

# A review of driver cognitive load detection using ECG signals

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**Abstract.** Detection of the driver's cognitive load while driving is crucial to prevent the likelihood of traffic collisions and improve road safety. A physiological-based approach has gained significant attention due to its potential to provide reliable indicators for the driver's state. The physiological signal of electrocardiography (ECG) is considered a promising biomarker for detecting the driver's cognitive load. Despite the interest in cognitive load detection using ECG, an attempt has yet to be made to identify the relationship between ECG measures and driver cognitive load level. This paper seeks to investigate this gap in cognitive load literature. The finding demonstrates that further research is still needed on ECG-based driver's cognitive load detection by examining and analyzing the limitations of research challenges and earlier studies. This study also addresses the performance and problems faced in the detection of a driver's cognitive load considering ECG. With a better understanding of how cognitive load affects ECG measures, both researchers and companies can design more effective driver's state detection systems.

## 1 INTRODUCTION

Driving under cognitive load is considered as significant causes of traffic accidents. High cognitive load negatively impacts driving behavior and often resulting in accidents that cause significant harm to both people and vehicles each year. According to the National Safety Council (NSC), 21% of all accidents are attributed to cognitive overload, characterized by distractions or inattention [1]. In addition, the National Highway Traffic Safety Administration (NHTSA) reported that driver inattention, including distracted attention from driving, is responsible for approximately 25% of all police-reported collisions [2]. The early detection and intervention of cognitive overload while driving is crucial to reduce the likelihood of traffic accidents.

An increasing number of studies have investigated the detection of driver states, including cognitive load, using diverse approaches [3]–[7]. These approaches can be broadly categorized into three primary categories based on the sources of information they rely on. The first category relates to the vehicle behavior-based performances, which involves the steering wheel's position and movement, vehicle acceleration, and speed. The second category is the driver behavior-based approach, including factors such as like head yawning, head pose, head movement, eye-gaze dynamics, and eye closure. Lastly, the third group relates to the driver physiology-based approach, such as measurements derived from

electrocardiography (ECG), electroencephalography (EEG), electromyography (EMG), and electrooculography (EOG).

The driver physiology-based approach has gained significant attention due to its potential to provide reliable biomarker of the driver's state. While the vehicle behavior-based approach is non-invasive and relatively straightforward to measure, its effectiveness hinges greatly on factors such as driver's skills, road conditions, and vehicle characteristics. Similarly, the driver behavior-based approach, which relies on cameras to monitor driver actions, is also non-invasive. However, it is constrained to identifying visual cues, which can be intentionally concealed by the driver and may only become apparent when it is too late. Furthermore, these methods involving camera-based data collection may raise privacy concerns and necessitate adequate ambient light. Contrarily, the physiology-based approach is emerging as a promising alternative to both the vehicle-based and behavior-based approaches for detecting driver states. This approach offers valuable insights into the driver's condition through capturing tell-tale physiological signals [8]–[10].

Physiological signals of driver's cognitive load offer a potential solution to address this challenge. Among the various physiological signals, ECG signals have emerged as a promising indicator for predicting a driver's cognitive load. This is due to their practicality, non-intrusiveness, reliability, and potential, as highlighted in previous studies [8], [10], [11]. Recent advancements in sensor technology have made it feasible to incorporate ECG sensors into various vehicle components, such as the steering wheel, seat belt, or driver's seat [12]–[14]. This integration enables effective, practical, and non-disruptive monitoring of ECG signals within a vehicle setting. Moreover, the autonomic nervous system (ANS) plays a crucial role in regulating heart rate, with both the sympathetic and parasympathetic nerves contributing significantly. Consequently, heart rate variability, derived from ECG signals, can serve as a reliable indicator of the driver's internal condition, which operates beyond conscious control, making it as a meaningful tell-tale sign [10], [15]–[17].

While numerous studies have reviewed various methods for detecting driver states, there is a limited of study investigating on ECG measures for driver's cognitive load. This review aims to summarize the existing literature regarding on the how ECG measurements respond to cognitive load, the effectiveness of ECG-based systems for detecting driver's cognitive load, and the potential application of ECG as an indicator of cognitive load in real-world driving scenarios. We conducted a brief review of studies that have investigated the relationships between ECG and driver cognitive load, as well as those that have developed ECG-based systems for detecting cognitive load in drivers.

## **2 LITERATURE REVIEW**

### **2.1 Driver Cognitive Load**

Driving is a dynamic activity involving three essential elements: driver, vehicle, and the driving surroundings [18]. To ensure the safety of life and property, a driver is responsible to make suitable decisions and executing actions in line with the surrounding environment and the present circumstances, while remaining vigilant and attentive [19]. When a driver becomes distracted, it can negatively impact their driving abilities, leading to unintended speed fluctuations, difficulties in controlling the vehicle, and veering out of the lane boundaries which ultimately elevates the risk of a car accident. The driver distraction occurs when a person operating a vehicle loses focus on the task at hand and becomes engrossed in another activity, or when something, either inside or outside the vehicle, diverts the driver's attention from the primary task of driving [19].

There are six categories of human driver distractions, which encompass visual, cognitive, manual, auditory, olfactory, and gustatory forms [19]. Specifically, the cognitive distraction, involves the driver shifting their mental focus away from driving and engaging in thoughts unrelated to operating the vehicle. Driving is a multitasking activity, requiring the allocation of a driver's attentional resources towards various aspects, including visual aspects (such as visual perception), cognitive aspects (like spatial working memory), and manual aspects (involving motor responses).

Prior works employed various terms to describe a subject's cognitive state, such as cognitive workload, mental workload, cognitive load (or workload), or task load. In this study, we adopted cognitive load and it could be defined as a metric that quantifies the extent to which a subject utilizes their working memory during a task. The working memory is regarded as the storage for conscious information, limited by one's capacity to hold and process information [20].

Cognitive load refers to the level of mental exertion being employed within working memory in a particular moment. It is often linked to the Cognitive Load Theory (CLT), which revolves around how cognitive resources are directed and utilized during the processes of learning and problem-solving [21]. The CLT highlights the concept that humans possess a restricted working memory capacity. In situations of high mental load, mental resources are allocated more towards processing information rather than addressing problem at hand.

## 2.2 Electrocardiography (ECG)

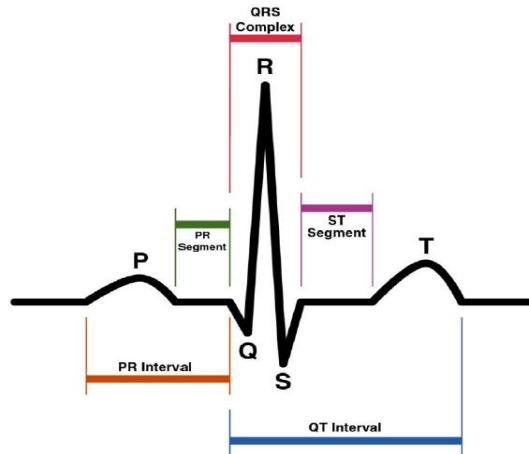
ECG signals are biological signals used to identify irregularities in heartbeats by analyzing the heart's bioelectrical and muscle activity [22]. An electrocardiogram recordings, usually abbreviated as "ECG" or "EKG", record the electrical potential present on the body's surface, which arises from the transmission of the electrical signal within the heart [23]. It captures the heart's electrical functions by positioning non-invasive electrodes (known as leads) on the individual's body, typically on the chest and limbs. These leads quantify the changes in voltage caused by the involuntary impulses of cardiac cells during the heart's contraction. Consequently, these fluctuations constitute the heartbeats, which are observed as a sequence of waves.

Figure 1 depicted an example of the components of ECG waveforms. ECG consists of five waves known as PQRST waves, which provide information regarding the heart's electrical activity. These waves have diagnostic value in identifying different heart conditions. The initiation of a heartbeat occurs when an electrical pulse originates from the sinoatrial (SA) node, located within the right atrium of the heart [22]. ECG serves as a valuable non-invasive instrument with diverse biomedical applications, including heart rate measurement, heart rhythm analysis, heart disorder diagnosis, emotion recognition, and biometric identification. In addition, ECG can effectively assess various conditions of driver, including stress, cognitive load, and drowsiness [24].

Heart rate refers to the number of heartbeats occurring within a minute. HRV represents the variations in the time intervals between successive heartbeats. HRV serves as an indicator of neurocardiac function and is generated by heart-brain interactions and dynamic non-linear autonomic nervous system (ANS) processes [25]. The heart rate variability (HRV) features were summarized in Table 1 [25], [26].

The standard HRV derived from ECG signals could be categorized in terms of time and frequency domains. The time-domain metrics of HRV assess the extent of variability in inter-beat interval (IBI) measurements, which represent the time intervals between consecutive heartbeats. Time domain measures including the mean inter-beat intervals (mean IBI), the standard deviation of IBIs (SDNN), and the root mean squared difference of adjacent IBIs (RMSSD). The mean IBI represents the time between successive heartbeats and is inversely

related to heart rate. These time domain measures tend to decrease as cognitive workload increases [3], [11]. In contrast, frequency domain measures estimate distribution of absolute or relative power into several frequency bands. As observed in previous studies [27], an elevation in cognitive load is typically associated with an increase in both the LF and LF/HF ratio, coupled with a decrease in HF.



**Fig. 1.** Illustration of an ECG signal [28]

**Table 1.** Summary of the HRV measures in time and frequency domains

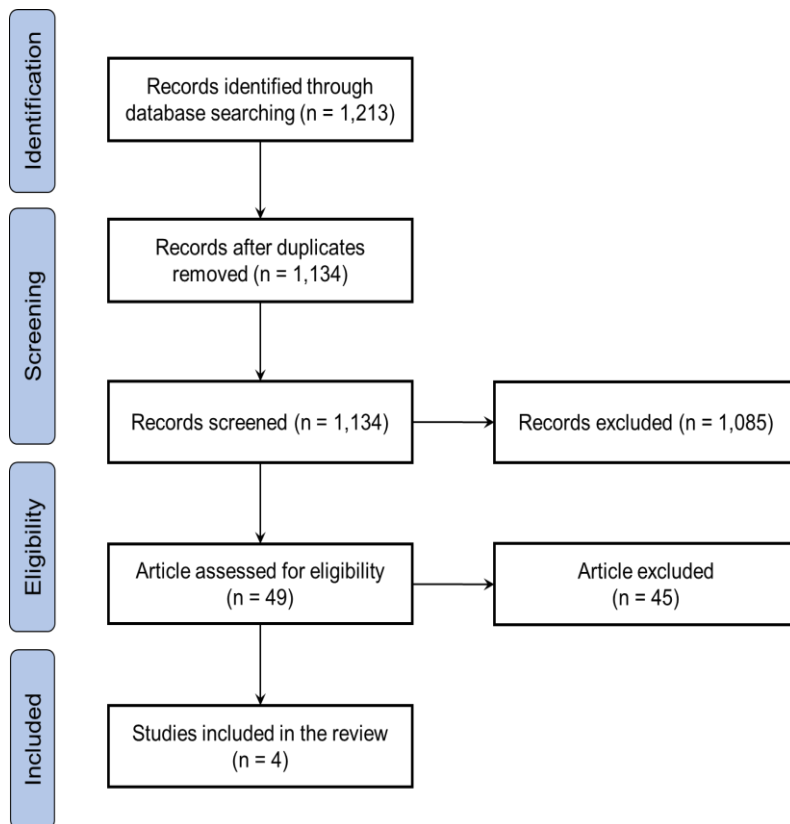
Domain	Measure	Unit	Description
Time	Mean IBI	ms	Mean of inter-beat interval (IBI) - the time period between successive heartbeats
	SDNN	ms	Standard deviation of normal-to-normal (NN) intervals
	RMSSD	ms	Root mean square of successive RR interval differences
	pNN50	%	Percentage of successive RR intervals that differ by more than 50 ms
Frequency	VLF	ms <sup>2</sup>	Absolute power of the very low frequency band (0.0033 - 0.04 Hz)
	LF	ms <sup>2</sup>	Absolute power of the low frequency band (0.04 - 0.15 Hz)
	LF norm	n.u.	Relative power of the low frequency band (0.04 - 0.15 Hz) in normalized units
	HF	ms <sup>2</sup>	Absolute power of the high-frequency band (0.15 - 0.4 Hz)
	HF norm	n.u.	Relative power of the high-frequency band (0.15 - 0.4 Hz) in normalized units
	LF/HF	-	Ratio between LF and HF

### 3 METHODS

In this review, we conducted searches across three databases considered highly relevant to our research topic: PubMed, Scopus, and Elsevier. These searches were carried out in July 2023, with the inclusion of studies published from the year 2019 onward. Our search terms “(heart rate variability OR heart rate OR electrocardiography OR hr OR hrv OR ecg) AND

(cognitive workload OR cognitive overload)”. We searched for these terms within the fields of title, abstract, and keywords. We then downloaded the metadata and abstracts of the articles from the search results, which were subsequently imported into the Rayyan software for the purpose of screening and selection.

This study specifically included original research journal articles written in English. Our focus was solely on exploring the relationship between ECG signals and driver cognitive load. Consequently, studies that combined ECG with other measurements were not considered for this review. Additionally, we excluded studies that did not involve car driving tasks (e.g., airplane, ship, or train driving). In total, we identified 1213 records across the three databases, and after eliminating duplicates, 1134 records remained. The journal articles in English were retained for initial screening. Following a review of the titles and abstracts, 1085 articles were excluded, leaving 49 articles for full-text assessment. Subsequently, after conducting a thorough examination of the full texts, 45 articles were excluded, resulting in 4 articles eligible for review as shown in Figure 2.



**Fig. 2.** Flow chart of articles review used in this study

## 4 RESULTS AND DISCUSSION

The summary of the review papers on cognitive load detection using ECG signal was summarized in the Table 2.

**Table 2.** Summary of research on the cognitive load using ECG

Paper	Features	Classification problem	Models	Performance
Yang et al. [29]	ECG measures	4 classes: baseline, N-back, texting, and N-back+texting distraction) in two repeated one-hour blocks	Random Forest (RF)	Accuracy: 76%
Tavakoli et al. [30]	ECG measures: RMSSD	2 classes: low and high cognitive load/stress (in various contextual settings of road, weather, and presence of a passenger)	Hierarchical modeling	RMSSD decreased as cognitive load increased
Huang et al. [10]	Spectrograms of ECG signal based on mean IBI	3 classes: low, medium, and high cognitive load	Convolutional Neural Network (CNN)	Accuracy: 92.8%
Amin et al. [31]	Scalogram images of ECG signal	3 classes: low, medium, and high cognitive load	GoogLeNet, DarkNet-53, ResNet-101, InceptionResNetV2, Xception, DenseNet-201, InceptionV3	Accuracy: 98.11%

A study conducted by Yang et al. [29] explored the robustness of detecting driver cognitive workload using ECG, while considering changes over time and individual variations in cognitive workload. They conducted a driving simulation experiment to categorize driver cognitive workload across four experimental scenarios (baseline, N-back task, texting, and N-back task with texting distraction). Heart rate and HRV were then assessed across the different experimental conditions and between the test blocks. To classify cognitive workload for various individuals and blocks, random forests were constructed based on HR and HRV data and achieved an accuracy of 76%.

Meanwhile, Tavakoli et al. [30] developed personalized hierarchical driver’s state models by considering the RMSSD measures in relation to the changes in various contextual factors like road conditions, weather, and the presence of a passenger, which could induce stress or a high cognitive load. Their experiment involved 12 participants and was conducted in real-world driving scenarios. They found that, on average, drivers experienced less stress on highways compared to city streets, when accompanied by a passenger compared to driving alone, and when driving in non-rainy conditions compared to rainy weather. Typically, the presence of a passenger, clear weather, and highway driving were associated with higher RMSSD. Conversely, lower RMSSD in rainy weather, solo driving, and city streets could suggest increased stress for drivers in these specific driving scenarios.

Huang et al. [10] proposed a novel classification method for a driver’s cognitive stress or high cognitive load level using convolution neural network (CNN) based on ECG pictures. The picture was generated from the inter-beat intervals extracted from ECG signal. The experiment was performed under driving simulation condition. In addition, an arithmetic task was utilized to induced driver’s cognitive stress while driving. They classified three driver’s cognitive load levels into low, medium, and high with reported accuracy of 92.8%. The findings presented in the paper demonstrate the viability of the approach, surpassing the

performance of methods relying on the artificial neural network (ANN) model, which have been frequently applied in recent studies.

Recently, Amin et al. [31] developed several deep transfer learning model (GoogLeNet, DarkNet-53, ResNet-101, InceptionResNetV2, Xception, DenseNet-201, and InceptionV3) to detect the three driver's cognitive load levels (low, medium, and high) from ECG based scalogram images. They achieved overall accuracy of 98.11%. The findings indicated that utilizing deep transfer learning techniques led to higher accuracy levels in driver stress models when compared to conventional machine learning and deep learning methods.

ECG signals considered as a valuable indicator for detecting a driver's cognitive load since it could reflect the ongoing driver's internal states of driver. However, more advancements are still necessary before ECG-based driver cognitive load detection could be effectively applied in real-world driving scenarios. The accuracies of ECG-based cognitive load detection systems varies from 76% to 98%. This variability can be attributed to individual differences and variations in measurement settings. It also found that ECG are usually gathered in relatively short driving experiment, typically less than one hour for cognitive load detection. The reliability of cognitive load detection might be decreased in prolonged driving if the algorithms used are trained solely with early-stage driving data [29]. This is due to temporal variations in the cognitive load. Cognitive load is also difficult to measure because of individual differences [3], [29]. Lastly, a notable trend in recent years has been the increasing adoption of deep learning models for the classification of a driver's cognitive load. Thus, future studies could explore the utilization of advanced transfer learning in deep learning to enhance the performance of ECG based detection.

## 5 CONCLUSION

The present study reviewed the recent existing literatures related to the detection of driver cognitive load based on ECG signals. ECG signals hold promise as a valuable tool for detecting a driver's cognitive load due to their convenience and non-intrusiveness. However, the issue in temporal variation and individual differences need to be considered in the development of the advanced driver assistance systems. Next, the performance of ECG based cognitive load detection systems show a wide range of accuracy (range: 76% ~ 98%). Lastly, there has been a growing trend in recent years towards the utilization of deep learning models for classifying a driver's cognitive load, particularly using images derived from ECG signals.

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