognition rate of the driver in the database is shown to achieve 100% through the experimental data using feature statistical distribution (FSD) mapping [34].

In another study, real driving datasets (e.g., CAN-bus) was utilized by measuring skin conductance, temperature, and ECG data to recognize drivers. The development incorporates machine learning algorithms (e.g., Random Forest, K-Nearest Neighbors, Extra Tree, Decision Tree and Gradient Boosting) to produce the verification predication. According to the experiment's findings, the proposed approach has achieved at least 90% accuracy [35]. Furthermore, physiological data (e.g., fingerprint) was analyzed using RFID for personal identification and verification tool development. The analysis of the identification and verification results proposes that the tool achieves a faster execution time than existing methods [36].

User authentication and identification model using physiological data was also proposed. The proposed work was simulated using Physionet Database, which includes an electrocardiogram, electromyogram, expansion respiration, and skin conductivity data. The experiment findings demonstrate that the accuracy of authentication with ECG data has achieved higher than 96% with one lead scenario [37]. On the other hand, an identification tool by measuring drivers' arm movement EEG signals was proposed. The proposed work was presented by incorporating a time delay neural network (TDNN) classifier. The experimental findings demonstrated a statistically significant positive correlation of the EEG signals with the actual participant's actions [38].

A driver identification scheme by measuring individual physiological data (e.g., fingerprints and ECG) and behavioral data (e.g., facial and voice) using a pre-configured processor was also proposed. The experimental findings emphasize that the proposed approach could identify the user and can be extended to personalize individual vehicle settings as desired [39]. In another work, an identification system using a photoplethysmographic (PPG) signal was presented to personalize a driver's identity. The proposed approach employs a temporal convolutional neural network (TCNN) architecture to acquire the features of the data generated from the PPG signal. The experimental results show that the algorithm herein proposed recognized the driver's identity with an accuracy of close to 99% [40].

4.2. Driver Alertness Monitoring

Driver alertness monitoring system is also known as driver distraction and driver vigilance monitoring system. A driver is considered distracted when he or she is pre-occupied or doing other tasks while driving [41] which prevents the driver from focusing on the road, traffic flow and vehicle control [42]. Critical safe driving is influenced by cognitive, manual and/or visual distractions [43].

Hence, wearable and non-wearable devices have been proposed to monitor the alertness of drivers while they are driving on the road. For instance, a wearable prototype device that integrates flexible dry electrodes and a custom 8-channel EOG signals acquisition board for recording forehead EOG signals was designed to construct alertness estimation models. Systematic experiments were performed in laboratory simulations i.e., four-lane highway, various cars, buses, traffic signs, buildings, and tunnel as well as in real-world scenarios under different illuminations and weather conditions i.e., sunny, cloudy, windy, rainy and at night. Simulation studies were conducted using a subset of SJTU Emotion EEG dataset known as SEED-EOG before actual road testing [44]. Similarly, a deep coupling recurrent auto-encoder (DCRA) was proposed to improve the accuracy of driver alertness detection monitoring system. EEG and EOG signals were combined to produce the data analysis model [45].

Moreover, during long and boring drives, most drivers exhibit deteriorating level of alertness. Additionally, high in-cabin temperatures, uncomfortable driving circumstances, and muscular tiredness in the neck, shoulder, or back region may easily distract a driver. Therefore, research was conducted to investigate the influence of muscle fatigue on driver's alertness state using surface EMG signals. EMG electrode was connected to driver's bicep brachii for two hours during a driving simulation to acquire the EMG signals. Next, the EMG signals were filtered based on time, frequency and time-frequency domain analysis. Afterwards, Artificial Neural Network (ANN) feature selection and classification method was implemented prior to applying EMG Signal Segmentation [21].

Besides, a comparison analysis of machine learning methods to detect driver alertness using physiological sensors (palm electrodermal activity (pEDA), heart rate and breathing rate) and visual sensors (eye tracking, pupil diameter, nasal EDA (nEDA), emotional activation and facial action units (AUs)) was also conducted. Based on the performance of classical machine learning methods i.e., decision tree, random forest, naïve Bayes, k-Nearest neighbor, Support Vector Machine, bagging, adaptive boosting (AdaBoost) and extreme gradient boosting (XGB), the study concluded that XGB have the highest performance [46].

Apart from that, vision-based approach implementation has been reported to recognize the physiological parameters for detecting driver lack of alertness or distraction. It has been demonstrated that both HR and RR are reliable predictors of the driver's degree of attentiveness. A ballistocardiograph sensor detects HR by detecting the minute movements of the body brought on by the heartbeat, while an electrocardiogram measures HR from the electrical potential of the heart [11]. Furthermore, electrodermal activity (EDA) features was proposed in driver state management and predicting lane takeover attempts. Skin conductance were obtained and decomposed into tonic and phasic components. Results suggest that phasic component dominates changes in EDA and has the largest effect on driver’s alertness [47].

4.3. Driver Fatigue Monitoring

Long-haul driving i.e., in 3 hours puts drivers at risk for both mental and physical exhaustion. When a driver is on the road for longer than three hours, fatigue happens more frequently [48]. Drivers who are exhausted have decreased cognitive performance and are less alert. In most situations, measurements of the physiological signal produce solid results to detect driver fatigueness [49]. Driver fatiguenss can be detected by monitoring changes in biological signals, such as those produced by the electroencephalogram (EEG), electrocardiogram (ECG), electro-oculography (EoG), and surface electromyogram (sEMG) [26]. Hence, ECG data was used to acquire patterns for assessing fatigue of the driver based on the age, time spent in traffic congestion and pre-congestion state prior. The study revealed that 10-12% of drivers begin to feel fatigue after 7–10 min trapped in traffic congestion [50] Besides that, continuous noise may also induce driver fatigueness. An investigation based on EEG data was conducted to measure the changes of brain wave activity when induced with broadband noise of 40 dBA, 55 dBA and 75 dBA during a 1.5-hour monotonous drive. The study concludes that monotonous drive caused progressive increase of alpha activity which represents driver fatigueness [51].

Earlier, two characteristics of EEG signals i.e., power spectral density (PSD) and sample entropy (SampEn) were integrated to assess cognitive fatigueness [52]. Integration of EEG signals with other features including facial expressions, yawning, and the percentage of eyelid closure over the pupil over time (PERCLoS) were also implemented to determine a driver fatigue state [53].

Moreover, driver fatigue monitoring system can be classified into machine learning [54, 55] and deep learning [56]. Machine learning and data fusion techniques make it possible to detect fatigue more reliably and precisely [57]. For example, EEG signals using gradient boosting decision tree model with sample entropy, fuzzy entropy, approximate entropy, and spectral entropy as the inputs of a decision tree reported average driver fatigue detection accuracy of 94% [55]. In another work, scalp electroencephalography (EEG) data was used to train Support Vector Machine to recognize driver extreme fatigue state of 36 hours. The detection accuracy obtained was reported up to 86% [58]. Besides, a two-level hierarchy Radial Basis Function (RBF) network known as RBF-TLLH has been designed for EEG-based driving fatigue detection which outperformed other methods [59].

Additionally, Recurrent Network-based Convolutional Neural Networks (RN-CNN) was proposed using EEG signals obtained during driving simulation. According to authors, the approach for detecting weariness has an average recognition accuracy of 92.95 percent [60]. It is also proposed to use deep Convolutional Neural Network–Long Short-Time Memory (CNN–LSTM) network to extract characteristics from raw EEG data to increase the accuracy of driver mental fatigue detection [56].

In another work, a fast support vector machine (FSVM) algorithm based on EEG and EOG modal data was implemented to recognize symptoms of driver fatigueness. When a symptom is visible, the driver and nearby vehicles will be informed via IoT technology [53]. On the other hand, the EEG signals were first reduced using the Weighted Principal Component Analysis (WPCA) algorithm before applying SVM to detect fatigue driver. Drivers will be notified and advised to reduce the vehicle speed, stop for a rest and at the same time, surrounding vehicles will be warned to take precautions by transmitting the data to the traffic management platform [61].

Nevertheless, the execution is challenging since EEG data collection is generally using obtrusive method, impractical to install [62] and substantial amounts of data must be gathered for reliable results [49]. Therefore, non-obtrusive method was proposed which embeds surface EMG sensors in vehicle steering wheel to provide early driver fatigueness [62]. For instance, flexible and thin electrodes made of polyurethane for long-term electrocardiogram (ECG) was designed to monitor driver psychological state while driving under four different scenarios including rest, city, highway, and rural [15].

4.4. Driver Drowsiness

A driver who is continuously yawning, has slower ability to react, causes them to have difficulty focusing on the road, and performs lazy steering. In addition, drivers also sway their head or body because they are falling asleep or daydreaming, has trouble keeping the vehicle in one lane, and shows sign of confusion and frustration. These symptoms indicate that a driver is feeling drowsy. Generally, a drive requires 0.15 second to respond and 0.15 second is critical to avoid accident [22]. There is evidence to show that as automation levels increase, drivers will be much more likely to nod off behind the wheel [63] Hence, previous research has been conducted to create reliable and efficient driver drowsiness detection systems which aims to prevent road accidents. Psychological-based systems have implemented ElectroEncephaloGram (EEG), ElectroOculoGram (EOG), ElectroCardioGram (ECG), skin temperature (ST), and galvanic skin response (GSR), and ElectroMyoGram (EMG) [9]. These signals may also be integrated to improve the accuracy of the detections. For instance, EEG and EOG signals were integrated to track the change in alpha waves and differentiate the two alpha-related phenomenon i.e., alpha blocking and alpha wave attenuation disappearance phenomenon in driver drowsiness detection [19].

In addition, heart rate (HR) and heart rate variability (HRV) analysis are also suggested for early detection of driver drowsiness [64]. HRV data was extracted from ECG signals to assess the reliability of HRV to detect driver drowsiness among alert and sleep deprive drivers in three actual road driving environment. The Karolinska Sleepiness Scale (KSS) was used as a benchmark for training the classifiers including k-Nearest Neighbors, Support Vector Machine, AdaBoost, and Random Forest. Results revealed that more factors need to be considered when using HRV to detect driver drowsiness [13]. Factors like a secondary task, driving through difficult traffic circumstances or congestions or the use of a driver aid system while driving may influence HR and HRV. The relationship between HRV and drowsiness was examined using consumer wearable devices i.e., Garmin brand sports watches and Polar H10 chest bands for recording RR intervals. Drowsy drivers for both manual and partially automated driving showed lower HR, increased HF, LF power and LF/HF [65] In addition, relationship between HRV and the KSS is not influenced by different pre-processing techniques for outlier heartbeat removal, spectrum transformation of HRV data [64].

Besides, an analysis of heart rate variability (HRV) has been used in [66] that provided an algorithm for detecting drowsiness in drivers. Evaluation of the algorithm was validated by comparing HRV with electroencephalography (EEG)-based sleep scoring from driving simulations. The study concluded that the HRV-based anomaly detection framework that was originally proposed for epileptic seizure prediction can be adapted for detecting driver drowsiness. Transitions between different drowsiness stages were also investigated based on Heart Rate Variability (HRV) and Electroencephalography (EEG). Eye blinks information extracted from video and subjective information were combined with the physiological data to increase the detection of driver drowsiness state [67]. EEG is said to be indispensable for accurate driver drowsiness detection system. Without EEG, a driver may be falsely classified as drowsy whenever he closes his eyes [63]. Also, a prototype built on PPG signals are usually acquired from the driver's hand palm. The PPG signal was analyzed based on heartbeat pulse duration and other waveform shape parameters to drowsy driver detection accuracy and time [25].

Moreover, alternative approaches for detecting driver drowsiness that are based on the grip or pressure applied to the steering wheel have been studied. Microneedle electrode (MNE) was used to acquire the EMG signal of the muscles from the forearm position of the driver. The results show that when the driver's pressure on the steering wheel decreased, the driver drowsiness level increased [68]. Driver's EMG was also studied with respiration, electrodermal activity (EDA), and electrocardiography (ECG) to determine potential physiological indictors for driver drowsiness detection during simulated autonomous driving scenario. The findings suggested that EDA and ECG characteristics may be used to identify driver drowsiness state when autonomous driving is activated [63].

Additionally, a driver drowsiness detection system was developed based on extracted features from EOG signals. The EOG signal acquisition circuit was designed based on ATmega2560 microcontroller on the Arduino board. The study found that k-Nearest Neighbors classifier (KNN) used to detect driver drowsiness achieved 95.34% accuracy [22]. However, when EEG and EOG features as well as contextual information provide input to classifiers including k-Nearest Neighbor (k-NN), Support Vector Machine (SVM), case based reasoning (CBR) and Random Forest (RF), the SVM results are most stable and obtained highest accuracy amongst other classifiers with 93% [69] Besides that, using combined Functional Brain Network (FBN) i.e., synchronization likelihood (SL) and minimum spanning tree (MST) as feature selection algorithm increase the accuracy of SVM, KNN, Logistic Regression (LR) and Decision Trees (DT) in detecting driver drowsiness from EEG signals which were acquired and decomposed into multiple frequency bands by wavelet packet transform (WPT). Result shows that integration of SL and MST with the KNN classifier gives the highest precision of 98.3% [70].

4.5. Drunk Driving Monitoring

Driving under the influence of alcohol is largely focused on the detection of a driver's blood alcohol concentration (BAC) by either functional or behavioral measures. An alcohol concentration monitoring tool by measuring the physiological data of a driver through steering and sensors (e.g., heart rate, respiration, blood pressure, and temperature) was proposed. Based on the experimental results, the proposed method has 95% accuracy rate [71].

Besides, a detection system for alcohol excess in drivers was designed by measuring EEG, ECG and heart rate data. This measurement was used as input to determine alcohol consumption under a simulated driving environment. The experiment results demonstrate that physiological data and driving performance can evaluate even a low dose of alcohol consumption of 0.03% BAC level [72].

A prediction tool for drunk driving using physiological measurement data (e.g., EMG, EDA and PPG) and driving performance is presented. The proposed approach employs the SVM algorithm to develop a more accurate prediction model. The experimental result demonstrates that the SVM classification correctly identified normal driving and driving while under the influence of alcohol with an accuracy of 70% [64, 73]. Later, a non-invasive alcohol detection tool using PPG signal data was proposed to include classification models using generalized linear (GLM) classifiers the experimental outcome indicates that the proposed approach has a potential screening test to classify people who consumed and non-consumed alcohol [74]. The alcohol consumption can also be identified by measuring the ECG, PPG, and alcohol concentration levels. The proposed approach was developed using the optimized SVM method to verify the identification performance. The experimental result shows that the proposed system has achieved 95% accuracy [75].

Another set of physiological data was utilized to detect alcohol consumption which includes EEG, EDA and cardiac activity as well as vehicle data (e.g., speed, lateral positioning and wheel steering). These parameters were used to calibrate machine learning models for predicting blood alcohol content (BAC) and functional states (e.g., performance and alertness). Experimental results demonstrate that the suggested method is effective, with an accuracy of 0.714 for BAC detection and an accuracy of 0.877 to 0.907 for functional state detection [76]. Moreover, a sobriety detection tool that employs using a PPG signal to detect an individual's BAC level shows that the tool is feasible for BAC level identification has been achieved with an accuracy of 85% [77]. In addition, an alcohol sensing tool that processes the data generated from EEG signals using machine learning algorithms (e.g., FURIA, Decision Tree, Random Forest and Bagging) is claimed to be more substantial with Random Forest, which achieves the highest identification accuracy and lowest error rate [78].

Combination of EEG, EDA, respiratory and skin temperature signals through SVM classification was also investigated for identifying the alcohol concentration of an individual. Results of the experiment demonstrate that the proposed method could predict alcohol concentration through changes in physiological data [79]. Additionally, a non-contact drunk driving monitoring technique was proposed using ECG and radar-based Doppler Cardiogram (DCG) signal data. The experimental result shows that the proposed approach provided accurate readings of HRV variation before and after alcohol intoxication [80].

5. Discussions

Commercial products are normally coupled with the implementation of vehicle-based driver monitoring systems to promote a safer driving experience for vehicle owners. These products are often referred to as "advanced driver assistance systems" and include features such as "lane keep assist," which will be activated in the event that the vehicle is recognized to have deviated out of its lane accidentally. This problem may occur when a driver is distracted or drowsy. For instance, STEER is a wearable product that combines EDA with HR to detect driver drowsiness. When a driver is detected as being drowsy, STEER will produce a gentle electric impulse and vibrate. Neurocom requires a GSR wristband and ring. Another example is known as StopSleep, which has 8 built-in electrodermal sensors to continuously analyze and measure skin conductivity to avoid microsleep and keep drivers' alert. A vibration signal of 2–5 minutes will be produced as the first level of warning, and a loud beep with vibration will be triggered as the second level of warning.

Various features have been explored to propose the implementation of physiological indicators for driver monitoring systems. These features could vary depending on environment, pre-processing, and feature selection methods as well as experiments set-ups. Moreover, physiological signals, especially EOG and EEG, are more intrusive. Although dry electrodes are useful for gathering physiological data while driving, intrusive signal collection is still favored and more frequently used since the non-intrusive sensors' accuracy depends on the vehicle's positioning. When it comes to the execution of procedures in a vehicle context, hybrid methods could be more practical to implement. The implementation of machine learning classifiers may also be influenced by the amount of data. Experiments and driving simulation studies also often include a limited number of test subjects. Hence, it is not possible to generalize the results to a larger population.

From the literature, most studies focused on driving simulations compared to actual on-road testing. The number of participants was also minimal. The pre-requisites or preparation of the participants also differ. This may be due to limitations in recruiting more participants, including the cost to conduct experiments in an actual road environment. Moreover, since many past methods used an obtrusive approach, there may be a loss of data from the sensors. Hence, whenever possible, physiological data should be collected in the actual driving environment during daytime and nighttime. Moreover, subjective information will provide more insights into the physiological state of drivers, which may be influenced by many confounding factors in different situations and times. The analysis of the data should use appropriate model validation and proper feature selection methods. Incorporating more than one physiological signal may also overcome the disadvantage of an intrusive approach. Nevertheless, these types of models are complex and costly.

Limited datasets from actual road experiments pose a challenge for machine learning approaches like deep learning to generate a reliable outcome to be implemented in actual driver monitoring systems (DMS). Besides that, access to the current vehicle-based DMS is also limited. Researchers have none or limited resources to assess the performance of the proposed physiological-based DMS with actual vehicle ergonomics. Hence, a fusion of physiological indicators with vehicle-based DMS that may demonstrate the potential of DMS to mitigate risks related to driving behavior and driver wellness is challenging.

Additionally, previous studies have used their own specific simulation or experimental setup with different participant's attributes, including type, age, gender, driving history, health, etc. Therefore, the studies lack homogeneity to be implemented on a larger scale, and different countries require different impact measures.

6. Conclusion

Driving is a complex task that requires the full attention of the driver. However, many drivers are known to be distracted, feeling drowsy, tired, or driving under the influence of alcohol or drugs, which have contributed to the increasing number of global road accidents. Hence, driver monitoring systems have been introduced in the market by auto manufacturers to reduce the accidents rate. The previous work in DMS focused on behavior or visual approach that acquires data from cameras installed in vehicles and vehicle-based approaches that placed sensors in vehicle compartments. Hence, this scoping review analyses recent five years' literature related to driver monitoring systems and identified physiological-based systems or tools proposed to monitor a driver's state in promoting safe road environment. Physiological-based DMS has been reported to have higher reliability compared to the two prior approaches. Our aim here is to assess driver alertness, driver fatigue, driver drowsiness, and drunk driving. Apart from that, the challenges associated with monitoring a driver's physiological state in the context of a moving vehicle were also presented and discussed. The most significant difficulties will arise throughout the process of bringing the task undertaken in a simulation environment to the real road environment and, eventually, during the deployment on a large scale. The incorporation of machine learning techniques into physiological-DMS has resulted in an increase in the accuracy of detection based on the study of physiological signals and analysis. However, more research has to be carried out to investigate the performance of the classifiers in real-world road environments.

7. Declarations

7.1. Author Contributions

Conceptualization, S.F.A.R. and S.Y.; methodology, S.F.A.R.; software, S.Y.; validation, N.H.K., and A.A.A.; formal analysis, S.F.A.R. and S.Y.; investigation, N.H.K. and A.A.A.; resources, A.A.A.; data curation, N.H.K. and M.F.A.A.; writing—original draft preparation, S.F.A.R. and S.Y.; writing—review and editing, M.F.A.A., A.A.A., and N.H.K.; visualization, S.F.A.R.; supervision, S.F.A.R.; project administration, M.F.A.A.; funding acquisition, S.F.A.R, and A.A.A. All authors have read and agreed to the published version of the manuscript.

7.2. Data Availability Statement

Data sharing is not applicable to this article.

7.3. Funding

This research was supported by Telekom Malaysia Research and Development (TM R&D), Grant No RDTC/221046.

7.4. Acknowledgements

Authors would like to thank Centre for Intelligent Cloud Computing (CICC) and Multimedia University (MMU) for the support and encouragement.

7.5. Conflicts of Interest

The authors declare no conflict of interest.

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