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Driver's Performance Under Different Secondary Tasks and Disruptions on Rural Road Environment

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ABSTRACT

Nowadays, detection of driver's fatigue is a major concern in vehicle design, road safety and transportation research. Driving tasks requires full attention from the drivers while operating the vehicle. Occasionally, drivers are exposed to perform other activities such as talking to a passenger and using an in-vehicle technology or phone which is known as secondary task while driving. Thus, this study aims to analyse the driver's performance via three types of physiological measurements in a simulated condition. An integrated approach by combining subjective and objective methods were used in this study. There are Karolinska Sleepiness Scale (KSS), Electroencephalogram (EEG) and Heart Rate (HR). Twelve participants were recruited to evaluate their responses towards different types of secondary tasks and disruptions in 25-minutes of driving duration. The findings showed that there are differences in physiological responses for this driving session. Beta Activity shows higher event-related power modulation values from start until the end of the driving session. In conclusion, the type of disruption during driving and secondary tasks shows different findings towards driver driving performances. This study can be used as reference to drivers and related agencies by taking into account the physiological effects of driver's performance based on different secondary tasks and disruptions while driving.

Keywords: Fatigue; safety; behaviour; EEG; heart rate

INTRODUCTION

Every year, 1.25 million of lives were cut short while over 50 million were suffered from injuries due to road crashes according to the World Health Organisation (WHO) in 2015. In Malaysia, road crashes were reported by Royal Malaysian Police are increasing every year with average of almost 20 people die every day on the road in 2017. It was also estimated that road crashes have contributed in RM 15.5 billion monetary losses in 2016 which shows that road crashes have always been a big issue as it will not just affected human life but has also affected the economics of a country.

Previous studies suggested road crashes are due to human factor whereby driver's physiological condition and behaviour were the factors that lead to human error road crashes (Seen, Mohd Tamrin, and Meng 2010). There were several factors that lead to human error related road crashes and fatigue has always been one of the main factors in serious road crashes. Any driving situation related to fatigue is difficult to control as fatigue affects driver's physiology and vehicle kinematics (Wang et al. 2017) in which it reduces driver alertness and focus which may result to sleepiness while driving (Pastor et al. 2006) Fatigue crash-related usually resulted in fatal or serious crashes. Driver's lifestyle is arguably one of the main causes of fatigue. Poor sleep and time management, food consumes and lack of daily exercises are some of the factors that lead to fatigue driver (Hwang et al. 2016).

A physically prepared driver may be fitted to drive. However, in a driving task, drivers may involve in an extreme fluctuation in mental workload (Horberry et al. 2006). This is due to multiple levels of workload have to be done by a driver during driving task whereby it requires driver to be able to do complex activity which involve visual and manual tasks such as focusing on the roadway and environment, understanding and operating the vehicle systems as well as processing the driving information (Charlton 2007; Edquist et al. 2011). Adding in with difficult driving environment such as heavy traffic, poor road condition and time pressure, this in turn, may affect the driver emotion to stress or angry (Hassan and Abdel-Aty 2013) and thus, lead drivers to speeding and aggressive which eventually, may reduce driver performances (Charlton 2007)

Physiological effect towards drivers is also likely to lead to human error road crashes especially when driver is distracted with a secondary tasks performed while driving (Naujoks, Purucker, and Neukum 2016; Wandtner, Schömig, and Schmidt 2018) explained that in any driving situations which indicate that distractions may lead to hazardous driving and cause road crashes. Several distractions often performed while driving such as mobile phone use, where it was recognized as a major issue in driving as it will affect both visual and cognitive distractions (Dingus et al. 2019; Gallagher and Satlin 2018). The other similar distraction is in-vehicle technologies in recent vehicles such as radio and navigations systems where it has the possibility to produce similar distraction as mobile phone (Jung et al. 2019). Distractions will significantly increase the chance of being involved in a crash or near crash as it also does affect driver's physiology and vehicle kinematics (Owens et al. 2015). It is often observed in Malaysia that rarely to observed that drivers are not participating in multiple non-driving related task. These task or activities include conversation with passenger and listening to radio, personal grooming and even reading (Torkamannejad Sabzevari et al. 2016)

Driver performance may change at any time, place and condition as it depends on driver behaviour on the road. Results shows from experiment by Sundfør, Sagberg, and Høye (2019) the driver engaging with secondary task was led to the nearest crash on the road. Good driving behaviour and fit may result in good and better driving performance. However, studies by Dingus et al. (2019) results shows that truck driver was engaged with the secondary task to prevent from the drowsiness and to make sure the driver to stay alert. Numerous studies on fragrance also can help the driver to maintain the driver's in full focus towards the drive, but in long duration driving the driver may immune with the fragrance (Mahachandra, Yassierli, and Garnaby 2015; Placidi et al. 2018).

Nowadays, it is normal to see drivers performing a secondary task while driving especially using their mobile phones and their performance while driving is questionable whether or not they would be able to be a good driver when they are distracted with multiple driving tasks. Therefore, this study aims to analyse driver's performance using different types of physiological measurements including Electroencephalogram, Heart Rate and Karolinska Sleeping Scale in a simulated condition.

METHODOLOGY

In this section, method used in this study including the experimental design, procedure, equipment, tasks and variables are being discuss.

PARTICIPANTS

The participants (drivers) were 12 university students, with the following criteria:

1. Having normal sleeping patterns
2. Not to consume any type of caffeine for the past 24 hours before the experiment
3. Keeping their hair in dry conditions and free from any hair cream or gel

Caffeine consumption is crucial where it can affect driving performance as suggested in previous studies (Biggs et al. 2007) while the dry hair is to ease the use of electroencephalogram (EEG) during the driving experiment. This activity is important because it may influence driver's condition (e.g: motion or simulator sickness) and reaction when involved in the actual experiment (Horrey et al. 2009). The subjects were accepted as the adequate range of participants criteria for a simple experimental investigation was between 10 to 20 participants (Sekaran and Bougie 2016). The research protocol was approved by the Ethical Committee of Universiti Kebangsaan Malaysia with the reference number UKM PPI/111/8/JEP-2016-200. All participants involved voluntarily and signed an informed consent form in accordance with institutional guidelines

APPARATUS

Car Simulator

This experiment will be conducted using a car simulator where according to previous studies Cantin et al. (2009) simulator are suitable to be used in order to obtain reliable observation of driver's behavior and to achieve the necessary experimental control. This simulator as shown in Figure 1 is located in the Ergonomics Laboratory, Faculty of Engineering and Built Environment, Universiti Kebangsaan Malaysia (UKM)

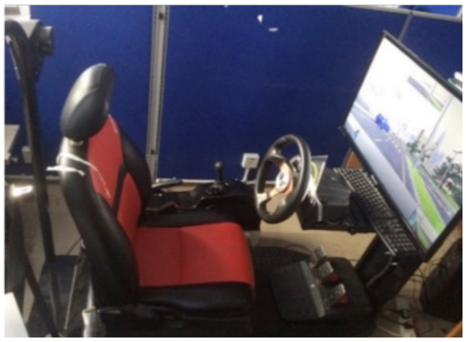

FIGURE 1. Car simulator

ELECTROENCEPHALOGRAM (EEG)

Emotive Epoc EEG is used in this study where it is used to measure the brain activity of the drivers during the experiment asn shown in Figure 2. Emotive Epoc comes with 14 active channels and it will be mounted on the driver's head. This EEG device measures the electrical impulse in human brain using its electrodes that are being placed on the scalp where these impulse consists of five different frequencies which are Alpha, Beta, Gamma, Theta and Delta. This study focus on only the Alpha and Beta values since that frequency are being evaluated for the interference imposed on driving performance. The raw data obtained by this device is analyzed on the computer using the Epoc control panel software and it is stored in the European Data Format so that it can be uploaded into the Brain Vision Analyzer and the noises and artifacts in the data will be filtered. Then, the resulting wave is imported to Microsoft Excel in order to calculate the Event-related power modulation (%) which is also known as ERPow by using the formula below

$$ERPow = \left[\frac{Pow\ event - Pow\ baseline}{Pow\ baseline}\right] x100$$

ERPow transformation is defined as the increase or decrease of the Power Density percentage by comparing the baseline data and the data during the driving activity. Furthermore, the increase of ERPow is considered as positive value while the reduction in ERPow is considered as a negative value.

FIGURE 2. Emotive Epoc 14-ch EEG (Fan et al. 2018)

Heart Rate (HR)

HR equipment that is being used for this study is known as Wahoo Fitness as shown in Figure 2. The HR fitness tracker will be mounted on the participant chest properly so that the Wahoo Fitness app on the mobile phone can produce the HR reading of the drivers. The Wahoo Fitness app can measure the participant heart rate per second and the data will be obtaining and downloaded into the computer in Excel form.

FIGURE 3. Wahoo Fitness

RESPONSE VARIABLES

Karolinska Sleepiness Scale (KSS)

KSS is one of the most widely used subjective measuring methods in determining driver's fatigue where it consists nine-point scale where 1 = extremely alert, 2=very alert, 3 = alert, 4=rather alert, 5 = neither alert nor sleepy, 6=some signs of sleepiness, 7 = sleepy, but no difficulty remaining awake, 8=sleepy but some difficulty to keep awake, and 9 = extremely sleepy, great difficulty to keep awake, fighting sleep. For this study, the participant will be asked to do the KSS twice which is before and after they undergo the driving activity.

Driving Simulator Experiment Design

All participants need to obey the experiment sequence flow as in Figure 1. The flow started with 15 minutes of setting up the equipment on the participants, followed by 5 minutes each of closing and opening the eyes and finally, participants had to drive for 25 minutes on a monotonous road with minimum traffic at 70km/h. The closing and opening the eye session is important to get the baseline while using the EGG analysis later.

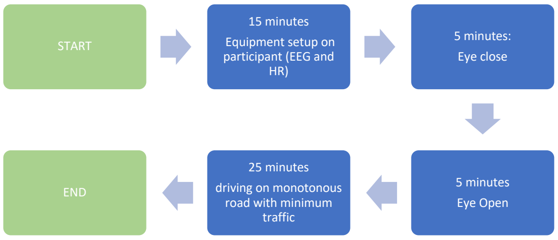

FIGURE 4. Simulator Experimental Design

Experimental Paradigm and Flow

Prior to experiment, each participant should be alert and ask to obey to all instructions given in this session. All participants were instructed to drive a car simulator for 25 minutes on the monotonous road with low traffic condition. Figure 2 depicts the experiment paradigm that has to be performed by each participant in this study with the preparation time and the duration taken for each step. Each participant should begin the experiment session by closing the eye and opening the eye for five minutes. It is useful to get the baseline for this study when comparing with the driving task session, particularly for EEG analysis.

In this case, normal driving refers to driving the car with both of their hands on the steering wheel. In addition, the participant needs to control their speed constantly at 70 km/h. Then, the first disruption (P2) was given in the form of visual stimulus. These sentences "Expressway starts, if you need help, please call toll-free online. Please be careful when driving. Have a safe trip and thank you" will be appeared at the top of the screen display for less than one minute. The next phase required the participant to drive as normal without any disruption for four minutes (P3). After four minutes of driving, a mobile phone will ring and the participant needs to take the call and hang it for less than a minute while controlling the car. This situation called as secondary task (P4) because the participant needs to control the car while responding to the phone call. Then at the next phase (P5), the participant needs to drive as usual without any disruption for four minutes. Later on, the next disruption (P6) will be given by the researcher. These sentences "Slow down the car to 50 km/h" will be appeared at the top of the screen display again. Compared to the P2, the participant needs to respond and act according to the instruction by controlling the car pedal slowly to 50 km/h. Lastly, the participant was required to drive the car as normal till the end of experiment session.

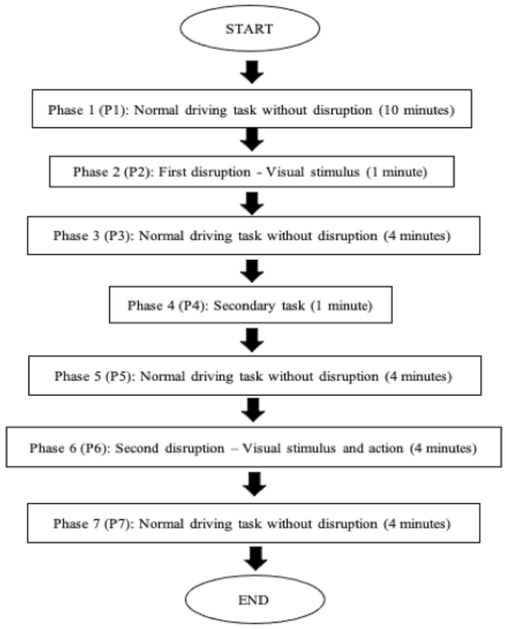

FIGURE 5. Driving Task Flow

Data Analysis

As mentioned earlier, this study used three types of physiological measurements, KSS, HR and EEG. The KSS is the popular measuring scale to determine driver's fatigue. It has nine point scales (1 = extremely alert, 2=very alert, 3 = alert, 4=rather alert, 5 = neither alert nor sleepy, 6=some signs of sleepiness, 7 = sleepy, but no difficulty remaining awake, 8=sleepy but some difficulty to keep awake, and 9 = extremely sleepy, great difficulty to keep awake, fighting sleep). In this study, the participant need to indicate his/her alertness level before and after driving activity.

Figure 4 shows the HR equipment known as Wahoo Fitness used in this study. The participant needs to put this equipment on his/her chest. Then, the researcher needs to ensure there is connection between the equipment and the Wahoo Fitness app that can be downloaded from the Google Store. This equipment can measure the heart rate per second. At the end of the experiment, heart rate and time data are uploaded to the computer. Data was obtained in the Excel format.

The EEG data were recorded by using the wireless Emotiv Epoc with 14 channels of electrodes; AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4. This equipment was placed on the scalp of the participant and then two electrodes mounted at the right and left ears of the participant as references. Figure 2 shows the Emotive Epoc system. Compared to several EEG sensors, Emotive used saline based electrodes. It means that there are no sticky gels used for the electrical connectivity purposes.

EEG Pre-processing

In order to obtain a good and clean data, EEG signals need to be filtered and artifacts removed. Artifacts are unwanted electrical potentials that do not originate from the brain and can cause inaccurate interpretation of EEG signals. There are two types of artifacts which are technical and physiological artifacts. Technical artifacts may be derived from power supply interference (50/60 Hz) due to high electrode impedance at contact and the fluctuations of electrode impedance due to loss of wire contacts or less applications of electrode conductive gel resulting in dried electrodes. While, physiological artifacts include body activities such as movements, bioelectrical potentials (generated by eyes, heart and pharyngeal muscle), skin resistance fluctuations (perspiration, vasomotor and sweat gland activities).

The artifacts rejection procedure can be done through a process known as filtering. This process can be performed using conventional low pass, high pass, band pass and notch filter (Fukuda et al. 2005). The artifact rejection involves the identification and removal of the artifacts from the raw EEG signal. In present study, EEG was carefully set-up to minimise the technical artifacts. The filtering process was done using Brain Vision Analyser 2.0. In EEG signals. The raw data was band filtered between 1 to 40 Hz, slope 24 dB/octave with notch filtered at 50 Hz to remove additional electrical noise and re-references to the average activity of 18 interest electrodes. A semi-automatic inspection-rejection procedure was applied to remove physiological artifacts of muscle and eye movements.

EEG Event-related Power (ERPow)

In the EEG spectral analysis, Event Related Power (ERPow) reflects the regional oscillatory activity of neural networks. In order to characterise how CT and CTQ interventions induced oscillations of ADHD children, the EEG data were analysed using Brain Vision Analyser 2.0, then were computed for ERPow. A Fast Fourier Transform (FFT) of 3 epochs (5 seconds) was computed for all electrodes and averaged under same conditions. Power spectra were calculated by selecting 18 electrodes: Fp1, Fz, F3, F4, F7, F8, Cz, C3, C4, Pz, P3, P4, T3, T4, T5, T6, O1 and O2 from the FFT power spectrum. Power spectra were estimated for all frequency bins between 0.5 and 40 Hz (0.5Hz of maximum bin width). The recordings were Hammingwindowed in order to control spectral leakage. Broadband power changes were obtained by averaging the power values for the frequency ranges chosen for the analysis; θ, (4-7 Hz), α (8-12 Hz) and β (13-30 Hz) frequency bands. Then, the FFT output was imported into Microsoft Excel to calculate ERPow. To reduce the effects of inter-subject and inter-electrode variation in absolute spectral power values and to quantify the event-related relative changes of EEG power at an electrode x (ERPowx), an accepted event-related ERD/ERS procedure was used using following equation.

RESULT & DISCUSSION

SUBJECTIVE METHOD: KSS ANALYSIS

The findings show that average KSS value for before driving is 2, then after driving, the KSS value increase to 4. It indicates the participant still alert even after 25 minutes of driving activity. It may be due to the tasks given during the experiment session, including the variety of secondary task and disruptions.

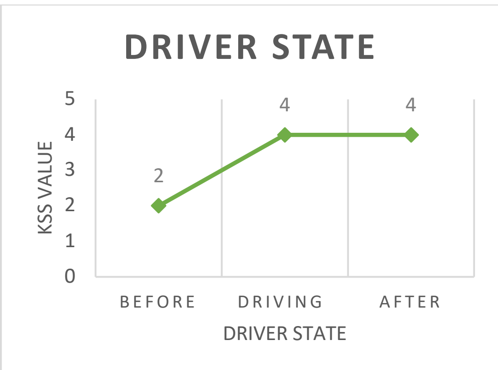

FIGURE 6. Driver Condition

OBJECTIVE METHODS: HR AND EEG ANALYSIS

Figure 7 illustrates the finding based on objective measurement. In term of HR, there is no significant difference between driving without or with disruptions. However, the HR value increases when it comes to a second disruption, which is at P6. Past study highlighted the HR will increase when the person is experiencing the mental stress and in high-demand situation (Brookhuis and de Waard 2010). The P6 phase is the situation which the participant is required to slow down the car to 50 km/h whereas before this instruction, the participants exceeded the speed limit. This affects the participant as it necessary to ensure the speed limit is only at 50 km/h.

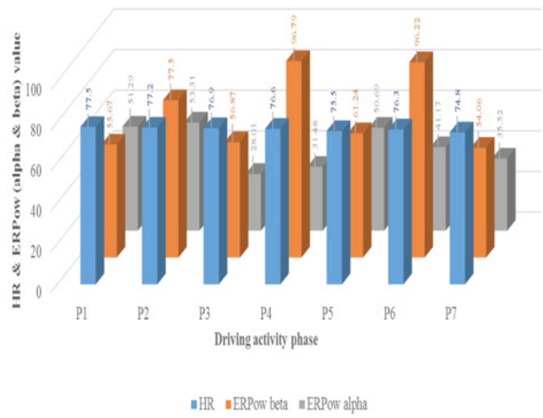

FIGURE 7. Objective Method Results

In term of EEG analysis, this study only considered the data from the Frontal lobe and Occipital lobes. Both lobes take into accounts the visual focus and stimuli. In terms of beta frequency in this study, ERpow is low in all four normal driving conditions (P1, P3, P5 and P7) ranging from 54.06% to 61.24%. The value of ERpow at the highest frequency beta was recorded at P5 (61.24%) and the lowest was recorded at P7 (54.06%). The value at P5 may be high due to the situation at a time after being subjected to two types of disruptions. Therefore, the participants become more alert.

When the participant was exposed to disruptions, there are different patterns of ERpow in beta frequency, with 77.5% at P2, 96.79% at P4 and 96.22% at P6 respectively. The high value trend of ERpow for three type of disruptions are in line with previous studies that pointed out the mobile phone usage and driving disturbances may affects driving performance (Zhang et al. 2014). In the findings of (Abd Rahman, Dawal, and Bahreininejad 2014) high beta and alpha levels are low when doing the task and give stress effects to the mind when doing the task.

RELATIONSHIP

Pairwise comparison (Paired sample T-test) by using statistical SPSS to compare between two related groups on continuous variable. This comparison in terms of KSS, before and after driving session. Based on value $p>0.05$ which shows no significant comparison for KSS value before and after driving. It means the value shows that the driver in alert situation to keep driving the safe condition in the driving demands.

CONCLUSION

This study shows secondary task and type of disruption play important roles in determining the driver's physiological performance and condition. A 25-minute drive in a state of disruption and secondary task shows different physiological effects on drivers. Based on the EEG and HR results obtained, there are quite significant differences that can be seen during driving with interruption and secondary tasks. The results of the EEG analysis in average found that high ERPow values for Beta activity and low alpha activity value were found throughout the driving activity. This condition shows disruption influence the driver's condition, which they will become more alert and feel more stress while driving. Generally, the findings of this study provide guidance and direction for future studies and for the development of fatigue prevention equipment and detectors. In addition, it can provide a guideline for the related agencies to improve the road safety issues.

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DECLARATION OF COMPETING INTEREST

None

REFERENCES

Abd Rahman, Nurul Izzah, Siti Zawiah Md. Dawal, and Ardeshir Bahreininejad. 2014. The effects of driving environment on the mental workload of train drivers. *Advanced Engineering Forum* 10(February 2016): 93–99.

Biggs, S.N., Smith, A., Dorrian, J., Reid, K., Dawson, D., van den Heuvel, C., & Baulk, S. 2007. Perception of simulated driving performance after sleep restriction and caffeine. *Journal of Psychosomatic Research* 63(6): 573-577.

Brookhuis, Karel A., and Dick de Waard. 2010. Monitoring Drivers' mental workload in driving simulators using physiological measures. *Accident Analysis and Prevention* 42(3): 898–903.

Cantin, Vincent, Martin Lavallière, Martin Simoneau, and Normand Teasdale. 2009. Mental workload when driving in a simulator: Effects of age and driving complexity. *Accident Analysis and Prevention* 41(4): 763–71.

Charlton, Samuel G. 2007. Article in Press. *Prevention* 39: 873–85.

Dingus, Thomas A. et al. 2019. The prevalence of and crash risk associated with primarily cognitive secondary tasks. *Safety Science* (January): 1–8.

Edquist, Jessica, Tim Horberry, Simon Hosking, and Ian Johnston. 2011. Effects of advertising billboards during simulated driving. *Applied Ergonomics* 42(4): 619–26.

Fan, Jing et al. 2018. EEG-based affect and workload recognition in a virtual driving environment for ASD intervention. *IEEE Transactions on Biomedical Engineering* 65(1): 43–51.

Fukuda, Kyosuke, John A Stern, Timothy B Brown, and Michael B Russo. 2005. Memory Task. 76(7): 75–85.

Gallagher, Jason C, and Michael J Satlin. 2018. "Ac c Ep Te d Us Cr Ip t Ac c Division of Infectious Diseases Ep Te d Us Cr T."

Hassan, Hany M., and Mohamed A. Abdel-Aty. 2013. Exploring the Safety implications of young drivers' behavior, attitudes and perceptions. *Accident Analysis and Prevention* 50: 361–70.

Horberry, Tim et al. 2006. Driver distraction: The effects of concurrent in-vehicle tasks, road environment complexity and age on driving performance. *Accident Analysis and Prevention* 38(1): 185–91.

Horrey, William J., Mary F. Lesch, Arthur F. Kramer, and David F. Melton. 2009. Effects of a computer-based training module on drivers' willingness to engage in distracting activities. *Human Factors* 51(4): 571–81.

Hwang, Taeho, Miyoung Kim, Seunghyeok Hong, and Kwang Suk Park. 2016. "Driver Drowsiness Detection Using the In-Ear EEG." *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS* 2016-Octob: 4646–49.

Jung, Tirza, Christina Kaß, Dieter Zapf, and Heiko Hecht. 2019. Effectiveness and user acceptance of infotainment-lockouts: A driving simulator study. *Transportation Research Part F: Traffic Psychology and Behaviour* 60: 643–56.

Mahachandra, Manik, Yassierli, and Erdo D. Garnaby. 2015. The effectiveness of in-vehicle peppermint fragrance to maintain car driver's alertness. *Procedia Manufacturing* 4(Iess): 471–77.

Naujoks, Frederik, Christian Purucker, and Alexandra Neukum. 2016. Secondary task engagement and vehicle automation - Comparing the effects of different automation levels in an on-road experiment. *Transportation Research Part F: Traffic Psychology and Behaviour* 38: 67–82.

Owens, Justin M. et al. 2015. Creation of the Naturalistic Engagement in Secondary Tasks (NEST) distracted driving dataset. *Journal of Safety Research* 54(June): 33.e29-36.

Pastor, G., P. Tejero, M. Chóliz, and J. Roca. 2006. Rear-view mirror use, driver alertness and road type: An empirical study using EEG measures. *Transportation Research Part F: Traffic Psychology and Behaviour* 9(4): 286–97.

Placidi, Giuseppe et al. 2018. Self-induced emotions as alternative paradigm for driving brain–computer interfaces. *Computer Methods in Biomechanics and Biomedical Engineering: Imaging and Visualization* 1163: 1–8.

RMP, *Road Accident Statistics Report 2016*. Malaysia: Royal Malaysian Police, 2017.

Seen, Kee Sze, Shamsul Bahri Mohd Tamrin, and Goh Yong Meng. 2010. Driving fatigue and performance among occupational drivers in simulated prolonged driving. *Global Journal of Health Science* 2(1): 167–77. http://www.ccsenet.org/journal/index.php/gjhs/article/view/4057.

Sekaran U. & Baugie R. 2016. *Research Methods for Business: A Skill Building Approach*. 7th edition. Chichester, John Wiley & Sons Ltd.

Sundfør, Hanne Beate, Fridulv Sagberg, and Alena Høye. 2019. Inattention and distraction in fatal road crashes – Results from in-depth crash investigations in Norway. *Accident Analysis and Prevention* 125(February): 152–57.

Torkamannejad Sabzevari, Javad et al. 2016. An observational study of secondary task engagement while driving on urban streets in Iranian safe communities. *Accident Analysis and Prevention* 96: 56–63.

Wandtner, Bernhard, Nadja Schömig, and Gerald Schmidt. 2018. Secondary task engagement and disengagement in the context of highly automated driving. *Transportation Research Part F: Traffic Psychology and Behaviour* 58: 253–63.

Wang, Bo, Shauna Hallmark, Peter Savolainen, and Jing Dong. 2017. Crashes and near-crashes on horizontal curves along rural two-lane highways: Analysis of naturalistic driving data. *Journal of Safety Research* 63: 163–69.

World Health Organization. 2015. Global Status Report on Road Safety. 2015.

Zhang, Yu et al. 2014. The effects of visual and cognitive distractions on operational and tactical driving behaviors. *Human Factors* 56(3): 592–604.