Penerbit Akademia Baru

Malaysian Journal on Composites Science and Manufacturing

Journal homepage:
https://www.akademiabaru.com/submit/index.php/mjcsm/
ISSN: 2716-6945

The Role of Brain Wave Activity by Electroencephalogram (EEG) in Assessing Cognitive Skills as an Indicator for Driving Fatigue: A Review

Open Access

Muhammad Shafiq Ibrahim[1], Seri Rahayu Kamat[1,*], Syamimi Shamsuddin[1]

[1] Fakulti Kejuruteraan Pembuatan, Universiti Teknikal Malaysia, 76100 Durian Tunggal, Melaka, Malaysia

ARTICLE INFO

Article history:
Received 19 June 2023
Received in revised form 12 July 2023
Accepted 17 July 2023
Available online 31 July 2023

Keywords:
Driving fatigue, Brain wave activity, Electroencephalogram, Cognitive skill

ABSTRACT

A number of studies have employed EEG to investigate the relationship between brain wave activity and fatigue. However, research on the relationship between brain wave activity and cognitive skills in detecting driving fatigue is scarce. This study thoroughly summarizes previous studies on electroencephalogram (EEG)-based brain wave activity and how to link it to cognitive skills as an indicator of driving fatigue. A thorough systematic literature review (SLR) was used to identify strong and high-potential material linked to the research topic. When a person went from alert to fatigue, alpha and theta waves increased while beta waves decreased. Alpha, theta and beta have previously been linked to attention, working memory capacity and decision making. As a result, if alpha and theta waves increase but beta waves drop, a person may become fatigued, indicating significant cognitive impairment in that individual. The misunderstanding about how brain activity changes when a person fatigues among the studies could be attributed to the use of a small number of participants and the number of electrodes used to assess EEG change. The study's findings will assist researchers, policymakers, and practitioners in developing a system that will greatly reduce fatigue-related traffic accidents, thereby improving road safety.

1. Introduction

Driver distraction and inattention due to fatigue have been identified as the leading causes of traffic accidents. Fatigue is a state of excessive physical and mental exhaustion. Driving fatigue impairs concentration, response time, recollection, hand-eye coordination and attentiveness, resulting in poor driving performance. Driving fatigue is thought to be a factor in 15-30% of all crashes in the United Kingdom [1], as well as 12% of the 318 fatalities and 6% of the 2,175 serious injuries in New Zealand in 2020 [2] and 80.6% of the 521,466 traffic collisions in Malaysia in 2016 [3]. As a result,

* *Corresponding author.*
E-mail address: seri@utem.edu.my (Seri Rahayu Kamat)

https://doi.org/10.37934/mjcsm.11.1.1931

a dependable system capable of detecting driver fatigue under varying driving demands and situations is urgently required.

Three techniques have been developed for fatigue detection [4]. The first technique employs vehicle-based parameters such as vehicle speed detection, steering wheel grip detection and steering wheel angle detection. The second technique employs behavioral-based parameters, in which computer vision technology is used to assess the visual characteristics like eye blinking, yawning, head pose and facial expression. The third technique employs physiological-based parameter that detects the onset of fatigue based on changes in subjects' physiological responses such as brain activity measured by electroencephalogram (EEG), heart electrical activity by electrocardiogram (ECG) and muscle electrical activity by electromyography (EMG). However, vehicle-based parameters like oscillations in steering wheel movement or standard deviation of lateral position typically manifest only later in the fatigue process. As a result, it is too late to avert a collision, and the probability of an accident has increased. Furthermore, computer vision-based algorithms are vulnerable to environmental factors such as road conditions and geometry, brightness and weather, which can effect fatigue detection accuracy [5]. Also, during the COVID-19 outbreak, it became usual for drivers to wear masks, making driver-based behavior interventions problematic.

Among them, physiology is a good indicator for detecting driving fatigue because it efficiently indicates how a human's body and mind are functioning under varied job conditions [6]. When a driver is fatigued, physiological systems such as the cardiovascular system, muscular system and nerve system can suffer. As a result, the physiological reactions slow down, the body's response to stimuli appears delayed and physiological indications deviate from normal [7]. Physiological-based parameter technologies detect these changes and inform the driver if he is fatigued. The advantage of this strategy is that it alerts the driver to take a break before physical indications of fatigue appear.

Regardless of the ECG and EMG characteristics, EEG is regarded as the most significant and reliable method for assessing driver fatigue because it can convey continuous brain status reactions [8] and intuitively depict the physiological activity of the human brain due to its high immunity to artefacts [9]. Scholars have recently proposed that mental and physical exhaustion may be caused by the same physiological source, because the muscle is the organ of physical activity and the brain is the organ of cognitive action, and both rely on limited energy supplies [10].

A number of recent research have used EEG to study the association between brain wave activity and fatigue. However, studies regarding the association between brain wave activity and cognitive skills in predicting driving fatigue are limited. As a result, the purpose of this study is to thoroughly summarize the findings of past studies on brain wave activity and how to correlate it with cognitive skills as an indicator of driving fatigue. The reasons behind the confusion in many studies surrounding how brain activity changes when a person experiences fatigue were also examined.

2. Methodology

A highly rigorous process known as a systematic literature review (SLR) was used to discover resilient and high potential literature linked to related topic. Three commonly used academic databases across various fields are Scopus, Google Scholar, and Web Science, all of which were utilized in this study. To get useful results, three simple Boolean operators: AND, OR, and NOT were used to connect the keywords in a logical form that the database could understand. The AND command unites two or more search phrases by instructing the database that all of these keywords must appear in the returning records, as in searching for "brain waves activity" AND "driving fatigue." If one key phrase in the item is returned but the other is not, the results will be quite limited because the item will not appear in the search result list. The OR command connects two or more synonyms, where any of the search terms may appear in the returned document, such as "urban" OR "city." The NOT command, meanwhile, narrows a search by excluding search results that contain the search terms that follow it, such as "brain waves activity by electroencephalogram" NOT "brain waves activity by electromyography". The system will only identify documents containing the phrase "brain waves activity by electroencephalogram" and will disregard any results that contain the phrase "brain waves activity by electromyography".

The screening procedure is clearly summarized in Figure 1. The first electronic searches yielded 985 records. The documents were then subjected to a de-duplication technique, which identified and eliminated duplicates. The procedure of de-duplication produced 621 papers. The following phase entailed a two-part process: (i) screening titles and abstracts for those linked to related topic, and (ii) selecting a full-text document for inclusion in the review. This batch's title and abstracts were examined, and 121 acceptable documents were extracted. 500 documents were considered during the full-text screening. 92 documents were identified as relevant to the research topic from a possibly relevant batch of 408 documents.

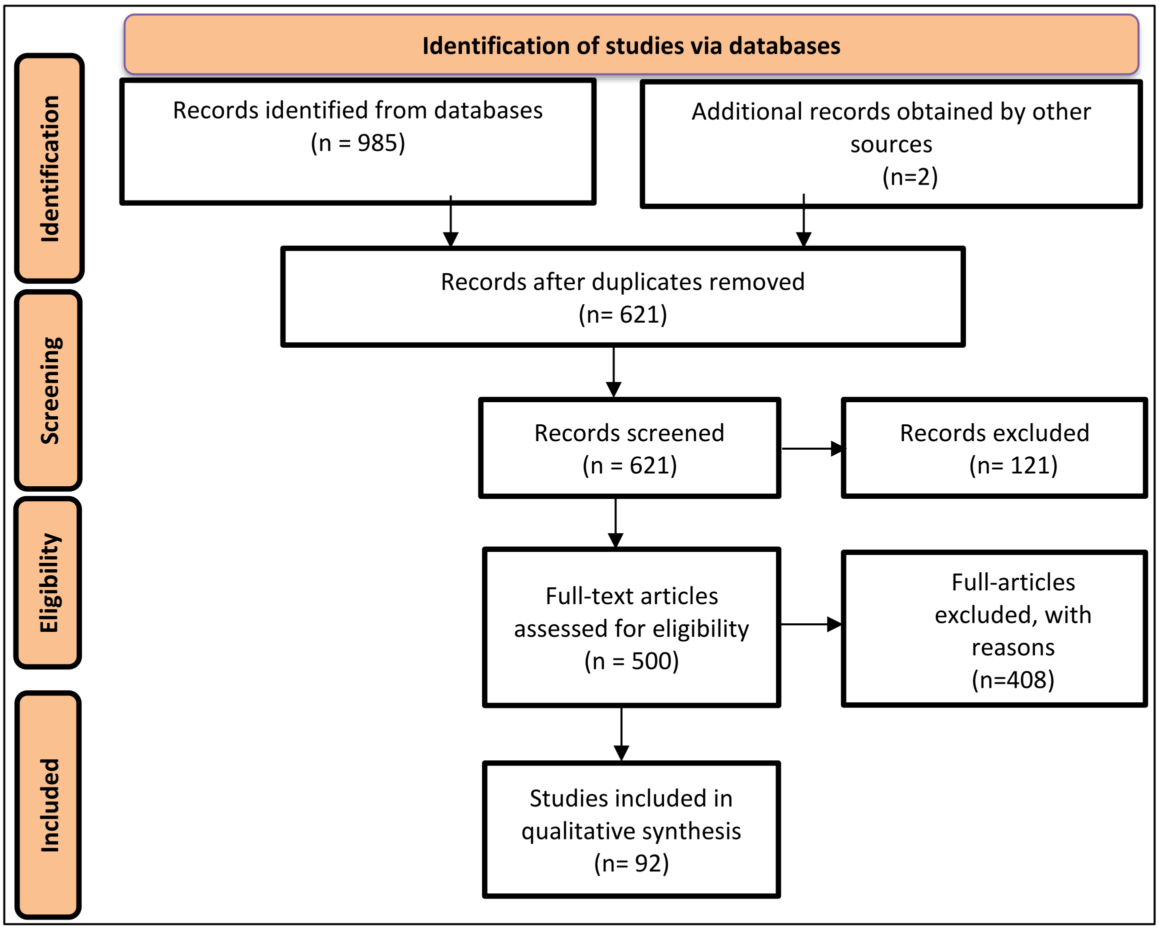

Fig. 1. PRISMA flow diagram illustrating selection of articles

3. Electroencephalogram (EEG)

Brain waves are the electrical activity produced by the human brain. A wave-like pattern is created when one set of neurons delivers a burst of electrical pulses to another group of neurons. An electroencephalogram (EEG) is a test that monitors electrical activity in the brain by attaching electrodes made up of small metal discs commonly composed of stainless steel, gold or silver covered with a silver chloride coating to the individual's scalp using an international 10-20 electrode placement technique as shown in Figure 2 [11]. The 10-20 method is the most extensively used system for EEG sensor positioning. The "10" and "20" relate to the fact that the actual distances between neighboring electrodes are either 10% or 20% of the overall front-back or right-left distance of the skull. The naming rules used in this technique are based on the electrode position and the underlying cortex area, such as the frontal, temporal, central, parietal and occipital lobes.

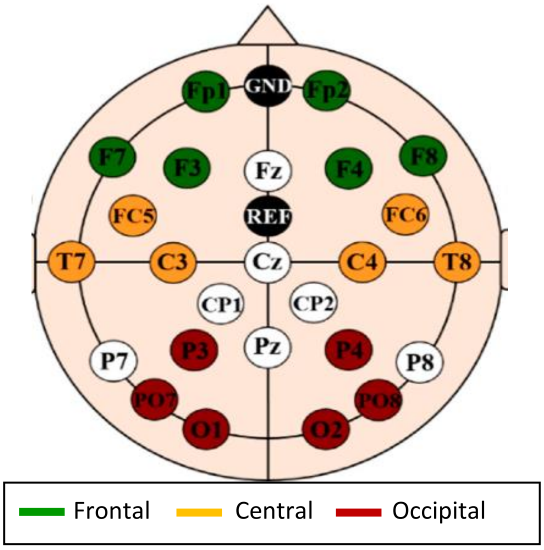

Fig. 2. 10-20 electrode placement technique [11]

4. Correlation between EEG and cognitive skills as an indicator to detect driving fatigue

Cognitive skills are brain-based abilities required for knowledge acquisition, information manipulation and thinking. These skills are important in all aspects of life, especially when performing complex tasks involving several distinct types of cognitive intelligence like operating a car. EEG signals are believed to be intimately associated to human cognitive skills and thus serve as an appropriate instrument in defining drivers' fatigue while driving because the human brain is at the center of every response to specific stimuli [12, 13]. Furthermore, EEG is a simple and subject-acceptable approach for gathering data for a driver's cognitive skills evaluation study. As a result, EEG signals have emerged as a key topic for future research into intelligent transportation-assisted driving and brain-computer interfaces. A study employed EEG to monitor brain activity to examine the influence of fatigue on a cognitive task, and discovered that participants showed reductions in task performance and physiological engagement [14]. Another study investigated the impact of several cognitive tasks (math and decision-making difficulties) on drivers' cognitive states using EEG and noticed that engaging the driver's cognitively with a secondary task greatly impacted the driver's driving performance as well as judgement capability [15].

5. Correlation between EEG frequency bands and cognitive skills

The EEG signal is split into five frequency bands that correspond to the principal components of the EEG spectrum: alpha, beta, delta, theta and gamma. The most popular EEG signal analysis frequencies are alpha, beta, delta and theta. The human brain generates these waves for a variety of cognitive functions. One of these frequency bands will be dominant depending on the task that the brain is doing at the time. The gamma frequency range, on the other hand, is responsible for processing many types of data. Gamma waves are also infrequent in raw EEG, have low strength and are tricky to record. Figure 3 shows the wave form of beta, alpha, theta and delta.

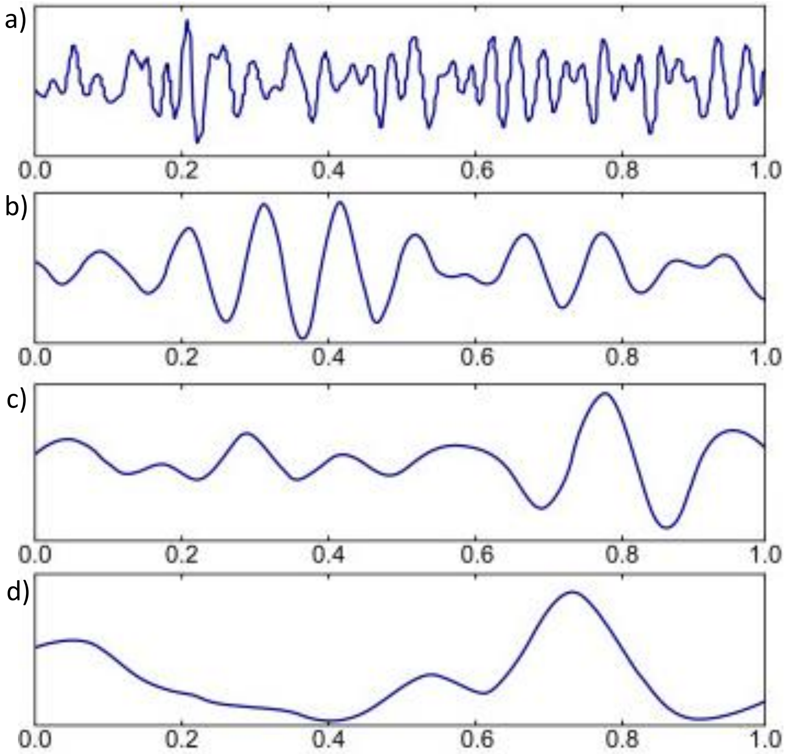

Fig. 3. Brain wave form: a) beta, (b) alpha, (c) theta and (d) delta

5.1 Alpha

Alpha waves are primarily generated in the brain's right cerebral hemisphere. Alpha waves can also be detected in the pre-frontal brain area and have the greatest amplitudes in the occipital regions [16]. In healthy, awake adults, alpha waves are produced while they are resting. The magnitude of alpha waves is larger when the eyes are closed compared when the eyes are open [17]. Alpha waves, which normally occur between 8 and 12 Hz, have a significant relationship with attention cognitive skills [18-21]. Increased alpha rhythm is connected with a loss in attentiveness and attention as an early indicator of fatigue [22]. A study found that greater alpha wave activity suggests increased efforts to maintain awareness levels [23].

5.2 Beta

The left hemisphere of the brain produces the majority of beta waves [24]. The beta waves have the greatest amplitudes in the frontal and central zones [25]. The frequency range of beta waves is commonly 13 to 30 Hz. Beta waves have a considerable association with decision making ability. A study demonstrated that beta waves appeared when completing mathematical tasks [26]. When humans have their eyes open and are listening and thinking during analytical problem solving, judgement, decision-making, and processing information about their environment, these waves are created [27]. Beta waves increase the body's energy level, allowing for greater information processing and integration. Brain work increases when beta signal power is dominating. Beta waves activate the neurological system. An increased beta wave indicates that an individual is cognitively active, acquiring and processing information to find solutions to difficulties [28].

5.3 Theta

Theta waves are largely generated in the brain's left hemisphere and have the greatest amplitudes in the frontal and central zones [25]. The frequency range of theta waves is commonly 4 to 8 Hz. Theta waves can appear in healthy people during the early phases of sleep or dreaming. Theta band brain oscillations are thought to be crucial in defining working memory (WM) ability [29-31]. A study tested this theoretical framework by measuring neuromagnetic responses from 10 volunteers performing the Sternberg task [32]. Subjects were asked to remember a list of 1, 3, 5, or 7 visually presented digits during a 3-second retention period. The task-dependent theta was found in the study during the retention phase and memory scanning. Following the memory task, theta activity diminished. Theta oscillations produced in frontal brain areas, according to the findings, play an active role in memory storage.

5.4 Delta

Delta waves are low-frequency waves that range in frequency from 0.1 to 3.9 Hz [33]. The delta band strength is used to characterize brain activity during deep sleep in people of all ages [34]. It is almost impossible to have delta-frequency power while awake [35]. Delta waves, which are associated with profound relaxation and restorative, healing sleep, are most typically detected in infants and young children. Furthermore, brain damage, learning problems, cognitive impairment, and severe attention deficit hyperactivity disorder (ADHD) all have these frequencies [36].

Table 1
Characteristics of different frequencies of brain wave

Type	Frequency, Hz	Physiological Condition	Explanation/Reference (Cognitive Skill)
Delta, δ	0-4	Deep rest, sleep	Visible during sober state usually when sleeping and under deep anesthesia.
Theta, θ	4-8	Deeply relaxed, inward focused	Visible during early stage of sleep, which influence the working memory.
Alpha, α	8-13	Very relaxed, calm, passive attention	The frequency promotes a feeling of relaxation, which is good for attention.
Beta, β	13-30	Alert, relaxed, anxiety dominant, active	Visible when involved in complex thought processes like problem solving or decision making.

6. Association of brain waves activity and fatigue

Table 2 summarizes prior research on the association between fatigue and brain waves as measured by EEG. These research studies employed EEG to estimate brain activity by analyzing changes in EEG waves as a person transitioned from alert to fatigue. According to the findings, there is a considerable relationship between fatigue and brain wave activity.

Table 2
Summary of EEG waves changes from previous studies
Notes: ↑ = significant increase in activity in EEG bands, ↓ = significant decrease in activity in EEG bands, NS = no significant change, NR = impact not reported

No.	Reference	No. of participant	No. of EEG electrodes	Alpha	Beta	Theta	Delta
1	[37]	35	24	↑	↑	↑	↑
2	[38]	10	32	↑	NR	↑	↑
3	[39]	20	24	↓	↓	↑	↑
4	[40]	52	32	↓	↓	↓	↓
5	[41]	20	24	↑	↑	↑	NR
6	[42]	9	8	↑	NR	↑	NR
7	[43]	48	32	↑	NS	↑	NS
8	[44]	-	-	↓	↓	↑	↑
9	[45]	9	8	↓	↓	NS	NR
10	[46]	13	14	↑	↑	↑	↓
11	[47]	7	18	↑	↓	↑	NR
12	[16]	8	32	↑	↑	↑	↑
13	[48]	20	19	↑	↓	↑	NR
14	[49]	10	12	↑	↑	↑	↑
15	[50]	9	2	↑	NR	↑	NR
16	[51]	8	2	↑	NR	↑	NR
17	[52]	8	8	↑	↓	↑	NR
18	[53]	46	4	↑	NR	↑	NR
19	[54]	52	19	↓	↓	↑	↑
20	[55]	13	10	↑	NR	↑	NR
21	[56]	20	16	↑	NR	↑	↓
22	[57]	68	11	NR	↓	NR	NR
23	[58]	22	32	↑	NR	↑	NR
24	[59]	8	5	↓	↓	NR	NR
25	[60]	10	19	↑	↓	NR	NR
26	[61]	50	14	↑	↑	↑	NR
27	[27]	13	32	↑	↓	↑	NR
28	[62]	18	11	NR	↓	NR	NR

Alpha wave activity (evaluated in all 26 studies) increased significantly in 20 and decreased in six studies. When a person is fatigued, alpha wave activity usually increases. Meanwhile, beta wave activity (examined in 19 studies) was found to increase significantly in six and decrease significantly in 13 studies. Based on these observations, it appears that as a person grows fatigued, beta activity decreases. The increase in beta activity may be due to the exertion of mental effort to remain vigilant, whereas the decrease in beta activity may be due to cognitive fatigue [63]. Theta wave activity rose significantly in 22 of the 23 studies and decreased in one. Based on these findings, theta activity is expected to increase when a person grows fatigued. On the other hand, delta wave activity was found to rise significantly in seven studies and drop substantially in three trials. The majority of research, however, did not discuss the impact of delta waves on fatigue analyses. This was not an unexpected discovery. Delta wave activity is assumed to be either a natural sleep wave or a pathological lethargic wave [64]. Because both groups had comparable fatigue levels and no health issues that might affect the reliability of the fatigue study, the bulk of relevant research assessed the fatigue level among young and healthy drivers. As a result, substantial rises in delta wave activity in a healthy participant sample were not expected [63]. Furthermore, a study discovered that the relationship between increased delta wave power and fatigue is unclear [37]. That is, the increased delta wave activity is caused by a failure to remove artefacts from the EEG signal, because artefacts considerably invade low EEG frequencies in the 1-4 Hz range [65]. Furthermore, delta waves are commonly detected in sleep stages 3 and 4, when no important cognitive functions can be measured. Delta-frequency power is nearly impossible to achieve while awake [35].

Figure 4 depicts an illustration of the association between brain wave activity and cognitive skill impairment, suggesting driving fatigue.

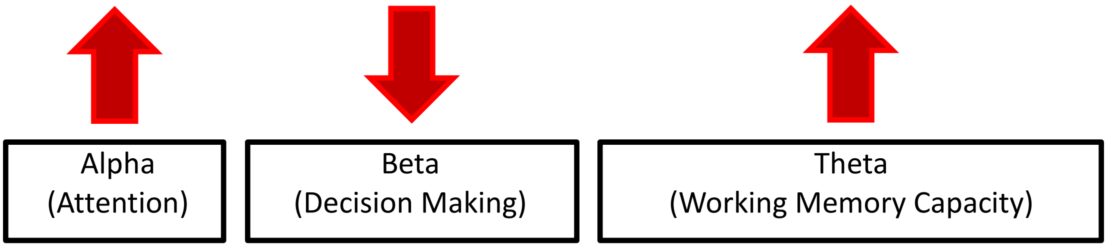

Fig. 4. Association between brain wave activity and cognitive skill impairment when a person fatigues

Several of the research cited have methodological flaws, which adds to the confusion about how brain activity changes when a person fatigues. The following are some limitations:

1) The use of a small number of participants. Nine studies had ten or fewer participants, while only 12 had more than 20. Small sample numbers reduce the ability to generalize findings, as well as reducing statistical power below the accepted level of 80%. A lack of statistical power reduces the likelihood of identifying real changes in brain wave activity. Assuming a modest effect size of 0.5 (i.e., the standardized mean effect of fatigue on brain activity), samples of 10 to 20 yield only 20% to 36% statistical power, respectively [66].

2) A second constraint is the number of electrodes used to assess EEG change. A low number of EEG electrodes limits the ability to investigate regional changes. Only nine of the 28 investigations used 20 or more EEG electrodes, with seven research projects using less than ten.

7. Conclusions

This paper extensively summarizes the findings of previous studies on electroencephalogram (EEG)-based brain wave activity and how to connect it with cognitive skills as an indicator of driving fatigue. A systematic literature review (SLR) was performed to identify robust and high-potential literature related to the research issue. According to the survey, when a person shifted from alert to fatigue, alpha and theta waves increased while beta waves declined. As previously established, alpha, theta and beta have strong links to attention, working memory capacity and decision making. As a result, a person may become fatigued if alpha and theta waves increase while beta waves decrease, indicating that this person has substantial cognitive impairment. The confusion regarding the brain activity changes when a person fatigues among the 28 studies might be due to the use of a small number of participants and the number of electrodes used to assess EEG change. The findings of the study will help researchers, policymakers, and practitioners create a system that will significantly minimize fatigue-related road accidents, thereby enhancing road safety.

Acknowledgment
The authors would like to thank the Ministry of Higher Education (MOHE), for sponsoring this work under the Fundamental Research Grant Scheme (FRGS/1/2020/TK02/UTEM/02/5). Also, many thanks go to the Faculty of Manufacturing Engineering, Universiti Teknikal Malaysia Melaka (UTeM) for the support.

References

[1] Anund, Anna, Jonas Ihlström, Carina Fors, Göran Kecklund, and Ashleigh Filtness, "Factors Associated with Self-Reported Driver Sleepiness and Incidents in City Bus Drivers," Industrial Health 54, no. 4 (2016): 337-346. https://doi.org/10.2486/indhealth.2015-0217

[2] "New Zealand's Poor Road Safety Worsens." 2022. World Highways. August 16, 2022. Accessed July 28, 2023. https://www.worldhighways.com/wh12/news/new-zealands-poor-road-safety-worsens

[3] MIROS. Road Accidents and Fatalities in Malaysia 2021; Available from: https://www.mot.gov.my/en/land/safety/road-accident-and-facilities

[4] Ibrahim, Muhammad Shafiq, Seri Rahayu Kamat, and Syamimi Shamsuddin, "The Application of Driving Fatigue Detection and Monitoring Technologies in Transportation Sector: A Review," International Journal of Technology Management and Information System 5, no. 2 (2023): 30-42. https://myjms.mohe.gov.my/index.php/ijtmis/article/view/22629

[5] Jiménez-Pinto, Javier, and Miguel Torres-Torriti, "Face Salient Points and Eyes Tracking for Robust Drowsiness Detection," Robotica 30, no. 5 (2012): 731-741. https://doi.org/10.1017/S0263574711000749

[6] Burlacu, Alexandru, Crischentian Brinza, Adrian Brezulianu, and Adrian Covic, "Accurate and Early Detection of Sleepiness, Fatigue and Stress Levels in Drivers Through Heart Rate Variability Parameters: A Systematic Review," Reviews in Cardiovascular Medicine 22, no. 3 (2021): 845-852. https://doi.org/10.31083/j.rcm2203090

[7] Zhou, Feng, Areen Alsaid, Mike Blommer, Reates Curry, Radhakrishnan Swaminathan, Dev Kochhar, Walter Talamonti, Louis Tijerina, and Baiying Lei, "Driver Fatigue Transition Prediction in Highly Automated Driving using Physiological Features," Expert Systems with Applications 147 (2020): 113204. https://doi.org/10.1016/j.eswa.2020.113204

[8] Liu, Yisi, Zirui Lan, Jian Cui, Olga Sourina, and Wolfgang Müller-Wittig, "Inter-Subject Transfer Learning for EEG-Based Mental Fatigue Recognition," Advanced Engineering Informatics 46 (2020): 101157. https://doi.org/10.1016/j.aei.2020.101157

[9] Chavarriaga, Ricardo, Marija Ušćumlić, Huaijian Zhang, Zahra Khaliliardali, Ruslan Aydarkhanov, Sareh Saeedi, Lucian Gheorghe, and José del R. Millán, "Decoding Neural Correlates of Cognitive States to Enhance Driving Experience," IEEE Transactions on Emerging Topics in Computational Intelligence 2, no. 4 (2018): 288-297. https://doi.org/10.1109/TETCI.2018.2848289

[10] Hancock, P. A., Paula A. Desmond, and Gerald Matthews, "Conceptualizing and Defining Fatigue," In *The Handbook of Operator Fatigue*, ed. Gerald Matthews, Paula A. Desmond, Catherine Neubauer, P.A. Hancock (CRC Press, 2017): 63-73.

[11] Choi, Soo-In, Chang-Hee Han, Ga-Young Choi, Jaeyoung Shin, Kwang Soup Song, Chang-Hwan Im, and Han-Jeong Hwang, "On the Feasibility of Using an Ear-EEG to Develop an Endogenous Brain-Computer Interface," Sensors 18, no. 9 (2018): 2856. https://doi.org/10.3390/s18092856

[12] Williams, Harold L., Allen M. Granda, Richard C. Jones, Ardie Lubin, and John C. Armington, "EEG Frequency and Finger Pulse Volume as Predictors of Reaction Time During Sleep Loss," Electroencephalography and Clinical Neurophysiology 14, no. 1 (1962): 64-70. https://doi.org/10.1016/0013-4694(62)90008-1

[13] Santamaria, Joan, and Keith H. Chiappa, "The EEG of Drowsiness in Normal Adults," Journal of Clinical Neurophysiology 4, no. 4 (1987): 327-382.

[14] Hopstaken, Jesper F., Dimitri van der Linden, Arnold B. Bakker, Michiel AJ Kompier, and Yik Kiu Leung, "Shifts in Attention during Mental Fatigue: Evidence From Subjective, Behavioral, Physiological, and Eye-Tracking Data," Journal of Experimental Psychology: Human Perception and Performance 42, no. 6 (2016): 878. https://psycnet.apa.org/doi/10.1037/xhp0000189

[15] Almahasneh, Hossam, Weng-Tink Chooi, Nidal Kamel, and Aamir Saeed Malik, "Deep in Thought While Driving: An EEG Study on Drivers' Cognitive Distraction," Transportation research part F: traffic psychology and behaviour 26 (2014): 218-226.
https://doi.org/10.1016/j.trf.2014.08.001

[16] Tran, Yvonne, Ashley Craig, Rachel Craig, Rifai Chai, and Hung Nguyen, "The Influence of Mental Fatigue on Brain Activity: Evidence from a Systematic Review with Meta‐Analyses," Psychophysiology 57, no. 5 (2020): e13554.
https://doi.org/10.1111/psyp.13554

[17] Salma, Nabila, Bin Mai, Kamesh Namuduri, Rasel Mamun, Yassir Hashem, Hassan Takabi, Natalie Parde, and Rodney Nielsen, "Using EEG Signal to Analyze IS Decision Making Cognitive Processes," In Information Systems and Neuroscience: Gmunden Retreat on NeuroIS 2017, pp. 211-218. Springer International Publishing, 2018.
https://doi.org/10.1007/978-3-319-67431-5_24

[18] Von Stein, Astrid, and Johannes Sarnthein, "Different Frequencies for Different Scales of Cortical Integration: From Local Gamma to Long Range Alpha/Theta Synchronization," International Journal of Psychophysiology 38, no. 3 (2000): 301-313.
https://doi.org/10.1016/S0167-8760(00)00172-0

[19] Foxe, John J., and Adam C. Snyder, "The Role of Alpha-Band Brain Oscillations as a Sensory Suppression Mechanism During Selective Attention," Frontiers in Psychology 2 (2011): 154.
https://doi.org/10.3389/fpsyg.2011.00154

[20] Nan, Wenya, Mengqi Wan, Yali Jiang, Xiaoping Shi, Feng Wan, and Dan Cai, "Alpha/Theta Ratio Neurofeedback Training for Attention Enhancement in Normal Developing Children: A Brief Report," Applied Psychophysiology and Biofeedback 47, no. 3 (2022): 223-229.
https://doi.org/10.1007/s10484-022-09550-6

[21] Chen, Zheng, Yujia He, and Yuguo Yu, "Attention Restoration During Environmental Exposure via Alpha-Theta Oscillations and Synchronization," Journal of Environmental Psychology 68 (2020): 101406.
https://doi.org/10.1016/j.jenvp.2020.101406

[22] Ng, Siew Cheok, and P. Raveendran, "EEG Peak Alpha Frequency as an Indicator for Physical Fatigue." In 11th Mediterranean Conference on Medical and Biomedical Engineering and Computing 2007: MEDICON 2007, 26-30 June 2007, Ljubljana, Slovenia, pp. 517-520. Berlin, Heidelberg: Springer Berlin Heidelberg, 2007.

[23] Balandong, Rodney Petrus, Rana Fayyaz Ahmad, Mohamad Naufal Mohamad Saad, and Aamir Saeed Malik, "A Review on EEG-Based Automatic Sleepiness Detection Systems for Driver," IEEE Access 6 (2018): 22908-22919.
https://doi.org/10.1109/ACCESS.2018.2811723

[24] Moini, Jahangir, and Pirouz Piran, "Chapter 6-cerebral cortex," Functional and Clinical Neuroanatomy (2020): 177-240.

[25] Vijayan, Sujith, Kyle Q. Lepage, Nancy J. Kopell, and Sydney S. Cash, "Frontal Beta-Theta Network during REM Sleep." elife 6 (2017): e18894.
https://doi.org/10.7554/eLife.18894

[26] Angrisani, Leopoldo, Pasquale Arpaia, and Deborah Casinelli, "Instrumentation and Measurements for Non-Invasive EEG-Based Brain-Computer Interface," In 2017 IEEE International Workshop on Measurement and Networking (M&N), pp. 1-5. IEEE, 2017.
https://doi.org/10.1109/IWMN.2017.8078383

[27] Zhao, Chunlin, Min Zhao, Jianpin Liu, and Chongxun Zheng. "Electroencephalogram and Electrocardiograph Assessment of Mental Fatigue in a Driving Simulator," Accident Analysis & Prevention 45 (2012): 83-90.
https://doi.org/10.1016/j.aap.2011.11.019

[28] Alfimtsev, A. N., M. A. Basarab, V. V. Devyatkov, and A. A. Levanov, "A New Methodology of Usability Testing on the Base of the Analysis of User's Electroencephalogram," Journal of Computer Sciences and Applications 3, no. 5 (2015): 105-111.
https://doi.org/10.12691/jcsa-3-5-1

[29] Wolinski, Nina, Nicholas R. Cooper, Paul Sauseng, and Vincenzo Romei, "The Speed of Parietal Theta Frequency Drives Visuospatial Working Memory Capacity," PLoS biology 16, no. 3 (2018): e2005348.
https://doi.org/10.1371/journal.pbio.2005348

[30] Alekseichuk, Ivan, Zsolt Turi, Gabriel Amador De Lara, Andrea Antal, and Walter Paulus, "Spatial Working Memory in Humans Depends on Theta and High Gamma Synchronization in the Prefrontal Cortex," Current biology 26, no. 12 (2016): 1513-1521.
http://dx.doi.org/10.1016/j.cub.2016.04.035

[31] Talukdar, Upasana, and Shyamanta M. Hazarika, "Estimation of Mental Fatigue During EEG Based Motor Imagery." In Intelligent Human Computer Interaction: 8th International Conference, IHCI 2016, Pilani, India, December 12-13, 2016, Proceedings 8, pp. 122-132. Springer International Publishing, 2017. https://doi.org/10.1007/978-3-319-52503-7_10
[32] Jensen, Ole, and Claudia D. Tesche, "Frontal Theta Activity in Humans Increases with Memory Load in a Working Memory Task," European journal of Neuroscience 15, no. 8 (2002): 1395-1399. https://doi.org/10.1046/j.1460-9568.2002.01975.x
[33] Liao, Chung-Yen, Rung-Ching Chen, and Shao-Kuo Tai, "Emotion Stress Detection using EEG Signal and Deep Learning Technologies." In 2018 IEEE International Conference on Applied System Invention (ICASI), pp. 90-93. IEEE, 2018. https://doi.org/10.1109/ICASI.2018.8394414
[34] Djordjevic, Vladana Radisavljevic, "Automated Nonlinear Analysis of Newborn Electroencephalographic Signals" (PhD diss., Czech Technical University, 2015).
[35] Svensson, Ulrika. Blink Behaviour Based Drowsiness Detection: Method Development and Validation (MSc Thesis, Linköping University, 2004).
[36] Moini, J. and P. Piran, Functional and Clinical Neuroanatomy: A Guide for Health Care Professionals (Academic Press, 2020).
[37] Lal, Saroj KL, and Ashley Craig, "Driver Fatigue: Electroencephalography and Psychological Assessment," Psychophysiology 39, no. 3 (2002): 313-321. https://doi.org/10.1017/S0048577201393095
[38] Caldwell, John A., Kecia K. Hall, and Bradley S. Erickson, "EEG Data Collected from Helicopter Pilots in Flight are Sufficiently Sensitive to Detect Increased Fatigue from Sleep Deprivation," The International Journal of Aviation Psychology 12, no. 1 (2002): 19-32. https://doi.org/10.1207/S15327108IJAP1201_3
[39] Jia, Huijie, Zhongjun Xiao, and Peng Ji, "End-to-end Fatigue Driving EEG Signal Detection Model based on Improved Temporal-Graph Convolution Network," Computers in Biology and Medicine 152 (2023): 106431. https://doi.org/10.1016/j.compbiomed.2022.106431
[40] Jap, Budi Thomas, Sara Lal, Peter Fischer, and Evangelos Bekiaris, "Using Spectral Analysis to Extract Frequency Components from Electroencephalography: Application for Fatigue Countermeasure in Train Drivers." In The 2nd International Conference on Wireless Broadband and Ultra Wideband Communications (AusWireless 2007), pp. 13-13. IEEE, 2007. https://doi.org/10.1109/AUSWIRELESS.2007.83
[41] Wu, Chao, Fuze Tian, Qiuxia Shi, Qinglin Zhao, and Bin Hu, "A Portable System of Mental Fatigue Detection and Mitigation based on Physiological Signals." In 2022 IEEE International Conference on Bioinformatics and Biomedicine (BIBM), pp. 2957-2963. IEEE, 2022. https://doi.org/10.1109/BIBM55620.2022.9995373
[42] Macchi, M. Mila, Ziad Boulos, Thomas Ranney, Lucinda Simmons, and Scott S. Campbell, "Effects of an Afternoon Nap on Nighttime Alertness and Performance in Long-Haul Drivers," Accident Analysis & Prevention 34, no. 6 (2002): 825-834. https://doi.org/10.1016/S0001-4575(01)00089-6
[43] Craig, Ashley, Yvonne Tran, Nirupama Wijesuriya, and Hung Nguyen, "Regional Brain Wave Activity Changes Associated with Fatigue," Psychophysiology 49, no. 4 (2012): 574-582. https://doi.org/10.1111/j.1469-8986.2011.01329.x
[44] Wang, Qingjun, and Zhendong Mu, "Application of Music in Relief of Driving Fatigue Based on EEG Signals," EURASIP Journal on Advances in Signal Processing 2021 (2021): 1-15. https://doi.org/10.1186/s13634-021-00794-8
[45] Jing, Difei, Dong Liu, Shuwei Zhang, and Zhongyin Guo, "Fatigue Driving Detection Method Based on EEG Analysis in Low-Voltage and Hypoxia Plateau Environment," International journal of transportation science and technology 9, no. 4 (2020): 366-376. https://doi.org/10.1016/j.ijtst.2020.03.008
[46] Tyas, Agnes Estuning, Adhi Dharma Wibawa, and Mauridhi Hery Purnomo, "Theta, Alpha and Beta Activity in the Occipital Based on EEG Signals for Mental Fatigue in High School Students." In 2020 International Conference on Smart Technology and Applications (ICoSTA), pp. 1-7. IEEE, 2020. https://doi.org/10.1109/ICoSTA48221.2020.1570614141
[47] Xavier, Gregory, Anselm Su Ting, and Norsiah Fauzan, "Exploratory Study of Brain Waves and Corresponding Brain Regions of Fatigue On-Call Doctors using Quantitative Electroencephalogram," Journal of occupational health 62, no. 1 (2020): e12121. https://doi.org/10.1002/1348-9585.12121

[48] Li, Gang, Shan Huang, Wanxiu Xu, Weidong Jiao, Yonghua Jiang, Zhao Gao, and Jianhua Zhang, "The Impact of Mental Fatigue on Brain Activity: A Comparative Study Both in Resting State and Task State using EEG," BMC Neuroscience 21 (2020): 1-9.
https://doi.org/10.1186/s12868-020-00569-1
[49] Tanaka, Hideki, Mitsuo Hayashi, and Tadao Hori, "Topographical Characteristics and Principal Component Structure of the Hypnagogic EEG," Sleep 20, no. 7 (1997): 523-534.
https://doi.org/10.1093/sleep/20.7.523
[50] Cajochen, Christian, Daniel P. Brunner, Kurt Krauchi, Peter Graw, and Anna Wirz-Justice, "Power Density in Theta/Alpha Frequencies of the Waking EEG Progressively Increases during Sustained Wakefulness," Sleep 18, no. 10 (1995): 890-894.
https://doi.org/10.1093/sleep/18.10.890
[51] Cajochen, Christian, Kurt Kräuchi, Marie-Anne von Arx, David Möri, Peter Graw, and Anna Wirz-Justice, "Daytime Melatonin Administration Enhances Sleepiness and Theta/Alpha Activity in the Waking EEG," Neuroscience letters 207, no. 3 (1996): 209-213.
https://doi.org/10.1016/0304-3940(96)12517-9
[52] Eoh, Hong J., Min K. Chung, and Seong-Han Kim, "Electroencephalographic Study of Drowsiness in Simulated Driving with Sleep Deprivation," International Journal of Industrial Ergonomics 35, no. 4 (2005): 307-320.
https://doi.org/10.1016/j.ergon.2004.09.006
[53] Campagne, Aurelie, Thierry Pebayle, and Alain Muzet, "Correlation between Driving Errors and Vigilance Level: Influence of the Driver's Age," Physiology & Behavior 80, no. 4 (2004): 515-524.
https://doi.org/10.1016/j.physbeh.2003.10.004
[54] Jap, Budi Thomas, Sara Lal, Peter Fischer, and Evangelos Bekiaris, "Using EEG Spectral Components to Assess Algorithms for Detecting Fatigue," Expert Systems with Applications 36, no. 2 (2009): 2352-2359.
https://doi.org/10.1016/j.eswa.2007.12.043
[55] Pal, Nikhil R., Chien-Yao Chuang, Li-Wei Ko, Chih-Feng Chao, Tzyy-Ping Jung, Sheng-Fu Liang, and Chin-Teng Lin, "EEG-based Subject-and Session-Independent Drowsiness Detection: An Unsupervised Approach," EURASIP Journal on Advances in Signal Processing 2008 (2008): 1-11.
https://doi.org/10.1155/2008/519480
[56] Papadelis, Christos, Chrysoula Kourtidou-Papadeli, Panagiotis D. Bamidis, Ioanna Chouvarda, Dimitris Koufogiannis, Evangelos Bekiaris, and Nikos Maglaveras, "Indicators of Sleepiness in an Ambulatory EEG Study of Night Driving," In 2006 international conference of the IEEE engineering in medicine and biology society, pp. 6201-6204. IEEE, 2006.
https://doi.org/10.1109/IEMBS.2006.259614
[57] Ahn, Sangtae, Thien Nguyen, Hyojung Jang, Jae G. Kim, and Sung C. Jun, "Exploring Neuro-Physiological Correlates of Drivers' Mental Fatigue Caused by Sleep Deprivation using Simultaneous EEG, ECG, and fNIRS Data," Frontiers in human neuroscience 10 (2016): 219.
https://doi.org/10.3389/fnhum.2016.00219
[58] Trejo, Leonard J., Karla Kubitz, Roman Rosipal, Rebekah L. Kochavi, and Leslie D. Montgomery, "EEG-based Estimation and Classification of Mental Fatigue," Psychology 6, no. 05 (2015): 572.
http://www.scirp.org/journal/PaperInformation.aspx?PaperID=55452&#abstract
[59] Di Stasi, Leandro L., Carolina Diaz-Piedra, Juan Suárez, Michael B. McCamy, Susana Martinez-Conde, Joaquín Roca-Dorda, and Andrés Catena, "Task Complexity Modulates Pilot Electroencephalographic Activity during Real Flights," Psychophysiology 52, no. 7 (2015): 951-956.
https://doi.org/10.1111/psyp.12419
[60] Fan, Xiaoli, Qianxiang Zhou, Zhongqi Liu, and Fang Xie, "Electroencephalogram Assessment of Mental Fatigue in Visual Search," Bio-Medical Materials and Engineering 26, no. s1 (2015): S1455-S1463.
https://doi.org/10.3233/BME-151444
[61] Zhang, Jia-Li, Jing Li, Guo Meng, and Ming-Gao Li, "Study on Fatigue of Pilots during Simulated Flight Training Based on Electroencephalogram," Zhongguo Ying Yong Sheng Li Xue Za Zhi 29, no. 3 (2013): 267-270.
https://pubmed.ncbi.nlm.nih.gov/23940965/
[62] Tanaka, Masaaki, Yoshihito Shigihara, Akira Ishii, Masami Funakura, Etsuko Kanai, and Yasuyoshi Watanabe, "Effect of Mental Fatigue on the Central Nervous System: An Electroencephalography Study," Behavioral and Brain Functions 8, no. 1 (2012): 1-8.
https://doi.org/10.1186/1744-9081-8-48
[63] Craig, Ashley, Yvonne Tran, Nirupama Wijesuriya, and Hung Nguyen, "Regional Brain Wave Activity Changes Associated with Fatigue," Psychophysiology 49, no. 4 (2012): 574-582.
https://doi.org/10.1111/j.1469-8986.2011.01329.x

[64] Steriade, Mircea, P. L. R. R. Gloor, Rodolfo R. Llinas, FH Lopes Da Silva, and M-M. Mesulam, "Basic Mechanisms of Cerebral Rhythmic Activities," Electroencephalography and clinical neurophysiology 76, no. 6 (1990): 481-508. https://doi.org/10.1016/0013-4694(90)90001-Z
[65] Makeig, Scott, Arnaud Delorme, Marissa Westerfield, Tzyy-Ping Jung, Jeanne Townsend, Eric Courchesne, and Terrence J. Sejnowski, "Electroencephalographic Brain Dynamics Following Manually Responded Visual Targets," PLoS Biology 2, no. 6 (2004): e176.
https://doi.org/10.1371/journal.pbio.0020176
[66] Cohen, Jacob, Statistical Power Analysis for the Behavioral Sciences (2nd ed.) (Hillsdale, NJ: Lawrence Erlbaum Associates, Publishers, 1988).