Automotive Experiences
Vol. 6 No. 1 (2023) pp. 149-161
p-ISSN: 2615-6202 e-ISSN: 2615-6636

Review Paper

Analyzing Cognitive Load Measurements of the Truck Drivers to Determine Transportation Routes and Improve Safety Driving: A Review Study

Adithya Sudiarno[1], Ahmad Murtaja Dzaky Ma'arij[1], Ishardita Pambudi Tama[2], Aisyah Larasati[3], Dewi Hardinigtyas[2]

[1]Department of Industrial and Systems Engineering, Sepuluh Nopember Institute of Technology, 60111, Indonesia
[2]Department of Industrial Engineering, Brawijaya University, 65145, Indonesia
[3]Department of Industrial Engineering, State University of Malang, 65145, Indonesia

adithya.sudiarno@gmail.com

https://doi.org/10.31603/ae.8301

Check for updates

Published by Automotive Laboratory of Universitas Muhammadiyah Magelang collaboration with Association of Indonesian Vocational Educators (AIVE)

Article Info
Submitted: 07/12/2022
Revised: 29/03/2023
Accepted: 30/03/2023
Online first: 17/04/2023

Abstract

As part of the Supply Chain (SC), oftentimes Land Logistic Driver (LLD) are held by various uncontrollable occurrences from the surroundings. This caused the cognitive load of the drivers to become higher, which could potentially affect the performance of the LLD to meet the Key Performance Indicator (KPI) of the SC overall. Not only the performance that is affected, but a higher load also could affect the driving behavior towards negativity, as anger and stress perceived become higher, hence a higher crash possibility. Therefore, the need to study the possibility to measure the cognitive load in a certain route that they are on, so any adjustments could be made during a transport activity, with Electroencephalogram (EEG) used as the means to measure it. This study is done by reviewing 15 available research as references regarding EEG and cognitive load. It is possible to use EEG in measuring cognitive load during driving activity, with the focus area of data gathering on the central lobe, parietal lobe, and temporal lobes, with the data extracted from EEG should use the most accurate classifier that focuses on analyzing beta (β) and alpha (α) band as the significant brain wave of the active state. The possible result of the brain wave analysis could be used to determine whether the current route option is burdening LLDs' cognitive load and should be corrected to improve safety driving. Further inclusion of the analysis result could be incorporated into a set of KPI in measuring SC performance.

Keywords: Electroencephalogram; Driving fatigue; Cognitive load; Safety driving; Transportation route

1. Introduction

The supply Chain (SC) holds a key place in ensuring the continuity of day-to-day activities in a manufacturing business. SC performance is often measured by the ability of the transportation or logistics provider to deliver products successfully within the allocated time frame. Any kind of failure to deliver products on time could cause a disruption in the SC performance overall [1]. Oftentimes, the disruptions could be found in the higher tiers, closer to the source of the supply chain network, such as manufacturers [2]. Further disruption could cause a ripple effect with reduced trust from the customers as one of the serious outcomes of the lack of SC performance [3]. Therefore, it is important to keep the SC performance at the optimum level. In doing so, it puts a high level of expectations on the transportation executor to deliver on time, especially Land Logistic Transport Drivers (LLD), with those having a lot of uncertainty and uncontrollable variables from the surroundings affecting their performance. The pressure put on the LLD, such as heavier traffic, tight delivery time, vehicle emergency, etc. causes the mental load to become higher, hence the higher cognitive load.

Tama *et al*. [4] depicted the relationship between the cognitive aspects of the driver with the delivery in SC activity throughout the system dynamics approach. The approach resulted in the importance of manageable cognitive load would lead to an optimum driving strategy, with mindful and careful driving, and high alertness of the LLDs could reduce the possibility of a vehicle crash to happen. The result of the optimum driving strategy would also mean better transportation safety, hence adding the possibility of a successful delivery higher. Another positive result is also a decrease in perceived stress and reduced anger during driving [5], which is caused by high pressure due to high cognitive load. Therefore, measuring cognitive load during driving activity would help manage cognitive load, increasing the chance of the delivery to success.

Measurement of the cognitive load could be implemented by capturing the brain wave, which is then processed with a processing application to interpret the result of the wavelength. Electroencephalogram (EEG) is used to help capture the brain wave, in which small sensors are used to detect brain activity. This method has been proven to be a reliable and accurate measure, yet non-invasive to the subjects. Oftentimes, an extensive set of EEG is used, with the sensors placed throughout the whole scalp of the head. But a recent study has found that it is possible to do the research using a simplified version of EEG, that has more limited nodes and fewer electrodes to detect, and still resulting in the reliable accuracy result [6]. In interpreting brain activity, several points of detection are placed, with researchers having put an effort to map the electrode map of the brain. Previous studies have shown the effectiveness of using EEG to capture brain activity, with various processing methods used showing positive results, such as finding feasibility in detecting drowsiness state in driving simulations. EEG was also used to define emotional states that could affect drivers in driving situations [7]. The use of EEG could also be found to monitor fatigue state in driving simulations [8]. EEG is also used in several ways, such as measuring human perception in assessing hazards throughout virtual reality [9].

The usage of EEG is important to measure the cognitive load of the brain activity, especially for LLD performing product delivery using the manual delivery method with trucks, as they have the most cognitive load compared with other transportation modes. Increasing cognitive load could affect the ability of the LLD to process information and decide a strategy to perform the delivery. Hopefully, the way to interpret brain activity could be the starting point to bridge the connection between SC activities and human factors affecting it. So that the human factor aspects, not only brain waves but also other aspects like Heart Rate (HR) could be incorporated into SC Key Performance Indicator (KPI) in an extensive manner as a way to ensure the safety of the SC activities.

This study is done from observation from relevant studies that have been done throughout the years. Findings from the studies outline the possibility to construct the basis of the non-invasive data-collecting activity using EEG for LLD. Data collecting construction considers the selection of the electrode chosen with the expectation to choose possible accurate relation with the brain area that manages the driving activities. It is expected that the use of EEG could help to manage cognitive load, ensuring better safety driving and bridging the connection between cognitive load and performance to achieve the target.

2. Methods

This study is done with the intention to discover the possibility of EEG usage in mapping cognitive load during the delivery process of LLD. Academic databases of Scopus and ScienceDirect are used to find relevant studies intended. A total of 1,733 records were found based on a search using the keywords of "Electroencephalogram" with the range of years published from 2016 to 2022. Further sortation only included released journals regarding the second keyword addition of "Cognitive", 1,378 records were eliminated, leaving 355 preselected studies. Further sortation eliminated 294 studies, due to the subjects were incompatible with the discipline of the study. 61 preselected studies were then narrowed down after abstract reading, with total of 11 studies selected for further analysis. Then four (4) studies were found to be suitable to be used as further reference in this review study, hence the inclusion as the important reference. **Figure 1** shows the process of filtering records of previous studies.

3. Results and Discussion

The selection process resulted in fifteen studies found to be relevant to the purpose of this study, which is to incorporate the possibility of EEG usage as a way to measure cognitive load during driving conditions. These studies are listed in **Table 1**, with the information regarding with the studies included.

It is found that from 15 studies regarding with the study of EEG usage have been done around the world, multiple studies were conducted in China and India indicating that more studies are conducted in densely populated countries, as both countries are ranked first and second in the most populated country [10]. Observably, more population in the country correlates with the more active individuals on the road, hence increasing the traffic level. The effect of the high traffic could lead to an increase in the cognitive level of driving. Hence the results of those studies are relevant to the direction of the possibility of EEG usage in mapping cognitive load. The complete distribution of the research based on its origin is shown in **Figure 2**.

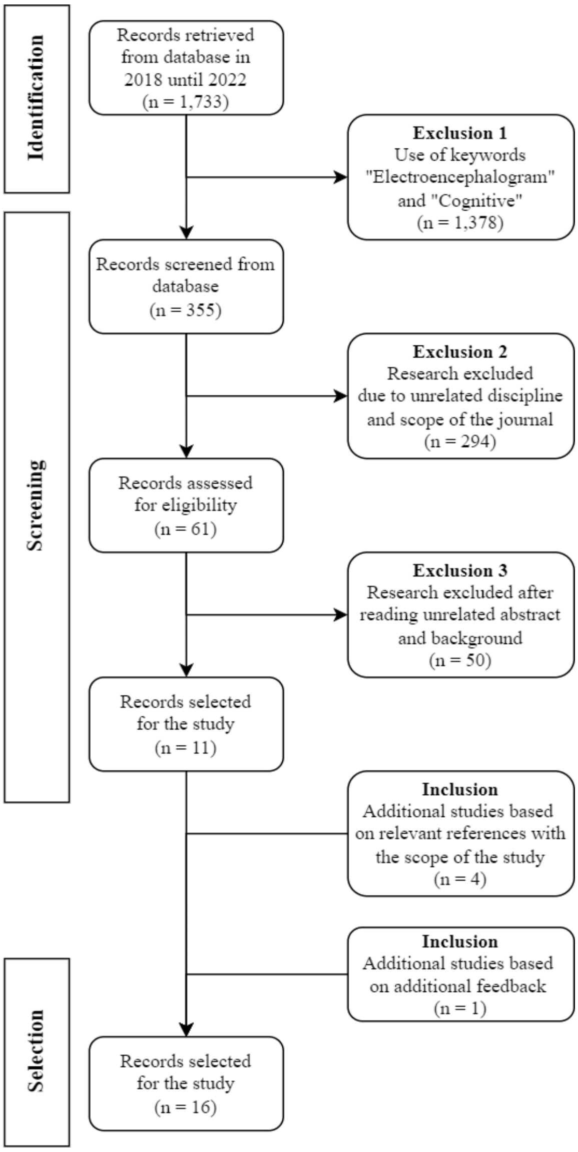

Figure 1. Selection process of related studies to use

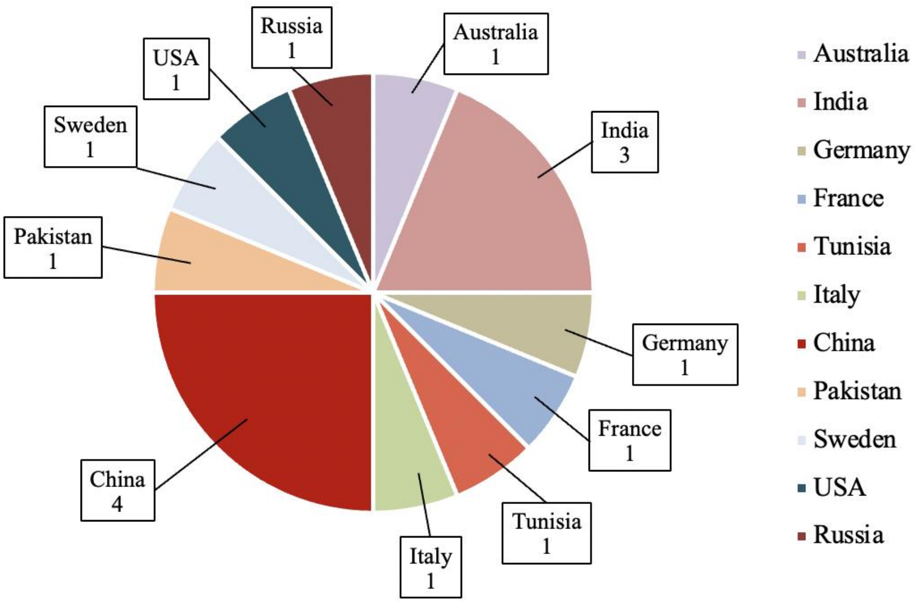

Figure 2. Distribution of the countries where the research originated

Table 1. List of selected articles

Num	Title	Refs.	Country	Journal	Type
1	Using EEG Spectral Components to Assess Algorithms for Detecting Fatigue	[11]	Australia	Expert Systems with Applications 36 (2009) p2352–2359	J
2	EEG Signal Analysis for The Assessment and Quantification of Driver's Fatigue	[12]	India	Transportation Research Part F 13 (2010) p297–306	J
3	EEG Alpha Spindle Measures as Indicators of Driver Fatigue Under Real Traffic Conditions	[13]	Germany	Clinical Neurophysiology 122 (2011) p1168–1178	J
4	EEG Index for Control Operators' Mental Fatigue Monitoring Using Interactions Between Brain Regions	[14]	France	Expert Systems with Applications 52 (2016) p91–98	J
5	Single-channel-based Automatic Drowsiness Detection Architecture with A Reduced Number of EEG Features	[15]	Tunisia	Microprocessors and Microsystems 58 (2018) p13–23	J
6	Towards Real-Time Monitoring of Fear in Driving Sessions	[16]	Italy	IFAC Papers OnLine 52-19 (2019) p299-304	P
7	Exploring the Fatigue Affecting Electroencephalography Based Functional Brain Networks During Real Driving in Young Males	[17]	China	Neuropsychologia 129 (2019) p200–211	J
8	On Identification of Driving-induced Stress Using Electroencephalogram Signals: A Framework based on Wearable Safety-critical Scheme and Machine Learning	[7]	Pakistan	Information Fusion 53 (2020) p66-79	J
9	Advanced Human-Robot Collaborative Assembly Using Electroencephalogram Signals of Human Brains	[18]	Sweden	Procedia CIRP 93 (2020) p1200-1205	P
10	Feature Extraction Method for Classification of Alertness and Drowsiness States EEG Signals	[19]	India	Applied Acoustics 163 (2020) 107224	J
11	Drowsiness Detection Using Portable Wireless EEG	[6]	India	Computer Methods and Programs in Biomedicine 214 (2022) 106535	J
12	Driver Fatigue Detection based on Prefrontal EEG Using Multi-entropy Measures and Hybrid Model	[8]	China	Biomedical Signal Processing and Control 69 (2021) 102857	J
13	Classification of Construction Hazard-related Perceptions Using Wearable Electroencephalogram and Virtual Reality	[9]	United States	Automation in Construction 132 (2021) 103975	J
14	Recognising Drivers' Mental Fatigue Based on EEG Multi-Dimensional Feature Selection and Fusion	[20]	China	Biomedical Signal Processing and Control 79 (2023) 104237	J
15	An Exploratory Study of Drivers' EEG Response During Emergent Collision Avoidance	[21]	China	Journals of Safety Research 82 (2022) 241–250	J
16	Influence of Long-term Cognitive Load on EEG Parameters	[22]	Russia	National Psychological Journal 13 (2014) 86-94	J

J: Journal; P: Proceeding

Some relevant studies were found to be conducted using similar topic. **Table 2** categorized and highlight the key point that could be used in the discussion of the possibility of EEG usage as the way to measure cognitive load during driving condition. Hence the classification in **Table 2** consists of focus detection type, simulation type conducted, and area of brain lobe observed selected in the study.

Focus detection of the study targets to differentiate the use of EEG in detecting any certain conditions that would like to reach. This category then divided into two categories: fatigue and others. 10 out of 15 studies used EEG to detect fatigue or situations indicating early signs of fatigue, such as drowsiness. 5 out of 15 studies used to detect condition other than fatigue, such as stress, fear, and perceived human response regarding to certain activities.

Following category is the simulation type, to differentiate the simulation or activity chosen to reach certain condition. This category is divided into two categories: driving simulation and others. 9 out of 15 studies used driving simulation for the EEG to capture brain activity as the selected main activity. 6 other studies used non-related with driving activity, such as controlling machine and construction activity.

Area of brain lobe category in **Table 2** is used to show the extend of the use of EEG. The distribution of brain lobe area uses five area division: frontal lobe, central lobe, parietal lobe, temporal lobe, and occipital lobe. Note that central lobe only exists to mediate between latter portion of frontal lobe and early portion of parietal lobe, as both lobes take a quite large area of the brain. It is known that different areas of the brain hold the activity of specific tasks.

The location of the electrode in the brain follows the 10-20 rule shown in **Figure 3**. The rule uses the first letter as the code of the brain area, with F denotes frontal lobe, C denotes central lobe, P denotes parietal lobe, T denotes temporal lobe, O denotes occipital lobe, and M denotes mastoid area or area behind the ears [23]. Followed by the number that shows the point, with odd numbers indicate left part of the brain, even numbers indicate right part of the brain, and z indicates the location of the electrode is in the center line of the brain [24].

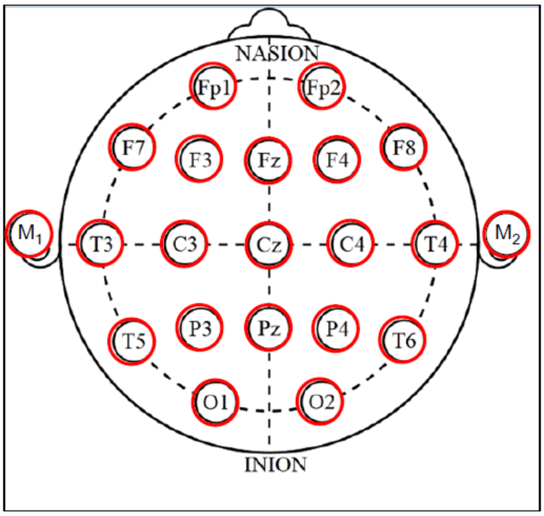

Figure 3. The International 10-20 System of Electrode Placement. Nasion marks as indentation between forehead and the nose, while Inion marks as a ridge in the back of the head. The left area marked with odd numbers, and right area marked with even numbers.

According to **Table 2**, selection of the focus detection and simulation type results in the selected parameters. These parameters should be aligned with the purpose of the study. The definition and the importance of the parameter are listed in **Table 3**. The outcome results in three main topics to construct this review study, namely fatigue, driving simulation, and brain lobe.

Fatigue has the importance as the condition that would likely be detected. A person is considered in fatigue condition if he/she shows signs of inability to perform driving actions [25] that could lead to the unwanted or unanticipated occurrences, such as decision-making error, unresponsive driving, or worse, leading the vehicle into crashing with others or objects on the road [26]. The purpose is to construct the possibility to use EEG to detect the earliest sign of fatigue, hence the relevant studies that used EEG to detect drowsiness are considered important, as drowsiness is one of the signs of fatigue [27]. Results from several studies confirm that it is possible to detect fatigue conditions that showed through the captured brain wave.

Jap et al. observed that there was a reduction in the beta (β) band as the time progresses, indicating that beta band represents the alertness level of the brain the most out of other three frequency bands, and drop in the brain activity means that the person started to regress its alertness [11]. The same result also found in the

Table 2. Reference breakdown based on parameters important to the study

Num	Refs	Title	Focus Detection		Simulation Type		Area of Brain Lobe Observed	Highlights of the Study
			Fatigue	Other	Driving	Other		
1	[11]	Using EEG Spectral Components to Assess Algorithms for Detecting Fatigue	✓		✓		Frontal, Central, Parietal, Occipital, Temporal	Differences in alertness over time detected in the entire brain, as implications for development of fatigue counter measures from algorithm that has been tested.
2	[12]	EEG Signal Analysis for The Assessment and Quantification of Driver's Fatigue	✓		✓		Frontal, Temporal, Parietal	A parameter based on higher entropy measures of EEG signals could be used for future tools to quantify the level of fatigue in human operator in safety critical human-machine interactions.
3	[13]	EEG Alpha Spindle Measures as Indicators of Driver Fatigue Under Real Traffic Conditions	✓		✓		Frontal, Central, Occipital, Parietal	Alpha spindle rate increased by the effect of 20 minutes driving. It is confirmed that alpha power is more suitable for measuring real-traffic experiment.
4	[14]	EEG Index for Control Operators' Mental Fatigue Monitoring Using Interactions Between Brain Regions	✓			✓	Frontal, Occipital, Parietal	EEG Index is in high correlation with fatigue evaluation of Karolinska Sleepiness Scale in measuring external sign of mental fatigue
5	[15]	Single-channel-based Automatic Drowsiness Detection Architecture with A Reduced Number of EEG Features	✓			✓	Occipital, Central	It is possible to use 2 points of electrode to help detect drowsiness as signs that led to fatigue condition with high accuracy.
6	[16]	Towards Real-Time Monitoring of Fear in Driving Sessions		✓	✓		Frontal, Central, Occipital	There is high correlation between alpha waves from EEG with time of reactive action in driving simulations.
7	[17]	Exploring the Fatigue Affecting Electroencephalography Based Functional Brain Networks During Real Driving in Young Males	✓		✓		Frontal, Central, Parietal, Occipital, Temporal	Using machine learning algorithm Support Vector Machine (SVM), it is possible to distinguish alert and fatigue states in driving conditions.
8	[7]	On Identification of Driving-induced Stress Using Electroencephalogram Signals: A Framework based on Wearable Safety-critical Scheme and Machine Learning		✓	✓		Frontal, Central, Parietal, Occipital, Temporal	SVM performs better to distinguish between rest and stress state than other two classifiers machine learning method.

Table 2 (cont). Reference breakdown based on parameters important to the study

Num	Refs	Title	Focus Detection		Simulation Type		Area of Brain Lobe Observed	Highlights of the Study
			Fatigue	Other	Driving	Other		
9	[18]	Advanced Human-Robot Collaborative Assembly Using Electroencephalogram Signals of Human Brains		✓		✓	Frontal, Central, Parietal, Occipital, Temporal	EEG signals are obtained from human activity in giving robot commands. Then signals are translated into framework, opening possibility to establish fully automated environment.
10	[19]	Feature Extraction Method for Classification of Alertness and Drowsiness States EEG Signals	✓			✓	N/A	Selection of suitable feature extraction of EEG classifiers is important to develop alertness or drowsiness detection.
11	[6]	Drowsiness Detection Using Portable Wireless EEG	✓			✓	Frontal, Temporal	Using consumer grade wireless EEG, it is possible to extract from limited selection of electrodes. Also, temporal lobe shows better significance than frontal lobe in indicating drowsiness.
12	[8]	Driver Fatigue Detection based on Prefrontal EEG Using Multi-entropy Measures and Hybrid Model	✓		✓		Frontal, Central, Parietal, Occipital, Temporal	Additional of prefrontal channel is effective to detect fatigue in driving condition with multi-entropy computation in extracting brain wave from prefrontal channel.
13	[9]	Classification of Construction Hazard-related Perceptions Using Wearable Electroencephalogram and Virtual Reality		✓		✓	Frontal	Selected EEG signals could be used to categorize signals regarding with perceived hazard with suitable classifiers.
14	[20]	Recognising Drivers' Mental Fatigue Based on EEG Multi-Dimensional Feature Selection and Fusion	✓		✓		Central, Parietal, Occipital, Temporal	Gaussian SVM shows highest accuracy (79.33%) in recognizing fatigue based on feature selection method using logistic-ARFE.
15	[21]	An Exploratory Study of Drivers' EEG Response During Emergent Collision Avoidance		✓	✓		Frontal, Central, Parietal, Occipital, Temporal	Analysis on four EEG bands resulting in consistent increasing band when drivers take action in driving condition.
16	[22]	Influence of Long-term Cognitive Load on EEG Parameters	✓			✓	Frontal, Central, Parietal, Occipital, Temporal	Long-term activity duration caused high cognitive load, resulting in decreasing power in alpha (α) and beta (β) rhythm, fatigue could be detected clearer with the eyes closed

Table 3. Focus topics determination of the study

Topic	Definition	Importance of topic	Related references
Fatigue	Inability for a person to perform task due to constant tiredness or weakness (physical, mental, or both).	Fatigue detection using EEG to identify drivers' cognitive load during delivery.	Jap et al. [11], Kar et al. [12], Charbonnier et al. [14], Belakhdar et al. [15], Chen et al. [17], Min et al. [8], Zhang et al. [20]
Driving Simulation	System to emulate the real-world condition of controlling the chosen vehicle in a certain or uncontrolled scenario.	Proper driving environment could estimate brain activity during delivery activity.	Zero et al. [16], Halim and Rehan [7], Li et al. [21]
Brain Lobe	Division of cerebrum into four sections with each has its own role in brain activity.	Selection of appropriate brain lobe responsible for driving activity.	Polikanova et al. [22], Chen et al. [17], Mohammed and Wang [18], Min et al. [8]

research conducted by Kar et al. who stated that the energy from alpha (α) and beta (β) bands reduces as the fatigue level increases [12]. This finding was also echoed by Borghini et al [28] and Chen et al [17], where there was a reduction in brain power spectrum of beta (β) band over testing time. Even if it is not possible to filter the beta (β) band, filtering the alpha (α) band would resulting in distinguishing alertness and drowsiness state satisfactorily [14]. Another measurement alternative from alpha (α) spindle could be used as important parameter, as it resulted in higher specificity and sensitivity than alpha (α) band power [13]. In addition to related finding mentioned above, Polikanova et al [22] suggested that the differentiation between alert and fatigue could be distinguished further after the eyes were closed, suggesting that fatigue state would be more detectable if the LLD get into or anywhere near microsleep phase.

Another key factor is also to develop a driving scenario that could emulate the situation as close as possible to the real driving conditions, especially in SC delivery using truck. Simulation could be used to help gather the data if the data collection in real-time driving condition could not be done yet. Multiple studies mentioned the use of simulator [16] that could define different traffic dynamics (vehicle surroundings, weather, traffic level). The use of active traffic scenario was also used in [7] to depict actual reaction of the drivers as closely related as possible. But not only the traffic situation that should be closely resemblant with the real condition, but also the driving time, as it is considered as important part in scenario design, as exemplified in [16], [21]. Therefore, the scenario of the delivery by truck could use the setting of the driving time around 40 – 75 minutes with vary traffic conditions based on the situations of relatively high level of traffic with usually low maximum speed, as the truck is usually used to distribute products in short to medium range (less than 50 km radius) in one go.

The use of EEG also takes account the area of the brain that would be observed, as different brain lobe responsible for different activity for the body. Driving is an activity that needed active collaboration between lobes of the brain, such as motoric movements, decision making, emotional aspect, vision range, and body senses to detect things around driver. Findings from [6] proved that temporal lobe gave better correlation regarding with drowsiness, as opposed with frontal lobe. Results from the studies that monitored the change of power spectrum of the brain [14], [17] showed that in alert state, the central lobe shows high changes in band power between before and after activity. It means that central lobe that handles motoric movement are affected significantly during driving activity. Interaction between brain regions mentioned in [14] also implied that interaction between lobes have impact in human-machine interactions, a finding that was also similarly echoed by Mohammed and Wang [18]. Hence it is important to measure the brain wave from multiple lobes of the brain.

Next important thing is the ability to extract the feature from the pre-processed raw EEG data. As the data collected from EEG is derived into four wavebands, then selecting the suitable method to help distinguishing the condition between alert and fatigue quickly and accurately. The feature extraction would help highlight the pre-processed data to help clarify the following step of classifying. The use of classifier is to identify which state the captured brain wave is in, for instance whether it is in alert state or fatigue state. Multiple algorithms and classifiers could be used individually or collectively, that would result in emotion recognition and differentiation [29]. Result in several studies [7], [17], [19], [20] mentioned the use of Support Vector Machine (SVM) as the selected classifier that resulted in over 80% of accuracy in distinguishing alert and fatigue state. Based on findings from [20], it is possible to use other classifier method other than SVM, and the use of SVM is not exclusive as the only classifier to be used.

It is possible to measure and map the cognitive load of the driver during delivery activity using EEG in a single, closed environment of driving simulation with the specific setup of driving scenario according to the Indonesian traffic. **Figure 4a** illustrated our attempt to visualize what the setup of the data collection was done with the use of EEG in normal driving condition in typical traffic situation in Indonesia, and **Figure 4b** presented the observed brain activity during trial attempt.

Although the pre-processing data of raw EEG data separates into delta (δ), theta (θ), alpha (α), and beta (β) bands, further processing should be focused on alpha and beta bands, with the use of machine learning algorithm to classify between the state of alert and fatigue, with SVM used as one of the classifier found to be effective in several studies [17], [30].

The result of the classified brain wave then could be used furthermore as the consideration of the current route for the LLD. With the intention to make the brain wave of the beta (β) band should not go lower than certain point. For example, the current route would be deemed "dangerous" as it causes drowsiness towards LLD, otherwise the route would be considered "safe". The drowsiness could be caused by multiple factors, mainly due to heavy traffic, especially at certain hours. The way of monitoring the current route on a real-time basis could be done using an open-access map (e.g., OpenStreetMap) to be incorporated into the development of the system. For example, **Figure 5** showed an example of the area of East Java passed by the truck in the delivery activity. Then some areas that could cause high cognitive load (stress, fatigue, etc.) would be marked with red color and should be avoided. From the result, an alternative suggestion of route, such as taking a tollway, should be available that could reduce the cognitive load of the LLD.

This preliminary study shows the possibility to incorporate the human factor aspect into the SC KPI, as usually it does not be considered as the monitored performance. The cognitive load of the LLD could be monitored, as it should not go beyond the point of fatigue indication, that would indicate the work of the LLD is not highly burdensome.

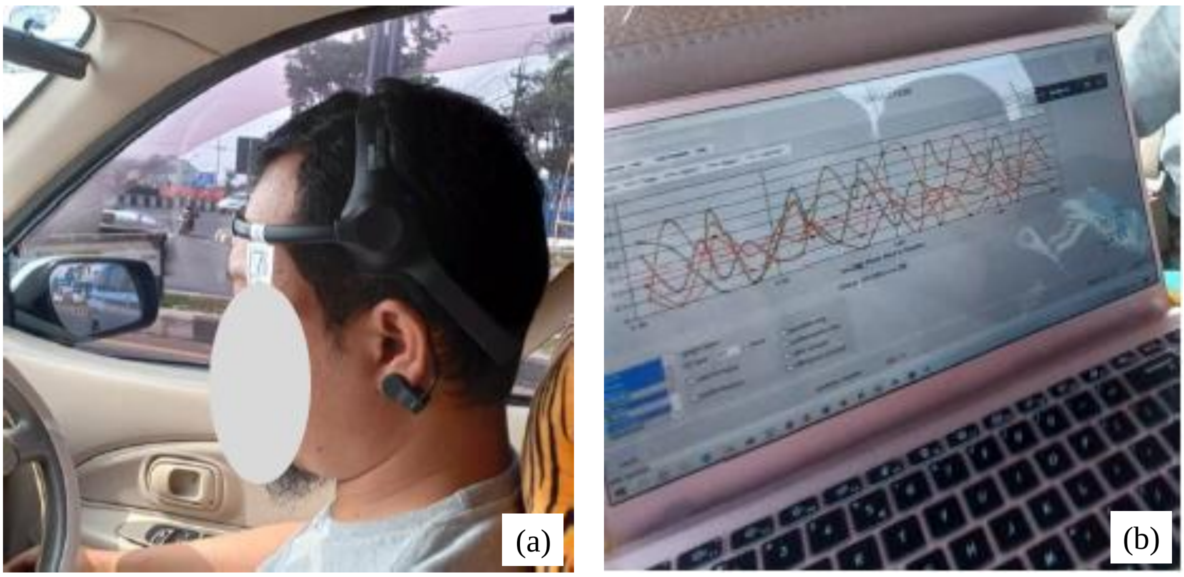

Figure 4. (a) Visualization of the use of EEG in driving condition and (b) Collected EEG data during driving attempt trial

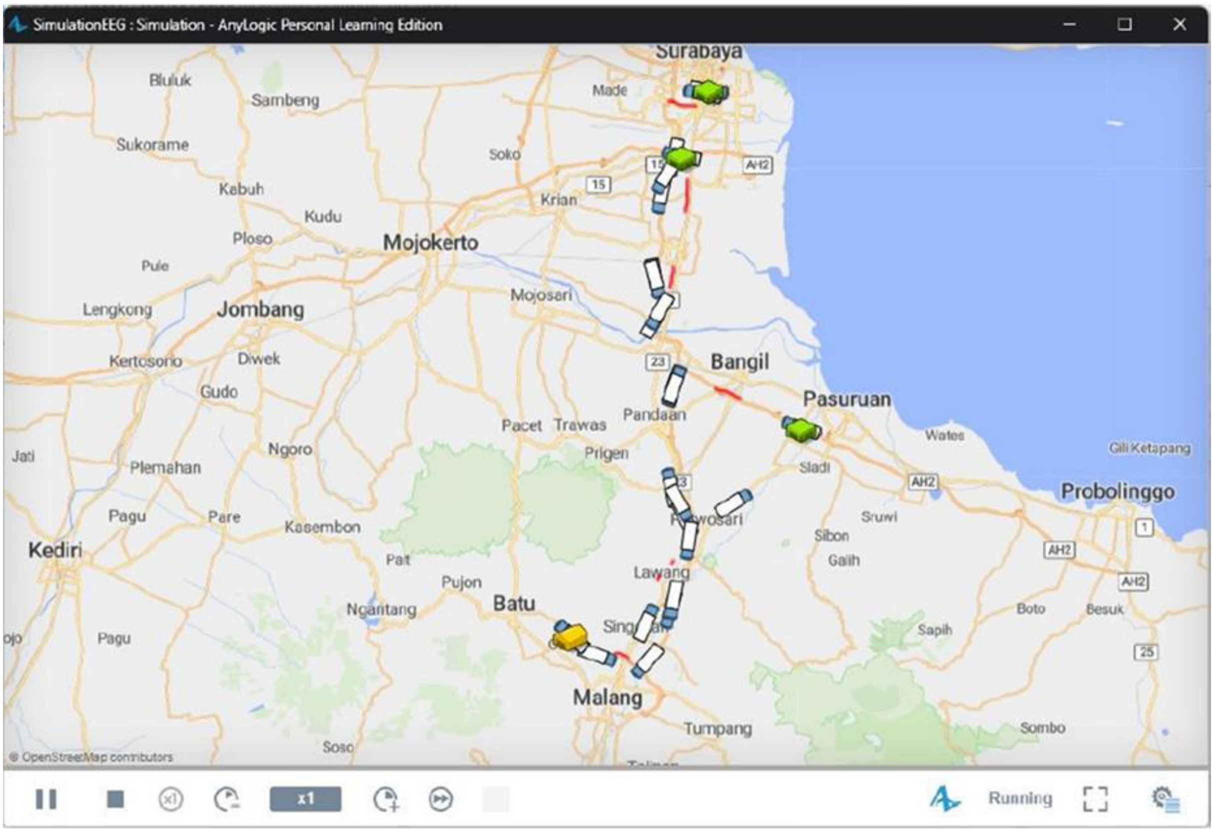

Figure 5. The proposed idea of open geographic database usage was added with a red mark as the suggestion that the path could cause a high cognitive load

The monitoring could be achieved in several ways. For instance, the average wave of the beta (β) band should not be below a certain value as the direct workload measurement. Another way to utilize the classification of alert and fatigue state into KPI is by calculating the percentage of time a driver is in a route with "safe" condition, with the target of higher percentage of being in "safe" route option could be arranged in objective strategy as "higher better" and more desirable. The indirect effect of route monitoring is to decrease driving difficulties, hence resulting in low level of stress that would result in lower risky behaviors [5]. Also, low mental pressure in the route option in the delivery means that the anger level could also be pressed down to a manageable level, resulting in lower accident rates [30], with the hope that the transportation activity could be done in a safe and unburdening way.

4. Conclusion

This study aims to construct the possibility of using EEG to measure cognitive load as a way to incorporate human factors into KPI as a tool to measure SC performance to ensure the safety and continuity of SC. 16 studies are reviewed and summarized into three main topics related to the study which are fatigue, driving, and the brain lobe region observed. 11 out of 16 studies were related to fatigue and 9 out of 16 studies were related to driving. Fatigue state could be detected from the reduction of power spectrum in alpha (α) and beta (β) bands over time, with decrease in power would indicate early signs or that drivers are in fatigue condition. Meanwhile, the use of simulation in setting the driving condition as close to real-time situation is just as important as the initial step in detecting fatigue, from the dataset of brain activity captured using EEG as the method to measure cognitive load. Findings from several studies indicated that it is possible to establish the concept of using EEG in driving conditions to obtain brain wavebands that would be processed to be able to distinguish between alert and fatigue states in driving activity.

Furthermore, steps of preprocessing, feature extraction, and classifier are needed to be able to read the result of the EEG conveniently. Altogether, the concept of this idea could be applied to the development of the tools to measure the impact of the route selection towards cognitive load based on the route they are on using EEG. The extracted and classified brain rhythm then could be associated with the routing in the map. This would help determine whether the current route is adding pressure for the drivers, as the measurement of the current route is determined either "safe" or "dangerous", hence prompting whether any changes of the route are deemed necessary in the route if it is considered as threatening or dangerous. This idea could be implemented as the inclusion of safety driving into SC KPI, an aspect that sometimes goes unmonitored. It could be incorporated through several aspects, such as average number of beta (β) waves or percentage of time in "safe" route. The authors hope that this research concept could be implemented as a way to associate psychological aspects with physical performance, along with the improvement ideas included in the future.

Acknowledgements

The authors would like to thank the Department of Industrial and Systems Engineering of Sepuluh Nopember Institute of Technology for providing study facilities.

Author's Declaration

Authors' contributions and responsibilities

Adithya Sudiarno made substantial contributions to the selection of study materials, manuscript writing and conception, and approved the final manuscript. Ahmad Murtaja Dzaky Ma'arij took responsibility for the initial manuscript writing, reviewing study materials, and final editing. Ishardita Pambudi Tama took responsibility for design of the study and providing additional supporting data. Aisyah Larasati contributed in additional refinement of the study. Dewi Hardiningtyas made substantial contributions to the early development idea of the collaborative study.

Funding

This study was conducted with funding from the Skema A of Riset Kolaborasi Indonesia (RKI), among Sepuluh Nopember Institute of Technology-Brawijaya University- State University of Malang, with official letter of 598/IT2/T/HK.00.01/2022, master contract letter number 1399/PKS/ITS/2022, and derivative contract letter number 1348/PKS/ITS/2022.

Availability of data and materials

All data are available from the authors.

Competing interests

The authors declare no competing interest.

Additional information

This study is in accordance with the attempt to reach Sustainable Development Goals (SDGs) number 8 (decent work and economic growth), specifically in quality of jobs and productivity aspect, and SDG number 9 (industry, innovation, and infrastructure), specifically in quality of life, roads, and transportation aspect.

References

[1] K. Katsaliaki, P. Galetsi, and S. Kumar, "Supply chain disruptions and resilience: A major review and future research agenda," *Ann. Oper. Res.*, vol. 319, pp. 965–1002, 2022, doi: 10.1007/s10479-020-03912-1.

[2] M. C. Wilson, "The impact of transportation disruptions on supply chain performance," *Transp. Res. Part E Logist. Transp. Rev.*, vol. 43, no. 4, pp. 295–320, 2007, doi: 10.1016/j.tre.2005.09.008.

[3] D. Ivanov, A. Dolgui, B. Sokolov, and M. Ivanova, "Literature review on disruption recovery in the supply chain," *Int. J. Prod. Res.*, vol. 55, no. 20, pp. 6158–6174, 2017, doi: 10.1080/00207543.2017.1330572.

[4] I. P. Tama, A. Sudiarno, A. Larasati, D. Hardiningtyas, and W. S. Nugroho, "The Analysis of Land Logistic Transport Driver Cognitive Load Impact to Supply Chain Performance using System Dynamics Approach," in *2nd International Conference on Engineering and Management in Industrial System*, 2022.

[5] P. Delhomme and A. Gheorghiu, "Perceived stress, mental health, organizational factors, and self-reported risky driving behaviors among truck drivers circulating in France," *J. Safety Res.*, vol. 79, pp. 341–351, 2021, doi: 10.1016/j.jsr.2021.10.001.

[6] S. Gangadharan and A. P. Vinod, "Drowsiness detection using portable wireless EEG," *Comput. Methods Programs Biomed.*, vol. 214, p. 106535, 2022, doi: 10.1016/j.cmpb.2021.106535.

[7] Z. Halim and M. Rehan, "On identification of driving-induced stress using electroencephalogram signals: A framework based on wearable safety-critical scheme and machine learning," *Inf. Fusion*, vol. 53, pp. 66–79, 2020, doi: 10.1016/j.inffus.2019.06.006.

[8] J. Min, C. Xiong, Y. Zhang, and M. Cai, "Driver fatigue detection based on prefrontal

EEG using multi-entropy measures and hybrid model," *Biomed. Signal Process. Control*, vol. 69, p. 102857, 2021, doi: 10.1016/j.bspc.2021.102857.

[9] J. Jeon and H. Cai, "Classification of construction hazard-related perceptions using: Wearable electroencephalogram and virtual reality," *Autom. Constr.*, vol. 132, p. 103975, 2021, doi: 10.1016/j.autcon.2021.103975.

[10] Worldometer, "Countries in the world by population (2022)," *United Nations, Department of Economic and Social Affairs*, 2022. https://www.worldometers.info/world-population/population-by-country/ (accessed Oct. 31, 2022).

[11] B. T. Jap, S. Lal, P. Fischer, and E. Bekiaris, "Using EEG spectral components to assess algorithms for detecting fatigue," *Expert Syst. Appl.*, vol. 36, no. 2, pp. 2352–2359, 2009, doi: 10.1016/j.eswa.2007.12.043.

[12] S. Kar, M. Bhagat, and A. Routray, "EEG signal analysis for the assessment and quantification of driver's fatigue," *Transp. Res. part F traffic Psychol. Behav.*, vol. 13, no. 5, pp. 297–306, 2010, doi: 10.1016/j.trf.2010.06.006.

[13] M. Simon *et al.*, "EEG alpha spindle measures as indicators of driver fatigue under real traffic conditions," *Clin. Neurophysiol.*, vol. 122, no. 6, pp. 1168–1178, 2011, doi: 10.1016/j.clinph.2010.10.044.

[14] S. Charbonnier, R. N. Roy, S. Bonnet, and A. Campagne, "EEG index for control operators' mental fatigue monitoring using interactions between brain regions," *Expert Syst. Appl.*, vol. 52, pp. 91–98, 2016, doi: 10.1016/j.eswa.2016.01.013.

[15] I. Belakhdar, W. Kaaniche, R. Djemal, and B. Ouni, "Single-channel-based automatic drowsiness detection architecture with a reduced number of EEG features," *Microprocess. Microsyst.*, vol. 58, pp. 13–23, 2018, doi: 10.1016/j.micpro.2018.02.004.

[16] E. Zero, C. Bersani, L. Zero, and R. Sacile, "Towards real-time monitoring of fear in driving sessions," *IFAC-PapersOnLine*, vol. 52, no. 19, pp. 299–304, 2019, doi: 10.1016/j.ifacol.2019.12.068.

[17] J. Chen, H. Wang, Q. Wang, and C. Hua, "Exploring the fatigue affecting electroencephalography based functional brain networks during real driving in young males," *Neuropsychologia*, vol. 129, pp. 200–211, 2019, doi: 10.1016/j.neuropsychologia.2019.04.004.

[18] A. Mohammed and L. Wang, "Advanced human-robot collaborative assembly using electroencephalogram signals of human brains," *Procedia CIRP*, vol. 93, pp. 1200–1205, 2020, doi: 10.1016/j.procir.2020.03.074.

[19] V. Bajaj, S. Taran, S. K. Khare, and A. Sengur, "Feature extraction method for classification of alertness and drowsiness states EEG signals," *Appl. Acoust.*, vol. 163, p. 107224, 2020, doi: 10.1016/j.apacoust.2020.107224.

[20] Y. Zhang, H. Guo, Y. Zhou, C. Xu, and Y. Liao, "Recognising drivers' mental fatigue based on EEG multi-dimensional feature selection and fusion," *Biomed. Signal Process. Control*, vol. 79, p. 104237, 2023, doi: 10.1016/j.bspc.2022.104237.

[21] X. Li, L. Yang, and X. Yan, "An exploratory study of drivers' EEG response during emergent collision avoidance," *J. Safety Res.*, vol. 82, pp. 241–250, 2022, doi: 10.1016/j.jsr.2022.05.015.

[22] I. S. Polikanova and A. V. Sergeev., "The effect of long-term cognitive load on the EEG parameters," *Natl. Psychol. J.*, no. 13, pp. 86–94, 2014, doi: 10.11621/npj.2014.0109.

[23] A. Morley, L. H. Hill, and A. G. Kaditis, "10-20 system EEG Placement," *ERS Education*, 2016. https://www.ers-education.org/lrmedia/2016/pdf/298830.pdf (accessed Oct. 27, 2022).

[24] R. Oostenveld and P. Praamstra, "The five percent electrode system for high-resolution EEG and ERP measurements," *Clin. Neurophysiol.*, vol. 112, no. 4, pp. 713–719, 2001, doi: 10.1016/S1388-2457(00)00527-7.

[25] Y. Zheng, Y. Ma, J. Cammon, S. Zhang, J. Zhang, and Y. Zhang, "A new feature selection approach for driving fatigue EEG detection with a modified machine learning algorithm," *Comput. Biol. Med.*, vol. 147, p. 105718, 2022, doi: 10.1016/j.compbiomed.2022.105718.

[26] B. C. Banz, D. Hersey, and F. E. Vaca, "Coupling neuroscience and driving simulation: A systematic review of studies on crash-risk behaviors in young drivers," *Traffic Inj. Prev.*, vol. 22, no. 1, pp. 90–95, 2021, doi: 10.1080/15389588.2020.1847283.

[27] W. Vanlaar, H. Simpson, D. Mayhew, and R. Robertson, "Fatigued and drowsy driving: A survey of attitudes, opinions and behaviors," *J. Safety Res.*, vol. 39, no. 3, pp. 303–309, 2008, doi: 10.1016/j.jsr.2007.12.007.

[28] G. Borghini, L. Astolfi, G. Vecchiato, D. Mattia, and F. Babiloni, "Measuring neurophysiological signals in aircraft pilots and car drivers for the assessment of mental workload, fatigue and drowsiness," *Neurosci. Biobehav. Rev.*, vol. 44, pp. 58–75, 2014, doi: 10.1016/j.neubiorev.2012.10.003.

[29] H. Liu, Y. Zhang, Y. Li, and X. Kong, "Review on emotion recognition based on electroencephalography," *Front. Comput. Neurosci.*, vol. 15, p. 84, 2021, doi: 10.3389/fncom.2021.758212.

[30] Z. Li, S. S. Man, A. H. S. Chan, and R. Wang, "Driving anger scale validation: relationship of driving anger with the aberrant driving behaviour of truck drivers," *Transp. Res. part F traffic Psychol. Behav.*, vol. 81, pp. 364–372, 2021, doi: 10.1016/j.trf.2021.06.018.