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The Vigilant Brain

MONITORING VIGILANCE: USING EEG TO ASSESS CHANGES IN DRIVERS' VIGILANT STATE.

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Abstract

Driving in a monotonous environment, such as a highway, facilitates a phenomenon known as driver fatigue which has been linked to the cause of many road accidents in Europe. Driver fatigue creates a possibility for accidents to occur due to vigilance decrement. In this study, an experiment was designed to investigate the ability of EEG to predict sleepiness and changes in driving performances. Alpha power and theta power were derived from the EEG, sleepiness was assessed using the Karolinska Sleepiness Scale and driving performance was assessed by determining steering errors and instruction misses. Multi-level model analyses were employed to explore the relations between the aforementioned variables. The results showed that alpha and theta power are related to sleepiness. Changes in alpha power was related to changes in instruction misses, though theta power was not related to instruction miss. Both alpha and theta power were not related to changes in steering errors. It can therefore be concluded that it is possible to monitor vigilant state using the EEG through observing levels of sleepiness and instruction misses.

Keywords: EEG, alpha, theta, karolinska sleepiness scale, performance measures, vigilance

Introduction

Driving is a complex task that a large percentage of the population engages in daily, which requires continuous attention (van der Hulst et al., 2001). Due to its complexity, infrastructure has been designed in such a way as to simplify the task. This simplification of the driving task can be seen by the implementation of highways in road systems (Larue et al., 2011). When driving on highways, the driving task is reduced to simply lane keeping, making the task highly predictable. According to Thiffault and Bergeron (2003), the highly predictable nature of the task results in the decline of the driver's ability to react to unpredictable events. Therefore, the monotony of driving on a highway impedes the driver's ability to respond to events that were not anticipated.

Statistics show that in Europe, 10% to 20% of traffic accidents occur because of a vigilance decrement (Bergasa et al., 2006; Ganesh & Gurumoorthy, 2021). Vigilance, often referred to as sustained attention, can be described as the ability to maintain attention and alertness over time (Al-Shargie et al., 2019; Zhou et al., 2021). Therefore, a vigilance decrement can be described as instances where an individual experiences a decline in performance efficiency over a period of time due to an inability to maintain attention and alertness (Helton & Russel, 2008). Research by Mackworth (1948) on vigilance has shown that as time on a task increases a decline can be observed in the efficiency of the task performance. This decrease in performance is likely due to a vigilance decrement. Road accidents that occur due to a vigilance decrement tend to be more serious when it involves heavy vehicles, for example freight trucks and busses (Vitols & Voss, 2021). Therefore, to reduce these accidents, it is necessary to detect when a driver may experience a vigilance decrement.

The following sections will describe theoretical accounts of vigilance decrement, the antecedents to vigilance decrement and how the vigilant state of an individual can be observed using EEG and behaviour measures.

Vigilance Decrement

Many theories seek to explain vigilance decrement and these theories make use of the concept of mental overload or underload (Neigel et al., 2020). Overload theories postulate that vigilance decrement is the result of a depletion of cognitive resources, while underload theories posit that the decrement occurs due to a lack of stimulation by the task (Helton & Warm, 2008). Two theories that make use of those mental overload and underload concepts, respectively, are the cognitive resource theory and the mindlessness theory (Helton & Warm, 2008; Neigel et al., 2020).

The cognitive resource theory assumes that individuals can only process a certain amount of information at a given time (Flanagan & Nathan-Roberts, 2019; Wickens, 2002). Therefore, it implies that as individuals spend time on a task, it is likely that the task can diminish their level of vigilance due to the depletion of resources. Additionally, Flanagan and Nathan-Roberts (2019) expressed a relationship between task difficulty and the amount of resources required to complete that task, such that a task with a high level of difficulty would increase vigilance decrement. A study conducted by Ralph et al. (2017) found that when breaks are taken during the task, this can be viewed as an opportunity for renewal of cognitive resources and thus, alleviating the vigilance decrement. Therefore, while resources are depleted during tasks, taking a break can restore these resources.

The mindlessness theory postulates that the vigilance decrement is a result of the monotony of a task (Helton & Warm, 2008; Manly et al., 1999; Robertson et al., 1997). According to this theory, cognitive resources are not depleted over time because these resources are thought to be limited but fixed (Ralph et al., 2017). Individuals are therefore more likely to experience lapses in vigilance due to the repetitive and monotonous nature of a task. According to Thomson et al. (2015), there is a withdrawal of attention from the task at hand, which results in a mindless approach to the task. This theory suggests that when engaging in simple tasks, rather than complex task, an individual is more likely to experience a vigilance decrement (Robertson et al., 1997). To account for the decrement experienced as time is spent on a task, it is proposed that cognitive resources are allocated elsewhere (Thomson et al., 2015). This allocation of cognitive resources could go towards "mind wandering", which is considered the default state of the mind (Flanagan & Nathan-Roberts, 2019).

Flanagan and Nathan-Roberts (2019) describe mind wandering as attention that is diverted away from the task at hand and directed inwardly. Mind wandering can be intentional, disengagement of attention from the task at hand, therefore, a conscious choice by the individual, or unintentional, disengagement of attention from the task which is not a deliberate act by the individual (Seli et al., 2016). Mind-wandering seeks to account for why there is a disengagement of attention on the task at hand, resulting in a vigilance decrement an individual may experience during simple, monotonous tasks (Flanagan & Nathan-Roberts, 2019; Neigel et al., 2020). According to Flanagan and Nathan-Roberts (2019) and Thompson et al. (2015), when engaging in a task with a highly monotonous stimulus, executive control is likely to allocate resources towards mind wandering which in turn leads to vigilance decrement.

Antecedents to Vigilance Decrement

Vigilance decrement can reduce a person's ability to respond to unanticipated events which can be due to driver fatigue (Merat & Jamson, 2013). Driver fatigue can be categorized as sleep-related fatigue and task-related fatigue (May & Baldwin, 2009; Peng et al., 2021). According to May and Baldwin (2009), sleep-related fatigue is described as a decline in body function due to circadian rhythms, sleep-deprivation, and sleep disorders, whereas task-related fatigue includes active and passive fatigue. Active fatigue occurs when a driver drives in a more complex or urban environment for a long period of time, while passive fatigue occurs in a more monotonous and repetitive environment (Helton & Russell, 2012; Körber et al., 2015).

According to Körber et al. (2015), active fatigue is caused by the driver being engaged in the driving task for an extended period which results in a depletion of mental resources. Active fatigue, as described, seems to be related to the cognitive resource theory which argues that as time on task increases, an individual will experience a depletion in cognitive resources. Passive fatigue, on the other hand, is seen as the opposite of active fatigue as attentional loss and performance decrement are due to the monotony of the task. This form of fatigue is related to the mindlessness theory which posits that an individual experiences vigilance and performance decrement due to task underload. That is, because the task is not demanding, attention on the task may be diverted to an unrelated task.

Passive fatigue is especially relevant in highway driving environments, as these can be described as monotonous and repetitive. Additional to the effect of a monotonous environment of driving on a highway, is the amount of time drivers spend in that environment. A study conducted by Peng et al. (2021) found that driver fatigue could be observed in drivers after driving for 19 to 33 minutes. Additionally, a study conducted by Zhang et al. (2021) found a decreased in driving performance after 40 minutes of driving. When driving for an extended period in a long and monotonous environment most drivers exhibit an increase in fatigue and a decrease in level of vigilance (Campagne et al., 2004; Körber et al., 2015). The monotony of the driving task situates the driver in a state where they may experience reduced cognitive demand which can result in an increase in fatigue and lapses of vigilance or vigilance decrements (Larue et al., 2011; Ma et al., 2018; McWilliams & Ward, 2021). This deterioration of vigilance, due to possible task monotony, could then lead to accidents because drivers fail to maintain attention on the driving task (Larue et al., 2011).

According to Dinges (1995), fatigue and sleepiness can be considered as antecedents of vigilance decrement. Sleepiness and fatigue are terms that are often used synonymously. Sleepiness is a ubiquitous phenomenon defined as the inability to remain awake when engaging in a task (Dement & Carskadon, 1982; Shen et al., 2006), whereas fatigue is described as an overwhelming sense of tiredness, lack of energy and exhaustion which is usually associated with reduced cognitive/physical functioning (Shen et al., 2006). A study conducted by Philip et al. (2005) investigated the relationship between sleepiness, fatigue and driving and found that individual subjective measures of sleepiness had a negative correlation with driving performance, whereas individual subjective measures of fatigue was found to not be an accurate predictor of driving performance. Therefore, subjective measures of sleepiness, rather than fatigue, seems to have a relationship with driving performance such that as sleepiness increases driving performance decreases.

According to Philip et al. (2010) and Verster and Roth (2013), one of the most common causes of accidents and crashes is driver's sleepiness. Therefore, extensive research into the effect of sleepiness on vigilance while driving has been done. A study conducted by Philip et al. (2005) explored the effect of sleep and fatigue on driving performance with randomized crossover design study where participants were either sleep deprived, or non-sleep deprived. In this study, participants' subjective measure of sleepiness was recorded using the Karolinska Sleepiness Scale (KSS) and fatigue was measured using a Visual Analogue Scale (VAS). The results showed that the driving performance of the sleep deprived participants significantly declined when compared to the non-sleep deprived participants. This finding further bolsters the understanding that a negative relationship between sleepiness and driving performance exists.

Furthermore, research has been conducted on vigilance decrement using a simulated environment. A study by Theresia et al. (2018) explored the impact of sleep deprivation on vigilance, fatigue and driving performance when operating a train. Participant's subjective measure of sleepiness was measured using the KSS, fatigue, using the VAS, and objective measure of vigilance, using the Psychomotor Vigilance Task (PVT). The results showed that there was a substantial decrement in vigilance in participants who were sleep deprived. These studies further support the idea that a decline in driving performance due to a vigilance decrement is associated with sleepiness. Therefore, sleepiness appears to play an integral role in the relationship between driving performance and vigilance.

Investigating Vigilance State using Performance Measures

There are various performance measures that are used to investigate the vigilance decrement. These measures include eye movement, psychomotor tests, vehicle parameters or driving behaviours and facial expression (Jagannath & Balasubrananian, 2014; Hu & Lodewijks, (2020); Lal & Craig, 2001; Zhou et al., 2020). Eye movements and facial expression coincided as measures as video recordings could be used to capture yawning, closure of the eyes, blinking rate and head inclination (Jagannath & Balasubrananian, 2014; Hu & Lodewijks, 2020). Specifically with eye movements, it was posited that little to no eye movements and small, fast rhythmic blinks could be observed in participants who were experiencing increased fatigue (Lal & Craig, 2000 as cited in Lal & Craig, 2001)

Psychomotor tests are used in research seeking to investigate fatigue and include reaction time tests and simulated driving (Grandjean, 1979; Lal & Craig, 2001). With these tests, it was expected that a degradation in performance would be observed as an individual fatigues (Lal & Craig, 2001). As mentioned in the previous section, Theresia et al. (2018) implemented the use of psychomotor tests, namely the Psychomotor Vigilance Task (PVT) to attain an objective measure of vigilance. While PVT is sensitive to detecting decreases in cognitive function, after reflecting on the method used by Theresia et al. (2018) a limitation was observed. When paired in a driving simulator research, PVT can only be conducted when the individual is not using the driving simulator. Therefore, it is not possible to get real-time measures of vigilance using this measure.

Vehicle parameters or driving behaviours included braking, lane tracking, speed and steering wheel manoeuvring (Jagannath & Balasubrananian, 2014). According to Lal and Craig (2001), a relationship between driving performance and fatigue exists such that as a person fatigues a decrease in their performance can be observed. A study by Feng et al. (2009) found that fatigued drivers had a tendency to preform less steering micro-corrections. Similarly, an increase in driving errors and driving lane variability can be observed as time on task increases (Wascher et al., 2016). These performance measures make it possible to have real-time measurements.

Investigating Vigilant State using EEG

Research into vigilance has been conducted by exploring several measures. Warm et. al (2006) identified task type, perceived mental workload, neural measures of resource demand in vigilance, and task-induced stress as methods currently used to investigate vigilance in signal detection. From these measures, neural measures are better suited when assessing vigilance as they offer a more direct measure of the cognitive processes that occurs when an individual performs a task or responds to a stimulus (Eichele et al., 2010; Martel et al., 2014). Neural measures of resource demand in vigilance can be assessed using the method known as electroencephalography (EEG) (Samima et al., 2017).

EEG allows researchers to acquire brain signal data in a non-evasive manner (Bandara & Kiguchi, 2018; Paszkiel, 2020). Alpha (α), beta (β), delta (δ), gamma (γ), theta (θ), mu (μ) are signal frequency bands that are used to characterized brain activities. Delta, theta, alpha, beta, and gamma signal frequency bands have been found to be sensitive to vigilance decrement as these frequencies are sensitive to the level of sleepiness/wakefulness (Tran et al., 2020). In a meta-analysis conducted by Tran et al (2020), 21 studies which investigated changes in EEG activity associated with fatigue were selected. The analysis posits that the theta and alpha frequency bands had a large increase as the participants fatigued. Bonnefond et al (2010) and Paszkiel (2020) also observed a connection with vigilance decrement and the alpha and low-frequency theta activity in which the power of the frequency bands increased with time on task (Bonnefond et al., 2010; Paszkiel, 2020).

The placement for electrodes can be divided into five regions: frontal, temporal, central,7osterior and occipital (Bian et al., 2014; Wang et al., 2019). According to Tran et al. (2020), as a person fatigues large increases in the power of the theta frequency band can be observed across the frontal, central and posterior regions while moderate to large increases in the power of the alpha frequency band can be seen in the central and posterior regions. Alternatively, in the systematic review conducted by Craig et al. (2012) an increase in activity over the entire cortex for theta and alpha power could be observed as the person fatigues. The systematic review investigated 17 studies and found that the theta and alpha frequency bands had the most significant changes in most of the studies reviewed. These changes were increases in the power of the alpha and theta frequency bands as the participant fatigued.

The alpha frequency band is thought to regulate the allocation of attention by helping to extract important information, while neglecting irrelevant information (Sokoliuk et al., 2019). According to Sokoliuk et al. (2019), two sources of alpha exist, visual and parietal, which both modulate attention though have different functional roles depending on the behavioural demand. This modulation of attention occurred in the occipital and parietal regions. The study by Sokoliuk et al. (2019) showed that visual alpha expressed a decrease in alpha power when there was an increase in attention to visual stimuli. It could therefore be assumed that when an individual is not attending, a decrease in alpha power would be expected. This assumption was proven in a study conducted by Lobier et al. (2018) which states that an increase in the alpha band frequency was associated with a decrease in reaction times to attended stimuli. Alternatively, Lobier et al. (2018) identified an increase in the alpha frequency band in the frontal, parietal and occipital regions whereas Sokoliuk et al. (2019) observed an increase in the parietal and occipital regions.

In addition, activity in the theta frequency band has been correlated with cognitive control (Cavanagh & Frank, 2014). A study conducted by Wascher et al. (2014) found that frontal theta was a reliable marker for changes in cognitive processing as an individual fatigues. Therefore, it can be inferred that driving errors that occur due to fatigue could be a result of an increase in theta power due to increase in cognitive processing as a result of an increased effort to maintain a high performance. Another study by Wascher et al. (2016) found that driving errors and driving lane variability increased as time on task increased. Similarly, an increase in both theta and alpha power was observed as time on task increased. This increase in alpha and theta power occurred in the posterior region (Wascher et al., 2016). Alternatively in an earlier study, Wascher et al. (2014) correlated mental fatigue with increases in the frontal theta and frontal and occipital alpha frequency bands. While increase in theta power is thought to be a result of increased cognitive processing, to compensate for a deteriorating cognitive control, due to fatigue (Arnau et al., 2021; Wascher et al., 2014), increases in alpha power is thought to be due to boredom or attentional withdrawal due to the monotony of the task (Wascher et al., 2016).

Purpose of study

The current study sought to explore the use of EEG to make inferences of the vigilant state of an individual while driving in a monotonous environment. To accomplish this, methods used in previous studies were applied to replicate the obtained results. This study used EEG to extract measures of the alpha and theta frequency bands to predict changes in the subjective measure of KSS and the performance measures of Steering Control and Instruction Miss to make inference about the vigilant state of an individual.

This study sought to answer the following research questions:

1) Is it possible to relate individual changes in level of sleepiness due to changes in EEG measures?
2) Is it possible to relate individual changes in driving performance measured through steering errors and instruction misses using EEG measures?

Method

Participants

A total of 23 participants took part in the experiment. Participants were recruited on a voluntary basis from the SONA test subject pool system or by the researcher. The group consisted of 12 (54.5%) males and 10 (45.5%) females, age range from 18 to 31 (M = 22.32, SD = 3.01). All participants completed a visual acuity test to assess their self-reported normal or corrected-to-normal vision. Participants filled out a questionnaire with demographic questions as well as questions that would help to identify and understand the EEG data if any anomalies were to appear. Examples of these questions are: 'Have you taken any mind-altering drugs in the last two weeks?' and 'Have you had alcohol in the last 24 hours?'. The data collected from participant 12 was removed as this participant requested to stop the study before it was completed. The study received approval by the ethical board of the University of Twente (project nr. 220181) and all participants signed informed consent prior to the experiment.

Materials and Apparatus

Hardware

EEG data was recorded using BrainVision Recorder software (Brain Products, 2018). The EEG signal was acquired using 32 electrodes attached to the ActiCap. Electrodes were attached on the face near the left and right eye to measure the horizontal EOG (hEOG) and vertical EOG (vEOG). The EOGs were placed in such a way that they were not too close to the eyes, did not obstruct the participant's view and did not irritate the participant. A ground electrode was placed on the forehead. The signal was amplified using the BrainProduct Amplifier Standard powered by ActiChamp amplifier.

The driving simulation included a "Next Level Racing" chair and the Logitech G920 Driving Force consisting of a steering wheel and foot pedals. An automatic transmission was used, therefore only the brake and gas pedals were used. In order to start driving, participants needed to shift into first gear which was done by clicking the metal level located at either side beneath the wheel. This lever was also used to put the car into reverse.

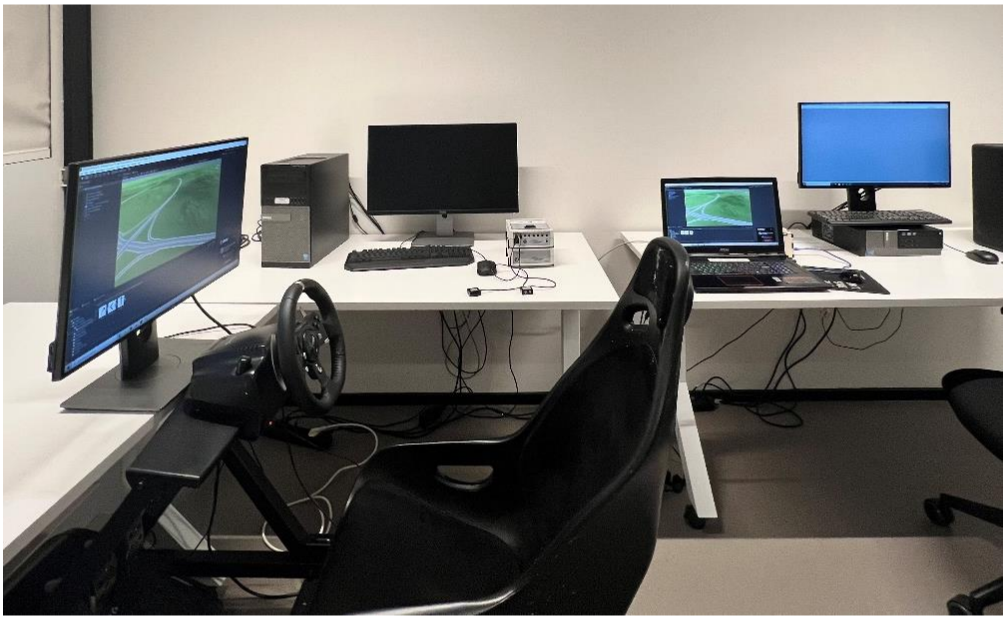


Figure 1
Set-up used during the experiment.

Software

The driving environment was developed in Unity (version 2019.2.21f1). It utilized pre-existing plugins like Fantastic City Generator, iTS (intelligent traffic system), Logitech SDK for handling user input and Vehicle Physics by NWH. The driving environment was a closed highway system with cloudy weather conditions and traffic. Traffic in this environment included other cars, however, no pedestrians or bikes.

Design

The focus of the study was the measurement of EEG activity to have a physiological measure of sustained vigilance over a prolonged period during a driving task to be able to predict moments where a vigilance decrement appeared, and errors could transpire. For this reason, the experiment used a repeated measures design where participants drove in a simulated environment for a long duration while receiving visual cues indicating directional driving instructions. The experiment required participants to drive in the simulated environment for one hour. Participants drove in a highway scenario, where they received visual cues in the driving environment of the driving instructions they were to perform.

The driving instructions were to drive straight, turn right, and switch to the left lane. When participants approached a junction, a visual cue was given which instructed the participant to make a right turn (Exit the highway) or drive straight ahead. Participants received another driving instruction which instructed them to switch to the left lane of the highway. Table B1 in Appendix B describes the driving instructions participants encountered in the driving environment, the trigger symbol that was used for the box collider in the driving environment and the marker symbol that was received by the BrainVision Amplifier.

Measures

Questionnaires

The Karolinska sleepiness scale (KSS) was used to measure the subjective level of sleepiness at moments throughout the driving task at five minute intervals (Ingre et al., 2006; Miley et al., 2016). These moments were at the start of the experiment and then every five minutes for the duration the experiment. The KSS is a 9-point scale ranging from 1 (extremely alert), 3 (alert), 5 (neither alert nor sleepy), 7 (sleepy, but no difficulty remaining awake), and 9 (extremely sleepy, fighting sleep), with 7–9 representing a high level of sleepiness (Ingre et al., 2006; Miley et al., 2016).

Performance Measures

The performance measures used in this study were steering control and instruction misses. Steering control was observed through the ability of the participant to remain in the driving lane and respond appropriately to directional changes of the driving environment. When the participant collided with the divider, lamppost and/or junction points within the driving environment this resulted in a count for steering control. As participants continue to collide with the divider, lamppost and/or junction points the count for steering control will increase by one per collision. Driving performance then decreases as steering control count increases.

These observations were made offline through the screen recordings of the driving environment and the trigger data file obtained from the EEG recordings. The trigger file recorded each time the participant drove into the divider, a lamppost and/or the junction point. The video recordings were used to confirm what the trigger data recorded. Instruction misses were observed when the participant did not follow the onscreen instructions that were displayed in the driving environment. Similar to the steering control, these observations were made offline through the screen recordings of the driving environment and the trigger data file obtained from the EEG recordings. As instruction misses increases, driving performance is considered to have decreased.

EEG

The EEG was measured from 32 Ag/AgCl ring electrodes located at: Fp1, Fp2, Afz, F3, F4, F7, F8, Fz, FC3, FC4, FT7, FT8, FCz, C3, C4, T7, T8, Cz, CP3, CP4, TP7, TP8, TP9, TP10, CPz, P3, P4, P7, P8, Pz, O1, O2, Oz (Appendix B, Figure B1).

Task and procedure

Specific measurements of the participant's head were taken to find the center and circumference of the participant's head and an EEG cap that would fit comfortably. The EEG and EOG electrodes were then connected to the cap after the participant was asked to sit in the driving simulator chair. The impedances of the electrodes were then measured to ensure they did not surpass 10 kΩ, which indicated that the signal is good or acceptable.

The participants received instructions on the tasks they would be performing. Additionally, participants received a brief explanation with visual examples of how to use the driving simulator. Any questions the participant had were answered at this time. Participants were instructed to drive at a speed where they still had enough control when making turns. A timer was started as participants began driving in the driving simulator. In five minute intervals, participants were asked to report their level on sleepiness using the KSS. Once an hour had gone by, the experiment concluded.

Data Analysis

EEG analysis

The raw EEG data were analysed using the BrainVision Analyzer version 2.2. The data was filtered using a lower cut-off of 0.1 Hz and an upper cut-off of 30 Hz to remove muscular movements and artifacts. An artifact rejection was performed using raw data inspection set to automatic with a gradient criterion of 30 µV/ms, minimum and maximum difference of maximum 300 µV/ms with an interval length of 200 ms and a low activity criterion of 0.5 µV/ms with an interval length of 100 ms. Following the artifact rejection, an ocular correction with independent component analysis (ICA) was conducted in semi-automatic mode for vertical and horizontal eye movements correction. On average, two components were move that were deemed to be depicting eye movement.

Another artifact rejection was done with a gradient criterion of 30 µV/ms, minimum and maximum difference of maximum 200 µV/ms with an interval length of 200 ms and a low activity criterion of 0.5 µV/ms with an interval length of 100 ms. A second artifact rejection was performed to further reduce noise in the data by removing any artifacts with a gradient over 200 µV/ms. The data was then segmented manually creating a segment of 3600 second (60 minutes). Another segmentation was carried out which segmented the data equally with a segment size of 300 seconds (five minutes) to create 12 segmented epochs. A final segmentation was performed on each of the 12 epochs to segment each equally with a segment size of three seconds. A Fast Fourier Transformation (FFT) was done on the final epochs. The FFT was done for all electrodes using a Hamming Window with a 10% overlap and variance correction was applied. The output of the FFTs was determined in power (μV^2).

The electrodes that were selected for statistical analyses were F_3, F_4, F_Z, C_3, C_4, C_Z, P_3, P_4, P_Z, O_1, O_2, O_Z. These electrodes were selected as they overlay four relevant brain regions, the frontal, central, posterior and occipital cortex. The data was exported for different frequency bands. The frequency domain for alpha was 8-12 Hz, therefore including both the lower and upper alpha, and the frequency domain for theta was 4-8 Hz. Grand averages of all participants were made, using all electrodes, across all participants. Using the grand averages, the topographical views of alpha (8-12 Hz) and theta (4-8 Hz) frequency bands were visually inspected and compared.

Statistical Analysis

The statistical analysis was conducted using R (Rstudio Team, 2022). The data sets for the theta and alpha frequencies were created to conduct further statistical analyses on the collected data. Each dataset consisted of 22 participant's data. This included participant number, acuity score, age, gender, nationality, education, driving experience, handedness, hours of sleep previous night, drug use, alcohol use, caffeine use, time, KSS, Frequency, Region, Electrode, continuous variable of alpha and theta power, continuous performance variables (Steering Errors and Instruction Miss).

Additional datasets were created which transformed the alpha and theta power. The ^{10}log of the alpha power and theta power were taken to normalize the data.

Descriptive statistics were conducted to get a better understanding. Additionally, a line graph was constructed to understand the relationship between the variables (alpha and theta power, KSS, Steering Errors and Miss). The line graph was constructed using the standard error of the mean for all variables (alpha and theta power, KSS, Steering Errors and Miss) against time. Additionally, boxplots were constructed with the aforementioned variables and time. These figures can be found in Appendix C. Further statistical analyses were performed to examine the relationship between the alpha and theta power and KSS scores, Steering Errors and Instruction Miss.

These analyses were done using multi-level analysis models. The first model was built using the log transform of alpha power as the outcome variable and the subjective measures (KSS scores) and behaviour performance measures (Instruction Miss and Steering Errors) as the predictors. Another multi-level analysis model was done using theta power as the outcome variable and the subjective and performance measures as the predictors. Both models made use of the individually dependent intercept. The models contained both population level and participant level effects. The results were compiled into a table which presented both the fixed effects and random effects. The results of the models were interpreted using the intra-class correlation (ICC), $\sigma2$ (within person residual variance) and $\tau00$ (between person variance). The ICC describes the proportion of variance which could be explained by between person differences (Kleiman, 2017).

Results

Descriptive Statistics

The descriptive statistics of all variables used in this data analysis can be found in Table 1. The mean of the alpha power was 0.25 with a standard deviation of 0.25. The mean of the theta power was 0.33 with a standard deviation of 0.26. The mean of the KSS scores was 4.56 with a standard deviation of 1.68, which positions this value approximately halfway between the min (1) and max (9). The mean of Steering Errors was 1.94 with a standard deviation of 2.11. This value is closer to the min (0) than the max (9) which means the driving performance was average to good. The mean of Instruction Miss was 0.16 with a standard deviation of 0.37. This value falls closer to the min (0) which indicates that not many instruction misses occurred throughout all participants.

Table 1

Descriptive Statistics of Alpha and Theta power, Karolinska Sleepiness Scale (KSS), Steering Errors and Instruction Miss

Variable	Min	Max	Mean (M)	Std. Dev (SD)
Alpha Power (μV^2)	0.04	2.84	0.25	0.25
Theta Power (μV^2)	0.06	3.02	0.33	0.26
KSS	1	9	4.56	1.68
Steering Errors	0	9	1.94	2.11
Instruction Miss	0	2	0.16	0.37

Figure 2 depicts how KSS changed over time. A sharp decrease in KSS score can be seen after the five minute mark. This indicates that between five and 10 minutes participants experienced a moment of alertness. At the 10 minute mark, an increase is observed in KSS score rating. This shows that as participants continued through the experiment, they reported increasing levels of sleepiness.

Figure 2

Line graph depicting how Karolinska Sleepiness Scale (KSS) changes over time.

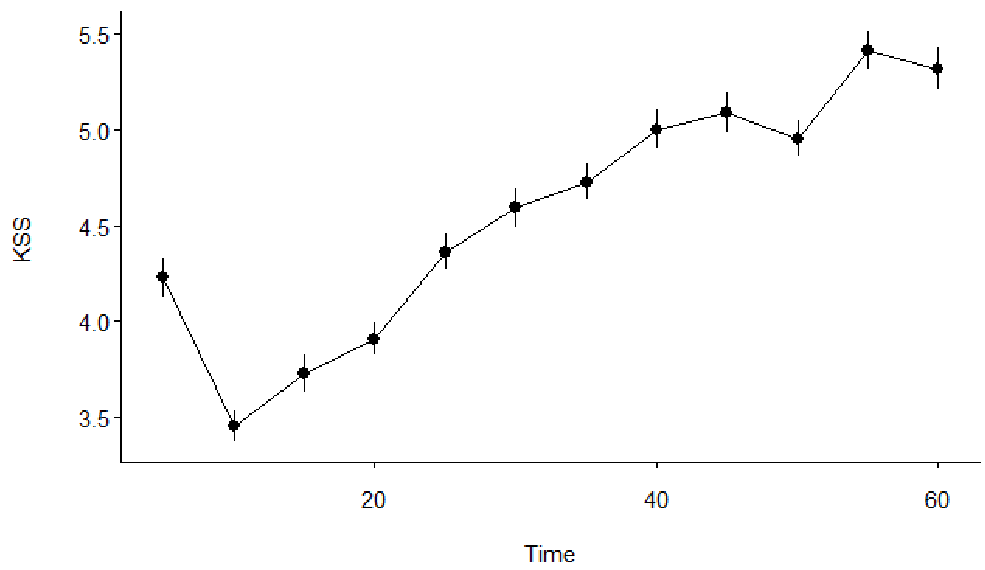


Figure 3 shows how Steering Errors changed over time. After 10 minutes a large decrease in Steering Errors can be observed, which indicated that participants made the most mistakes during the first 10 minutes of driving in the driving environment. The 10 minute period where a high rate of Steering Errors occurred is thought to be due to a learning effect, where participants are assimilating to the driving environment.

Figure 3

Line graph depicting how Steering Errors changes over time.

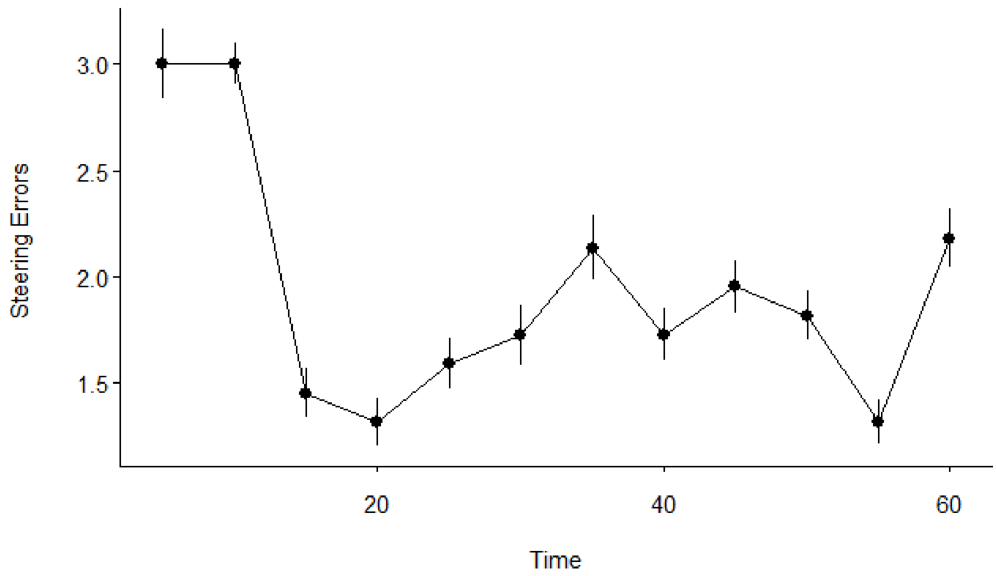


Figure 4 depicts how Instruction Miss changed over time. As time increases, it can be observed that Instruction Miss fluctuates with the most misses occurring in the first 15 minutes of the experiment.

Figure 4

Line graph depicting how Instruction Miss changes over time.

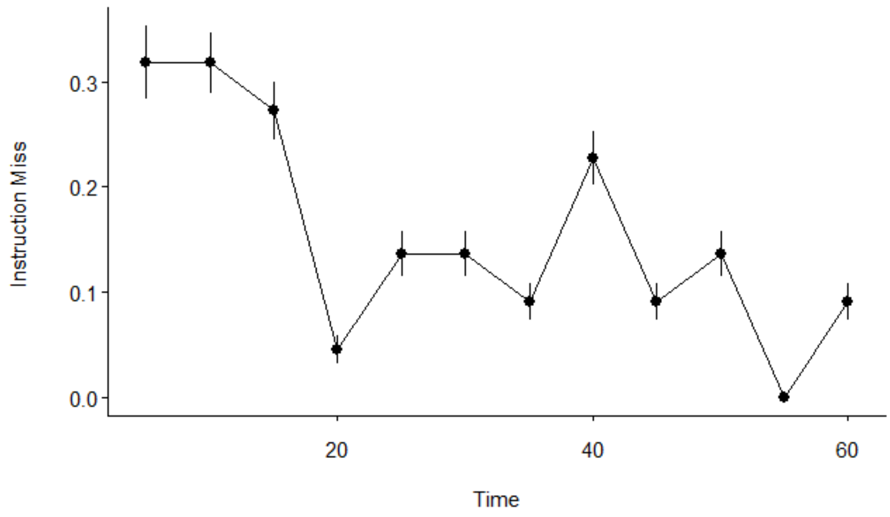
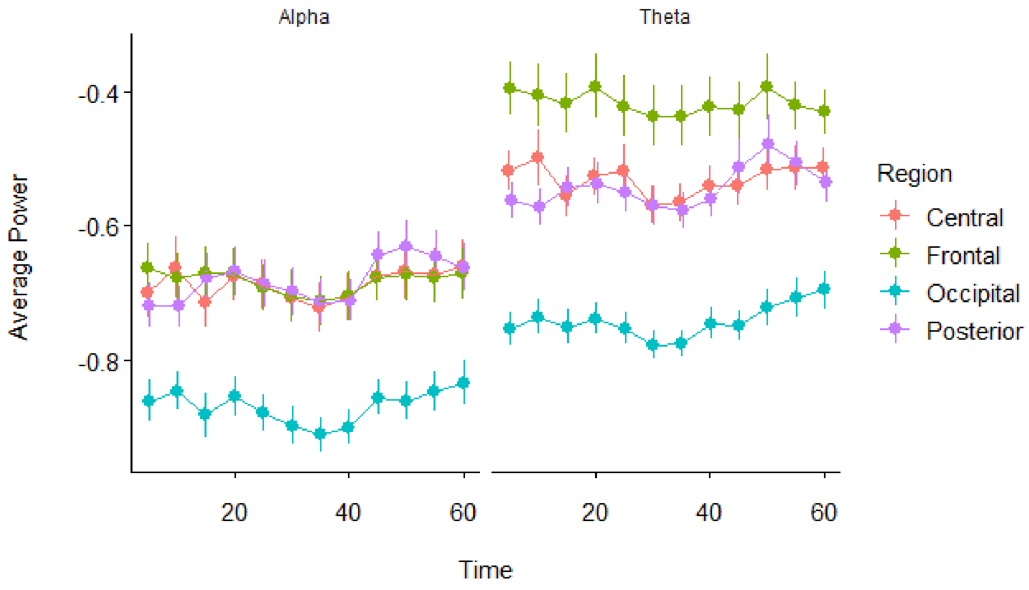


Figure 5 shows how the average power (μV^2) of the alpha and theta frequency bands changed over time. Further distinction was made for the four different regions, central, frontal, posterior and occipital. It can be observed that alpha and theta power fluctuated throughout the 60 minutes.

Figure 5

Line graph depicting changes of alpha and theta power over time.



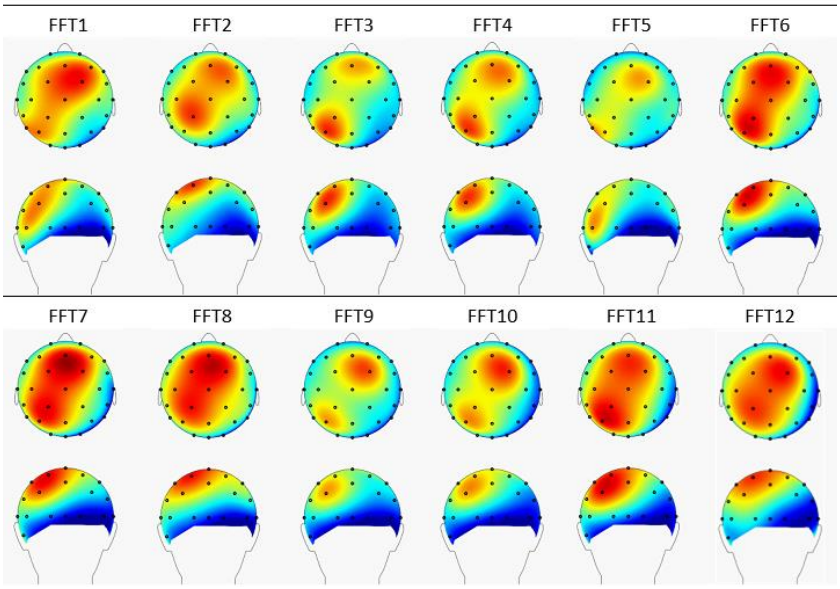
EEG Topography

Alpha

The grand average taken using all 12 FFTs to examine the activity which could be observed for the alpha frequency band, as seen in Figure 6. FF 1 represented the first five minutes while FFT 12 represented the last five minutes as all 12 FFTs allot to 60 minutes. From the figure, the frontal and posterior regions show the highest alpha activity throughout all the FFTs, with the occasional appearance of activity in the central region. It can be observed that FFT 7 (35 minutes) and FFT 8 (40 minutes) shows the highest activity in the frontal region. Conversely, FFT 6 (30 minutes) and FFT 11 (55 minutes) has the highest activity in the posterior region.

Figure 6

Grand Average Fast Fourier Transforms (FFT) Topographical View of the Alpha Frequency Band over time

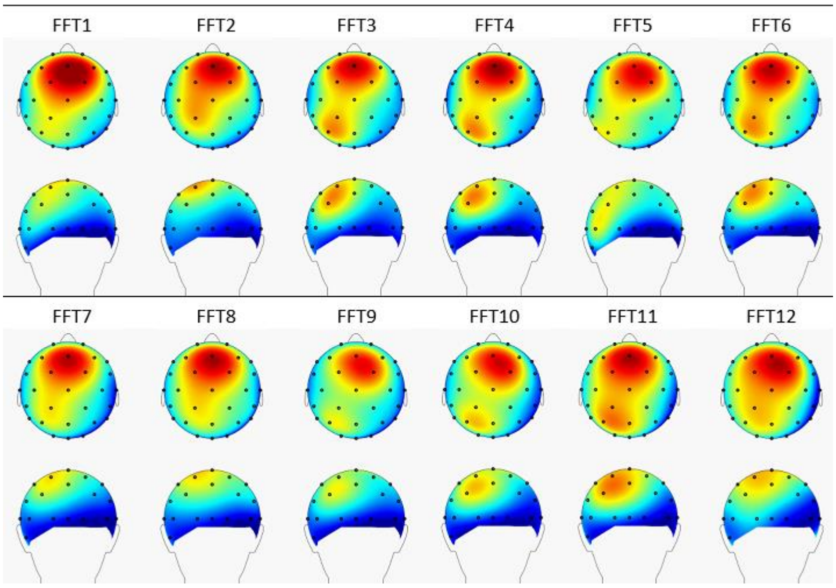


Theta

The grand average taken using all 12 FFTs to observe the activity of the theta frequency band throughout the duration of the experiment, as seen in Figure 7. The 12 FFTS combine allot to 60 minutes where FF 1 represented the first five minutes while FFT 12 represented the last five minutes. Throughout all the 12 FFTs, the frontal region has shown consistently high activity. Occasionally some activity in the posterior region was visible, however, not as high or as frequent as the frontal region. It can be observed that FFT 1 (five minutes) shows very high activity in the frontal region, which correlates to the first five minutes of the driving task. The pattern of high activity in the frontal persists, with varying intensities, throughout the 12 FFTs.

Figure 7

Grand Average Fast Fourier Transforms (FFT) Topographical View of the Theta Frequency Band over time



Multilevel Linear Model

Alpha

Table 2 depicts the model built using alpha as the outcome variable. The ICC of the model shows that 62% of the variation in KSS scores, Steering Errors and Instruction Miss is due to individual differences. The variation within participants is 0.03 and the variation between participants is 0.06. The first parameter estimate for KSS yields $10^{0.0092}$ (1.0214) µV^2 and is statistically significant ($p = 0.003$). This shows that as KSS increases by one unit, alpha power will increase by 1.0214 µV^2. The second estimate yields $10^{0.0034}$ (1.0079) µV^2 and is not statistically significant ($p = 0.126$), indicating that there is no statistical relationship between Steering Error and alpha power. The third parameter estimate Instruction Miss yields $10^{0.0337}$ (1.0807) µV^2 and is statistically significant ($p <0.001$). This indicates that Instruction Miss increases by one unit, alpha power will increase by 1.0807 µV^2.

Table 2

Model for the Relationship of the log transformed alpha power µV^2 with KSS scores, Steering Errors, Instruction Miss

Predictor	Alpha power			
	Estimates	std. Error	CI Lower – Upper	p
(Intercept)	-0.7795	0.0423	-0.8832 – -0.6758	<0.001

KSS	0.0092	0.0028	0.0031 – 0.0154	0.003
Steering Errors	0.0034	0.0020	-0.0009 – 0.0077	0.126
Instruction Miss	0.0337	0.0087	0.0148 – 0.0526	<0.001
Random Effects				
σ^2	0.03			
$\tau_{00\ \text{Participant}}$	0.06			
ICC	0.62			
$N_{\text{Participant}}$	22			
Observations	3168			
Marginal R^2/Conditional R^2	0.004/0.621			

The first ten minutes of the data was removed, to remove the assumed learning effect, and another multilevel model was built using the modified data. This was done to see if the influence of steering errors on alpha power would become statistically significant. Table 3 shows that though the first 10 minutes was removed, this did not improve the relationship between alpha power and Steering Errors ($p = 0.657$). Alternatively, Instruction Miss now does not have a statistically significant relationship with alpha power ($p = 0.097$). KSS, however, had a statistically significant relationship ($p = 0.025$) with alpha power such that as KSS increases by one unit, alpha power had an increase of $10^{0.0082}$ (1.0190) μV^2.

Table 3

Model for the Relationship of the log transformed alpha power μV^2 with KSS scores, Steering Errors, Instruction Miss using modified data set

Predictor	Alpha power			
	Estimates	std. Error	CI Lower – Upper	p
(Intercept)	-0.7684	0.0552	-0.8766 – -0.6602	<0.001
KSS	0.0082	0.0037	0.0010 – 0.0155	0.025
Steering Errors	0.0012	0.0027	-0.0041 – 0.0065	0.657
Instruction Miss	0.0189	0.0114	-0.0034 – 0.0412	0.097
Random Effects				
σ^2	0.03			

τ_{00} Participant	0.06
ICC	0.66
N Participant	22
Observations	2640
Marginal R^2/Conditional R^2	0.003/0.656

Theta

Table 4 depicts the model built using theta as the outcome variable. The ICC of the model shows that 49% of the variation in KSS scores, Steering Errors and Instruction Miss is due to individual differences. The variation within participants is 0.05 and the variation between participants is 0.04. The first parameter estimate yields $10^{0.0084}$ (1.0195) μV^2 and is statistically significant ($p = 0.029$). This shows that as KSS increases by one unit, theta power will increase by 1.0195 μV^2. The second estimate Steering Errors yields $10^{0.0027}$ (1.0062) μV^2 and is not statistically significant ($p = 0.294$). The third parameter estimate yields $10^{-0.0005}$ (0.9988) μV^2 and is not statistically significant ($p = 0.964$).

Table 4

Model for the Relationship of the log transformed theta power μV^2 with KSS scores, Steering Errors, Instruction Miss

Outcome	Theta power			
	Estimates	std. Error	CI Lower – Upper	p
(Intercept)	-0.6044	0.0482	0.2176 – 0.3812	<0.001
KSS	0.0084	0.0036	0.0013 – 0.0155	0.020
Steering Errors	0.0027	0.0025	-0.0023 – 0.0076	0.294
Instruction Miss	-0.0005	0.0111	-0.0223 – 0.0213	0.964
Random Effects				
σ^2	0.05			
τ_{00} Participant	0.04			
ICC	0.49			
N Participant	22			
Observations	3168			

Marginal R^2/Conditional R^2	0.002/0.489

To test the learning effect that is assumed to have occurred the first 10 minutes of the experiment reflected in the data for Steering Errors, the first ten minutes of the data was removed and another multilevel model was built using the modified data. Table 5 shows that removing the first 10 minutes from the data did not improve the relationship between Steering Errors and theta power. The relationship between KSS and theta power became not statistically significant (p = 0.071).

Table 5

Model for the Relationship of the log transformed theta power μV² with KSS scores, Steering Errors, Instruction Miss using modified data set

Predictor	Theta power			
	Estimates	std. Error	CI Lower – Upper	p
(Intercept)	-0.5963	0.0500	-0.6943 – -0.4983	<0.001
KSS	0.0078	0.0043	-0.0007 – 0.0164	0.071
Steering Errors	-0.0012	0.0032	-0.0075 – 0.0050	0.699
Instruction Miss	-0.0038	0.0135	-0.0302 – 0.0227	0.779
Random Effects				
σ^2	0.04			
$\tau_{00\ \text{Participant}}$	0.04			
ICC	0.50			
$N_{\text{Participant}}$	22			
Observations	2640			
MarginalR^2/Conditional R^2	0.002/0.505			

Discussion

The first goal of this study sought to explore whether it was possible to relate changes in individual sleepiness to changes in EEG measures. It was found that a relationship exists between changes in EEG measures and an individual's level of sleepiness. The results of the multi-level analysis model expressed in Table 2 showed that alpha power increases as KSS scores increases by one unit. This increase of alpha power is 1.0214 μV^2. Table 4 depicted an increase of theta power as KSS scores increased by on unit resulting in an increase of theta power by 1.0195 μV^2. This finding is in line with the prior work of Philip et al. (2005) and Theresia et al. (2018) who found that a relationship exists between sleepiness, alpha and theta power and vigilance decrement such that increases in alpha and theta power and sleepiness are observed when an individual experiences a vigilance decrement.

Therefore, based on these findings the notion that as an individual drives in a monotonous highway environment, an increase in alpha and theta power and an increase the level of sleepiness that individual experiences can be expected. Based on the findings of this study, it can then be assumed that participants driving in the simulated environment experienced a vigilance decrement which is expressed by the increase in sleepiness and in the alpha and theta power. This assumption is in line with previous literature. According to Dinges (1995), sleepiness can be considered as the antecedent to a vigilance decrement. Additionally, increases in alpha and theta power has been found to be associated with increased in levels of sleepiness in numerous studies (Craig et al., (2012); Tran et al., 2020).

Moreover, the relationship between KSS and power in theta showed an increase of 1.0195 µV2, whereas for alpha this increase was 1.0214 μV^2. It is then arguable that the relationship between KSS and power yielded a higher increase in alpha power than theta power. The increase in theta power is related to an increase cognitive process in an attempt to maintain high performance (Arnau et al., 2021; Wascher et al., 2014) whereas increases in alpha is assumed to be a result of boredom or attentional withdrawal (Wascher et al., 2016). Because increase in the theta and alpha power are related to different mechanisms, it offers a possible insight as to why the power of both frequency bands have differing relationships with sleepiness. Taking into account the mindlessness theory, it is possible that alpha power reflects a shift in focus from the task to something unrelated (Thomson et al., 2015). Considering the cognitive resource theory, it is possible that theta power reflects the mental fatigue experience as an individual spends time on a task resulting in a depletion of cognitive resources due to the increased cognitive effort to maintain high performance (Flanagan & Nathan-Roberts, 2019; Wascher et al., 2014; Wickens, 2002).

Furthermore, looking at the topographical views of alpha, higher alpha power can be observed in the frontal region and the posterior region. In the topographical view of the theta, higher theta power can be observed in the frontal region. These findings contradict that of Tran et al. (2020). According to a metanalysis by Tran et al. (2020) within the theta frequency band, a large increase in the band power could be observed in the frontal, central and posterior regions and in the central and posterior regions for the alpha frequency band. According to Wascher et al. (2014) increases in frontal theta is considered an indicator of mental fatigue caused by an increase in cognitive effort to maintain performance. This is reflected in the topography of the activity of theta power depicted in Figure 7 which clearly indicates high activity of theta frontal. It can be assumed that participants experienced mental fatigue as they participated in the driving task and this is reflected in the relationship between theta power and KSS scores.

The second goal of this study sought to explore whether a relationship exists between changes in driving performance measured through steering errors and instruction misses and EEG measures. The results of the current study showed that changes in alpha power have a relationship with changes in the performance measure of Instruction Miss. Table 2 depicts an increase in alpha power as Instruction Miss increases by one unit. Alpha power increased by 1.0807 μV^2, whereas no statistically significant relationship existed between Instruction Miss and theta power. Due to the cues being presented to participants as visual stimuli, missing those cues would indicate an issue with visual perception. As a result, it is expected to see an interaction with alpha power and Instruction miss as increases in alpha power have been linked to a decrease in attention to visual stimuli. This is supported by the findings of Sokoliuk et al. (2019) which posits that a decrease in alpha power is expressed when there is an increase in attention to visual stimuli. This therefore implies that an increase in alpha power can be observed when there is a decrease in attending to visual stimuli.

However, theta power did not have a statistically significant relationship with Instruction Miss. It can then be assumed that theta power is not linked to visual stimuli. Therefore, theta power does not seem to reflect attentional issues an individual may experience when engaged in a monotonous task such as driving. This further substantiated the notion that changes in alpha and theta power are related to different processes. This assumption is supported by the topographical views of theta power (Figure 7) and alpha power (Figure 6) throughout the experiment. Figure 7 shows high activity in frontal theta which has been lined to mental fatigue as stated earlier in the discussion. Figure 6 depicts the topography of the activity of alpha power which shows high activity in the frontal and posterior regions. This finding is supported by Lobier et al. (2018) who found that increases in alpha power in the frontal, parietal and visual cortex are linked to decreases in reaction time to attend to visual stimuli. This indicates that participants might not have been attending to the visual stimuli, leading to misses of the visual instruction cues.

Additionally, there was no significant relationship between the alpha and theta power with the performance measure Steering Errors as depicted in Table 2 and Table 4. This finding contradicts that of Feng et al. (2009) who found that as a person fatigues, drivers had a tendency to preform less steering micro-corrections. Additionally, a study by Wascher et al. (2016) observed an increase in driving errors and driving lane variability a time on task increased. Based on these two studies, it would be expected to observe a statistically significant relationship between alpha and theta power and Steering Errors, however, this was not the case. Initially, it was suspected that the learning effect that could be observed in Steering Errors (Figure 3) influenced the relationship between Steering Errors and alpha and theta power. After removing the first 10 minutes from the data it did not improve the relationship observed between alpha and theta power with Steering Errors (Table 3, Table 5).

To conclude, a relationship exists between the changes in alpha power and the changes in sleepiness and Instruction Miss, while a relationship exists between theta power and sleepiness. The relationship with alpha and theta power with sleepiness was such that as alpha power and theta power increased, the driver would experience an increase in level of sleepiness. Moreover, the relationship with Instruction Miss showed that as alpha power increases, the driver is likely to miss the visual instruction cues. Additionally, increases in alpha power could be related to boredom or attentional withdrawal/shift while increase in theta power are possibly due to mental fatigue as a result of increase cognitive processing. Therefore, changes in alpha power seem to be related to the mindless theory, whereas changes in theta power appear to be related to the cognitive resource theory.

Limitations and Recommendations for Future Studies

There were several potential limitations to be addressed regarding this study. The first limitation was the study design as participants did not have time allotted to practice in the driving environment. Participants needed the first 10 minutes of the experiment time to adjust and become familiar with the driving environment. This was reflected in the collected data, specifically Steering Errors. It was observed that during the first 10 minutes of the experiment, participants made many steering errors. This number declined as time in the driving environment increased for each participant before increasing again closer to the last 10 minutes of the experiment. Therefore, it can be assumed that participants made so many steering errors at the start of the experiment due to time needed to adjust to using the driving simulator. A recommendation for future studies would be to include a practice moment of approximately 20 minutes before starting the experiment. This way, the participant has sufficient time to become familiar with the driving environment.

Moreover, another variable could be considered for assessment in future studies. This variable is that of workload which could be measured using the NASA Task Load Index (NASA-TLX). This measure is a commonly used assessment tool to get information on workload. The result of the present study eluded that alpha power and theta power were influenced by different mechanism. Theta power was thought to be influenced by the occurrence of mental fatigue, whereas alpha power reflected changes in attention. By including a measure of workload, perhaps it can give more insight into the interaction of theta power as drivers drive in a monotonous environment, such as a highway.

Regarding the data analysis, there are several limitations in this study which occurred due to time restraints. First, the number of events each participant encountered was not included as a variable in the analysis due to time limitations. During the experiment, it was apparent that participants that encountered more events also made more steering errors. Although there was no way to gauge time within the driving environment, using the trigger marker file produced from the recorded EEG data gave some indication as to how fast the participant drove. This indication could be justified with how many events the participant encountered. A higher number of events encountered indicated how fast the participant was driving. Participants who encountered more events frequently made a steering error. Because driving speed is typically used as a behavioural measure when investigating vigilant state, including the number of events would have been a creative way to assess 'speed' of each participant.

Second, how much sleep each participant got the night before was not included as a variable. This data was recorded from each participant via questionnaire. In previous studies, it was found the fatigue state influenced the vigilance decrement (Philip et al., 2005; Theresia et al., 2018). For example, the study conducted by Theresia et al. (2018) found that significant vigilance decrement was observed in individuals who were sleep deprived compared to their counterparts. Third, another level could have been added to the multi-level model which would have considered the time the participant came in to do the experiment. During the experiment phase, two experiments were done per day. One experiment was conducted in the morning and the other was conducted in the afternoon. Therefore, a recommendation for future studies would be to include these variables in the data analysis to gain a clearer picture of individual participant's vigilant state. In the current study, due to time limitations it was not possible to include these two aforementioned variables.

Lastly, in this study the following electrodes were used: F_3, F_4, F_Z, C_3, C_4, C_Z, P_3, P_4, P_Z, O_1, O_2, O_Z. The analysis that was conducted took the grand average of all electrodes, not the selected electrodes. A recommendation for future studies would be to take the grand average of the electrodes selected for the study rather than all electrodes measured. Additionally, a statistical analysis should have been done with the electrodes that represented specific regions. For example, frontal regions: F_3, F_4, F_Z, central region: C_3, C_4, C_Z, posterior region: P_3, P_4, P_Z and occipital region: O_1, O_2, O_Z. Having this division of the regions would allow for more insightful and meaningful data about the regions and how they influenced the relationship between the variables.

Implications

The findings of this study further support the existing literature which describes a relationship between the subjective measure of sleepiness and vigilant state whereby as sleepiness increases, a decline in vigilant state can be observed. This can be seen in the current study through the relationship between KSS and theta power and alpha power, where as a participant experienced higher levels of sleepiness an increase in alpha power and theta power is expected. Moreover, the findings of this study showed a relationship between Instruction Miss and alpha power, such that as Instruction Miss increases an increase in alpha power is expected. Additionally, the findings of this study raise intriguing questions regarding the mechanisms behind increases in theta power and alpha power. It showed that theta power increased to reflect mental fatigue whereas alpha power increased to show attentional disengagement from visual stimuli.

References

Al-Shargie, F., Tariq, U., Mir, H., Alawar, H., Babiloni, F., & Al-Nashash, H. (2019). Vigilance decrement and enhancement techniques: a review. *Brain sciences*, *9*(8), 178. doi: https://doi.org/10.3390/brainsci9080178

Amre, S., & Sun, Y. (2021, July). Effects of Non-driving Task Related Workload and Situational Awareness in Semi-autonomous Vehicles. In *International Conference on Applied Human Factors and Ergonomics* (pp. 247-254). Springer, Cham. doi: https://doi.org/10.1007/978-3-030-79763-8_30

Arnau, S., Brümmer, T., Liegel, N., & Wascher, E. (2021). Inverse effects of time-on-task in task-related and task-unrelated theta activity. *Psychophysiology*, *58*(6), e13805. doi: https://doi.org/10.1111/psyp.13805

Bandara, D. S. V., & Kiguchi, K. (2018, December). Brain signal acquisition methods in BCIs to estimate human motion intention–a survey. In *2018 International Symposium on Micro-NanoMechatronics and Human Science (MHS)* (pp. 1-7). IEEE. doi: 10.1109/MHS.2018.8887072

Bennett, J. M., Challinor, K. L., Modesto, O., & Prabhakharan, P. (2020). Attribution of blame of crash causation across varying levels of vehicle automation. *Safety Science*, *132*, 104968. doi: https://doi.org/10.1016/j.ssci.2020.104968

Bergasa, L. M., Nuevo, J., Sotelo, M. A., Barea, R., & Lopez, M. E. (2006). Real-time system for monitoring driver vigilance. *IEEE Transactions on Intelligent Transportation Systems*, *7*(1), 63-77. doi: 10.1109/TITS.2006.869598.

Bian, Z., Li, Q., Wang, L., Lu, C., Yin, S., & Li, X. (2014). Relative power and coherence of EEG series are related to amnestic mild cognitive impairment in diabetes. *Frontiers in aging neuroscience*, *6*, 11. doi: 10.3389/fnagi.2014.00011

Bonnefond, A., Doignon-Camus, N., Touzalin-Chretien, P., & Dufour, A. (2010). Vigilance and intrinsic maintenance of alert state: an ERP study. *Behavioural brain research*, *211*(2), 185-190. doi: https://doi.org/10.1016/j.bbr.2010.03.030

Campagne, A., Pebayle, T., & Muzet, A. (2004). Correlation between driving errors and vigilance level: influence of the driver's age. *Physiology & behavior*, *80*(4), 515-524. doi: 10.1016/j.physbeh.2003.10.004

Cavanagh, J. F., & Frank, M. J. (2014). Frontal theta as a mechanism for cognitive control. *Trends in cognitive sciences*, *18*(8), 414-421. doi: https://doi.org/10.1016/j.tics.2014.04.012

Craig, A., Tran, Y., Wijesuriya, N., & Nguyen, H. (2012). Regional brain wave activity changes associated with fatigue. Psychophysiology, 49(4), 574-582. doi: 10.1111/j.1469-8986.2011.01329.x574

Dement, W. C., & Carskadon, M. A. (1982). Current perspectives on daytime sleepiness: the issues. *Sleep*, *5*(suppl_2), S56-S66. doi: https://doi.org/10.1093/sleep/5.S2.S56

Dinges, D. F. (1995). An overview of sleepiness and accidents. *Journal of sleep research*, *4*, 4-14. doi: https://doi.org/10.1111/j.1365-2869.1995.tb00220.x

Drummond, S. P., Bischoff-Grethe, A., Dinges, D. F., Ayalon, L., Mednick, S. C., & Meloy, M. J. (2005). The neural basis of the psychomotor vigilance task. *Sleep*, *28*(9), 1059-1068. doi: https://doi.org/10.1093/sleep/28.9.1059

Feng, R., Zhang, G., & Cheng, B. (2009, March). An on-board system for detecting driver drowsiness based on multi-sensor data fusion using Dempster-Shafer theory. In *2009 international conference on networking, sensing and control* (pp. 897-902). IEEE. doi: 10.1109/ICNSC.2009.4919399.

Flanagan, J., & Nathan-Roberts, D. (2019, November). Theories of vigilance and the prospect of cognitive restoration. In *Proceedings of the Human Factors and Ergonomics Society Annual Meeting* (Vol. 63, No. 1, pp. 1639-1643). Sage CA: Los Angeles, CA: SAGE Publications. doi: https://doi.org/10.1177/1071181319631506

Grandjean, E. (1979). Fatigue in industry. *Occupational and Environmental Medicine*, *36*(3), 175-186. doi: http://dx.doi.org/10.1136/oem.36.3.175

Ganesh, S., & Gurumoorthy, R. (2021). Real Time Vigilance Detection using Frontal EEG. *arXiv preprint arXiv:2103.02169*.

Helton, W. S., & Warm, J. S. (2008). Signal salience and the mindlessness theory of vigilance. *Acta psychologica*, *129*(1), 18-25. doi: https://doi.org/10.1016/j.actpsy.2008.04.002

Helton, W. S., & Russell, P. N. (2012). Brief mental breaks and content-free cues may not keep you focused. *Experimental brain research*, *219*(1), 37-46. doi: https://doi.org/10.1007/s00221-012-3065-0

Hu, X., & Lodewijks, G. (2020). Detecting fatigue in car drivers and aircraft pilots by using non-invasive measures: The value of differentiation of sleepiness and mental fatigue. *Journal of safety research*, *72*, 173-187. doi: https://doi.org/10.1016/j.jsr.2019.12.015

Ingre, M., Åkerstedt, T., Peters, B., Anund, A., & Kecklund, G. (2006). Subjective sleepiness, simulated driving performance and blink duration: examining individual differences. *Journal of sleep research*, *15*(1), 47-53. doi: https://doi.org/10.1111/j.1365-2869.2006.00504.x

Jagannath, M., & Balasubramanian, V. (2014). Assessment of early onset of driver fatigue using multimodal fatigue measures in a static simulator. *Applied ergonomics*, *45*(4), 1140-1147. doi: https://doi.org/10.1016/j.apergo.2014.02.001

Kleiman, E. (2017). Understanding and analyzing multilevel data from real-time monitoring studies: An easily-accessible tutorial using R. doi: https://doi.org/10.31234/osf.io/xf2pw

Körber, M., Cingel, A., Zimmermann, M., & Bengler, K. (2015). Vigilance decrement and passive fatigue caused by monotony in automated driving. *Procedia Manufacturing*, *3*, 2403-2409. doi: 10.1016/j.promfg.2015.07.499

Lal, S. K., & Craig, A. (2001). A critical review of the psychophysiology of driver fatigue. *Biological psychology*, *55*(3), 173-194. doi: doi: https://doi.org/10.1016/S0301-0511(00)00085-5

Larue, G., Rakotonirainy, A., & Pettitt, T. (2010). Driving performance on monotonous roads. In *Proceedings of the 20th Canadian Multidisciplinary Road Safety Conference* (pp. 1-13). Canadian Association of Road Safety Professionals. https://eprints.qut.edu.au/33001/

Larue, G. S., Rakotonirainy, A., & Pettitt, A. N. (2011). Driving performance impairments due to hypovigilance on monotonous roads. *Accident Analysis & Prevention*, *43*(6), 2037-2046. doi: https://doi.org/10.1016/j.aap.2011.05.023

Lobier, M., Palva, J. M., & Palva, S. (2018). High-alpha band synchronization across frontal, parietal and visual cortex mediates behavioral and neuronal effects of visuospatial attention. *Neuroimage*, *165*, 222-237. doi: https://doi.org/10.1016/j.neuroimage.2017.10.044

Ma, J., Gu, J., Jia, H., Yao, Z., & Chang, R. (2018). The relationship between drivers' cognitive fatigue and speed variability during monotonous daytime driving. *Frontiers in psychology*, *9*, 459. doi: https://doi.org/10.3389/fpsyg.2018.00459

Manly, T., Robertson, I. H., Galloway, M., & Hawkins, K. (1999). The absent mind:: further investigations of sustained attention to response. *Neuropsychologia*, *37*(6), 661-670. doi: https://doi.org/10.1016/S0028-3932(98)00127-4

May, J. F., & Baldwin, C. L. (2009). Driver fatigue: The importance of identifying causal factors of fatigue when considering detection and countermeasure technologies. *Transportation research part F: traffic psychology and behaviour*, *12*(3), 218-224. doi: https://doi.org/10.1016/j.trf.2008.11.005

McWilliams, T., & Ward, N. (2021). Underload on the road: measuring vigilance decrements during partially automated driving. *Frontiers in psychology*, *12*, 1113. doi: https://doi.org/10.3389/fpsyg.2021.631364

Merat, N., & Jamson, A. H. (2013). The effect of three low-cost engineering treatments on driver fatigue: A driving simulator study. *Accident Analysis & Prevention*, *50*, 8-15. doi: https://doi.org/10.1016/j.aap.2012.09.017

Miley, A. Å., Kecklund, G., & Åkerstedt, T. (2016). Comparing two versions of the Karolinska Sleepiness Scale (KSS). *Sleep and biological rhythms*, *14*(3), 257-260. doi: https://doi.org/10.1007/s41105-016-0048-8

Neigel, A. R., Claypoole, V. L., Smith, S. L., Waldfogle, G. E., Fraulini, N. W., Hancock, G. M., ... & Szalma, J. L. (2020). Engaging the human operator: a review of the theoretical support for the vigilance decrement and a discussion of practical applications. *Theoretical issues in ergonomics science*, *21*(2), 239-258. doi: https://doi.org/10.1080/1463922X.2019.1682712

Paszkiel, S. (2020). Data acquisition methods for human brain activity. In *Analysis and Classification of EEG Signals for Brain–Computer Interfaces* (pp. 3-9). Springer, Cham. doi: https://doi.org/10.1007/978-3-030-30581-9_2

Peng, Z., Rong, J., Wu, Y., Zhou, C., Yuan, Y., & Shao, X. (2021). Exploring the different patterns for generation process of driving fatigue based on individual driving behavior parameters. *Transportation research record*, *2675*(8), 408-421. doi: https://doi.org/10.1177/0361198121998351

Philip, P., Sagaspe, P., Moore, N., Taillard, J., Charles, A., Guilleminault, C., & Bioulac, B. (2005). Fatigue, sleep restriction and driving performance. *Accident Analysis & Prevention*, *37*(3), 473-478. doi: https://doi.org/10.1016/j.aap.2004.07.007

Philip, P., Sagaspe, P., Lagarde, E., Leger, D., Ohayon, M. M., Bioulac, B., ... & Taillard, J. (2010). Sleep disorders and accidental risk in a large group of regular registered highway drivers. *Sleep medicine*, *11*(10), 973-979. doi: https://doi.org/10.1016/j.sleep.2010.07.010

Ralph, B. C., Onderwater, K., Thomson, D. R., & Smilek, D. (2017). Disrupting monotony while increasing demand: Benefits of rest and intervening tasks on vigilance. *Psychological research*, *81*(2), 432-444. doi: https://doi.org/10.1007/s00426-016-0752-7

Robertson, I. H., Manly, T., Andrade, J., Baddeley, B. T., & Yiend, J. (1997). Oops!': performance correlates of everyday attentional failures in traumatic brain injured and normal subjects. *Neuropsychologia*, *35*(6), 747-758. doi: https://doi.org/10.1016/S0028-3932(97)00015-8

RStudio Team (2022). *RStudio: Integrated Development Environment for R* (Version 2022.7.1.554) [Computer Software]. RStudio, PBC, Boston, MA URL http://www.rstudio.com/.

Samima, S., Sarma, M., & Samanta, D. (2017, July). Correlation of P300 ERPs with visual stimuli and its application to vigilance detection. In *2017 39th Annual international conference of the IEEE Engineering in Medicine and Biology Society (EMBC)* (pp. 2590-2593). IEEE. doi: 10.1109/EMBC.2017.8037387

Schmidt, E. A., Schrauf, M., Simon, M., Fritzsche, M., Buchner, A., & Kincses, W. E. (2009). Drivers' misjudgement of vigilance state during prolonged monotonous daytime driving. *Accident Analysis & Prevention*, *41*(5), 1087-1093. doi: https://doi.org/10.1016/j.aap.2009.06.007

Seli, P., Wammes, J. D., Risko, E. F., & Smilek, D. (2016). On the relation between motivation and retention in educational contexts: The role of intentional and unintentional mind wandering. *Psychonomic bulletin & review*, *23*(4), 1280-1287. doi: https://doi.org/10.3758/s13423-015-0979-0

Shen, J., Barbera, J., & Shapiro, C. M. (2006). Distinguishing sleepiness and fatigue: focus on definition and measurement. *Sleep medicine reviews*, *10*(1), 63-76. doi: https://doi.org/10.1016/j.smrv.2005.05.004

Sokoliuk, R., Mayhew, S. D., Aquino, K. M., Wilson, R., Brookes, M. J., Francis, S. T., ... & Mullinger, K. J. (2019). Two spatially distinct posterior alpha sources fulfill different functional roles in attention. *Journal of Neuroscience*, *39*(36), 7183-7194. doi:

Thiffault, P., & Bergeron, J. (2003). Monotony of road environment and driver fatigue: a simulator study. *Accident Analysis & Prevention*, *35*(3), 381-391. doi: https://doi.org/10.1016/S0001-4575(02)00014-3

Thomson, D. R., Besner, D., & Smilek, D. (2015). A resource-control account of sustained attention: Evidence from mind-wandering and vigilance paradigms. *Perspectives on psychological science*, *10*(1), 82-96. doi: https://doi.org/10.1177/1745691614556681

Theresia, C., Iridiastadi, H., & Pratama, G. B. (2018, March). Impacts of sleep deprivation on vigilance, fatigue, and performance during simulated train driving. In *Proceedings of the 2nd International Conference on High Performance Compilation, Computing and Communications* (pp. 45-50). doi: https://doi.org/10.1145/3195612.3195625

Tran, Y., Craig, A., Craig, R., Chai, R., & Nguyen, H. (2020). The influence of mental fatigue on brain activity: Evidence from a systematic review with meta-analyses. Psychophysiology, 57(5), e13554. doi: 10.1111/psyp.13554

van der Hulst, M., Meijman, T., & Rothengatter, T. (2001). Maintaining task set under fatigue: a study of time-on-task effects in simulated driving. *Transportation research part F: traffic psychology and behaviour*, *4*(2), 103-118. doi: https://doi.org/10.1016/S1369-8478(01)00017-1

Verster, J. C., & Roth, T. (2013). Vigilance decrement during the on-the-road driving tests: The importance of time-on-task in psychopharmacological research. *Accident Analysis & Prevention*, *58*, 244-248. doi: http://dx.doi.org/10.1016/j.aap.2012.10.005

Vitols, K., & Voss, E. (2021, June 2). *Driver Fatigue in European Road Transport*. European Transport Workers' Federation (ETF). https://www.etf-europe.org/wp-content/uploads/2021/05/Driver-Fatigue-in-European-Road-Transport-Report.pdf

Wang, C., Guragain, B., Verma, A. K., Archer, L., Majumder, S., Mohamud, A., ... & Tavakolian, K. (2019). Spectral analysis of EEG during microsleep events annotated via driver monitoring system to characterize drowsiness. *IEEE Transactions on Aerospace and Electronic Systems*, *56*(2), 1346-1356. doi: 10.1109/TAES.2019.2933960.

Wascher, E., Rasch, B., Sänger, J., Hoffmann, S., Schneider, D., Rinkenauer, G., ... & Gutberlet, I. (2014). Frontal theta activity reflects distinct aspects of mental fatigue. *Biological psychology*, *96*, 57-65. doi: https://doi.org/10.1016/j.biopsycho.2013.11.010

Wascher, E., Getzmann, S., & Karthaus, M. (2016). Driver state examination—Treading new paths. *Accident Analysis & Prevention*, *91*, 157-165. doi: https://doi.org/10.1016/j.aap.2016.02.029

Wickens, C. D. (2002). Multiple resources and performance prediction. *Theoretical issues in ergonomics science, 3*(2), 159-177. 10.1080/14639220210123806

Zhang, Y., Ma, J., Zhang, C., & Chang, R. (2021). Electrophysiological frequency domain analysis of driver passive fatigue under automated driving conditions. Scientific Reports, 11(1), 1-9. doi: https://doi.org/10.1038/s41598-021-99680-4

Zhou, F., Alsaid, A., Blommer, M., Curry, R., Swaminathan, R., Kochhar, D., ... & Lei, B. (2020). Driver fatigue transition prediction in highly automated driving using physiological features. *Expert Systems with Applications, 147*, 113204. doi: https://doi.org/10.1016/j.eswa.2020.113204

Appendix A – Development Report

Previously, studies have been done at the University of Twente which include investigating the vigilant state of an individual. These studies included experiment designs where participants had to preform target centred task. However, no study has yet been done the required the participant to drive in a driving simulator and investigate their vigilant state while driving. This current study sought to investigate just that and because of the novelty of the experiment, developmental steps needed to be taken. This development was necessary as there was no previous procedure in place that dictated how the study design should be done. Consequently, research needed to be conducted to devise a design that stratified the goal of the study.

The development process was done in collaboration the BMSLab of the University of Twente, the supervisor of this Master thesis and the student researcher. The initial meeting was held to introduce the student researcher and the supervisor to the development team at the BMSLab and to discuss what support they offered and what could be expected. During the second meeting, ideas for the study design were discussed. The two initial ideas that were proposed by the student researcher were:

Idea 1

- Use a continuous task performance (CPT) and/or Mackworth Clock Test (MCT)
    - Introduce tactile warnings when unwanted stimulus is present
        - The steering wheel vibrates
    - Introduce auditory warnings when unwanted stimulus is present
        - A beeping sound
    - Compare those with only visual warning of unwanted stimuli
    - If vigilance improved/hindered/remains the same?
- Use the method Event Related De-synchronization (ERD) for the EEG
    - However, there is also ERS event related synchronization
        - Which would be the better option?
- Use spectral analysis of the EEG (Perhaps easier?)

Idea 2

- Use a continuous task performance (CPT) and/or Mackworth Clock Test (MCT)
    - Manipulate the frequency of crisis/unwanted stimulus

    - Compare to see the difference between frequencies
- Use the method Event Related De-synchronization (ERD) for the EEG
    - However, there is also ERS event related synchronization
        - Which would be the better option?

Ultimately a more simpler design idea was proposed that involved the participant simply driving in an environment which would have some driving difficulty. An example of the difficulties proposed was an obstacle appearing and moving across the street. To create a connection between the EEG and the driving simulator it would take the development team head one week. This could be achieved using Unity. The overall development would take approximately 80 hours of work. Possible issues that were identified with the driving simulator were:

- head movements
- Projector of the driving simulator may cause interference
- Eye movement
- Motion sickness can be an issue

In the simulated world it is possible to adjust the driving conditions, such as:

- Increasing or decreasing traffic
- Types/amounts of obstacles
- Weather conditions is not possible to manipulate at the moment
- Possible to have more traffic/obstacles spawn based on EEG readings

It was decided that participants would need to drive in the driving environment for 1 hour. Additionally, a pilot test was proposed to test the connection between the driving simulator and the EEG to see if any of the problems identified would cause issues to the EEG data. A to do list was devised at the end of the second meeting.

To do

- Register project with BMS lab
- Attend EEG workshop
- Reserve driving simulator for 20^{th}-27^{th} December
- Review manual from Lucia

  - Research more into EEG and vigilance

- The pilot test
  - Pilot test was done using a video game
    - Two participants
    - Connected to EEG and allowed to drive in the environment
    - Evaluated the EEG data to see if driving disrupted readings
  - Report was devised

The pilot test was conducted on two participants. Participants were connected to the EEG and were asked to play a driving video game with the driving simulator. This pilot test was conducted to see if the problems stated earlier would affect the EEG data. Both participants drove for approximately 30 minutes and their EEG data was recorded while they did so. During the pilot test, observations and notes were made for both participants. A report can be seen below.

Observations

These observations are based on what was seen during the pilot testing and is not related to the analysis of the EEG readings.

- When participants made dramatic and large turns the EEG seemed to drop or rise rather than continuing in a seemingly straight line, which is typical
- The same applies for when the participant made sharp and quick turns
- Driving at a higher speed makes taking turns more difficult so participants overcompensate with hand movements/turning the wheel
- Unless told to, participants rarely moved their heads
  - This does not include the full body movements that were frequently observed
- Participants also typically stayed in a reclined position in the driving simulator and only moved back and forth when told to.

Recommendations

- Participant should not drive faster than a speed exceeding 3rd gear.
- Turns in the road should be as wide as possible to reduce the need of the participant to make sharp turns
  - Making these sharp turns disrupts the EEG readings
- Participants should be asked to keep completely still and only move their hands

   - Straps on the driving simulator can be used, however I don't think it is necessary

The report was sent to the supervisor along with the recorded EEG data. After reviewing the EEG data, it was found that the act of driving the simulator while connected to the EEG did not affect the data as much. What was identified was that participants needed to limit their head movements, they should not drive too fast as to lose control of the driving task and they should not move their arms in exaggerated movements.

Requirements

The driving environment had to be designed in such a way that the participants can make turns without prompting exaggerated hand movements to compensate for speed. Therefore, the driving environment needed to be free of sharp turns. The roads needed to be two laned and a closed circuit. The initial track design can be seen below.

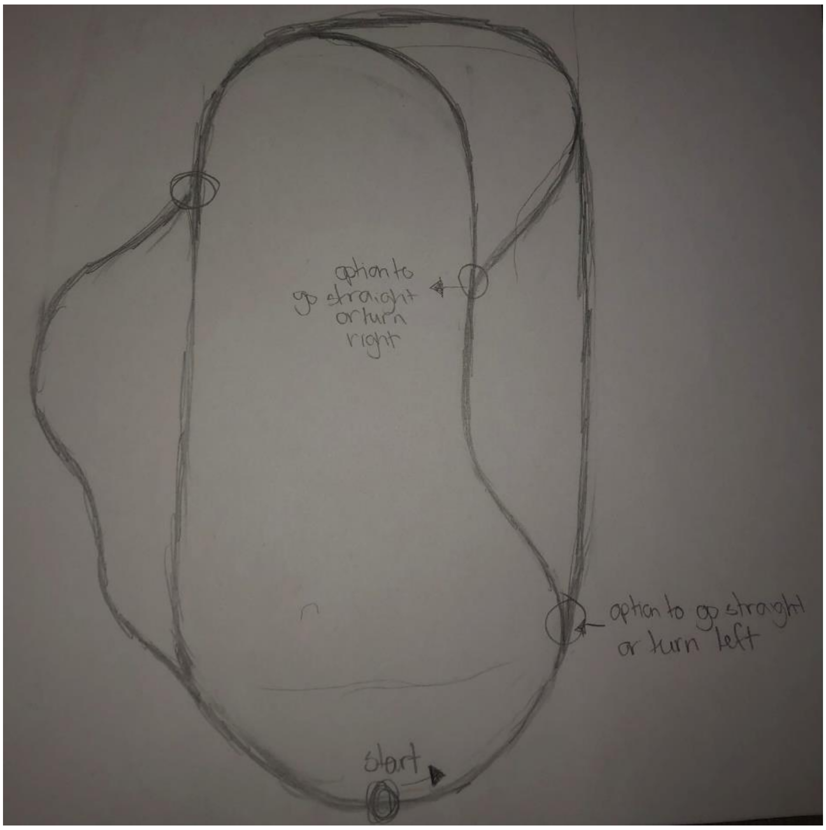


Figure A1. Drawing of initial track.

Due to the limitations of Unity, the exact design could not be used. The track design that was used can maintained all the stated requirements.

Figure A2. Track used in experiment.

The next step was to elaborate on the requirements that were needed for the experiment. The first step was to provide detailed information on the equipment and the program.

Equipment Overview

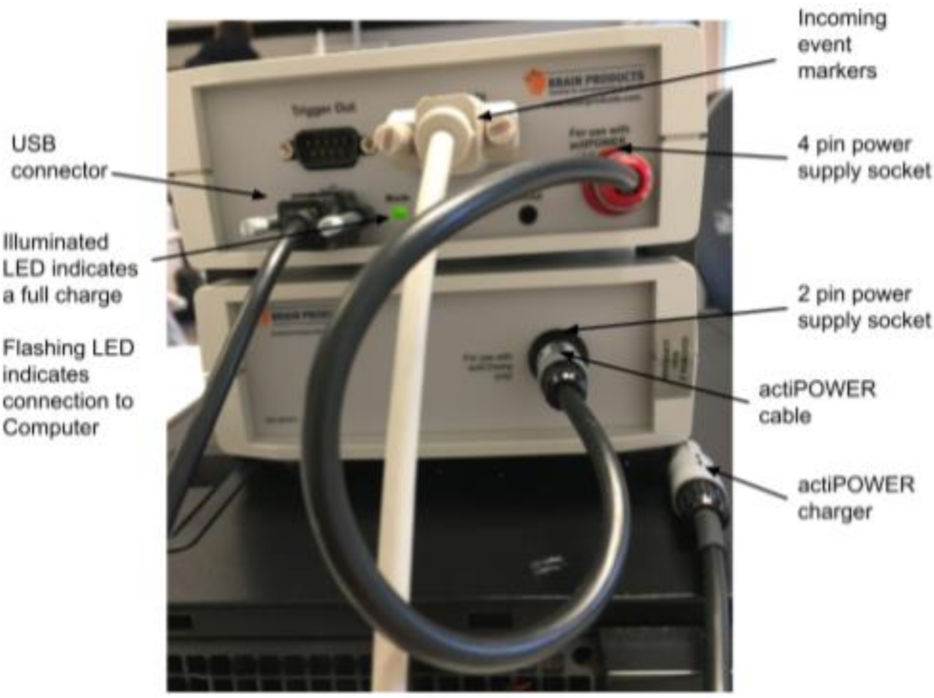


Figure A3. Labelled image of back of the amplifier.

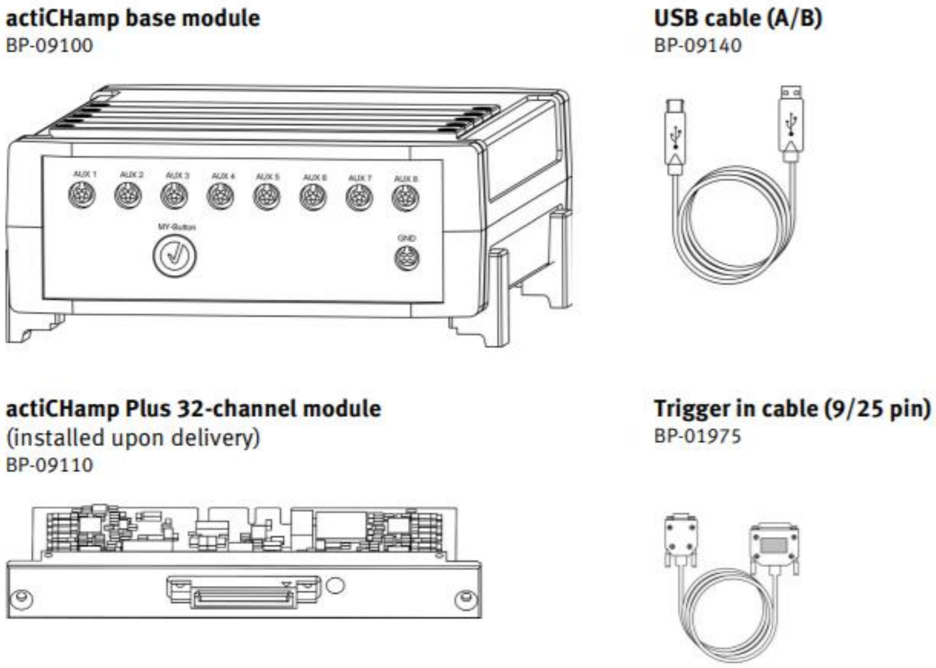


Figure A4. Specification of the amplifier and components.

Set-up Schematic

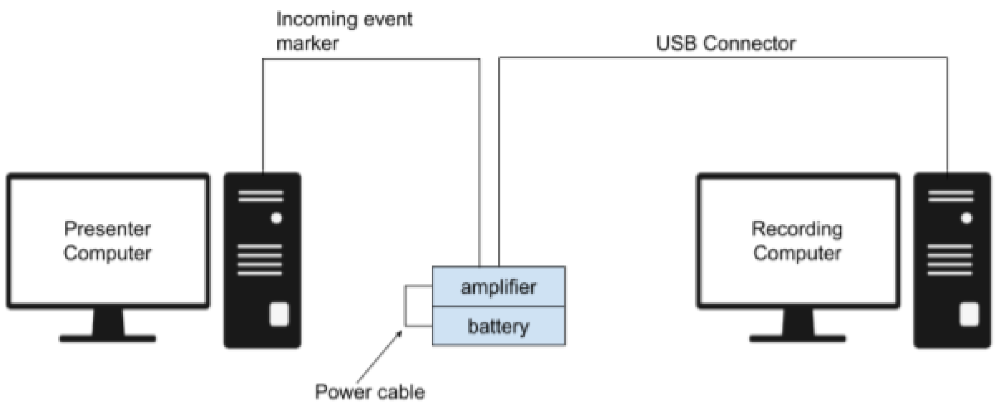


Figure A5. Schematic set-up of the process of sending information to the recording computer.

There was no need to use the presentation software commonly used when conducting experiments using EEG. Triggers could be sent from the Unity to the Amplifier using 8-bit. Triggers are the events that happen in the driving simulation that need to be marked and sent to the amplifier and recorded in the EEG data. If an intermediary was needed, perhaps a simple

Python code would suffice. Laptop should have external port to connect to the amplifier (Labelled Incoming events marker)

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BRAIN PRODUCTS
Solutions for neurophysiological research

At a glance:
Brain Products Amplifiers in Comparison (page 2 of 4)

actiCHamp (compared to BrainAmp Standard and DC)

	actiCHamp	BrainAmp Standard	BrainAmp DC
Number of channels per unit	32	32	32
Max. number of channels	160 EEG + 8 AUX	256 (using 8 x BrainAmp Standard, 2 x USB 2 Adapter (BUA) and dualBUA)	256 (using 8 x BrainAmp DC, 2 x USB 2 Adapter (BUA) and dualBUA)
Channel type / reference	EEG channels: referential channels / internal Reference	Referential channels / acquisition of a reference using a single electrode ("unipolar")	Referential channels / acquisition of a reference using a single electrode ("unipolar")
Measurement range	0 to 100 kΩ	available, measurement incl. ground and reference electrode at 15 Hz	available, measurement incl. ground and reference electrode at 15 Hz
Input impedance (for DC)	EEG channels: > 1,000 MΩ AUX channels: Rev. 01: > 2,000 MΩ; as of Rev. 02: > 40 MΩ	10 MΩ	switchable: 10 MΩ / > 10,000 MΩ
Input noise for EEG channels	≈ 2 µVpp (0.1 Hz - 30 Hz)	≤ 2 µVpp (0.016 Hz - 1,000 Hz)	≤ 1 µVpp (0.016 Hz - 250 Hz)
Common-mode rejection (CMR)	> 100 dB	≥ 90 dB (at 50/60 Hz)	≥ 110 dB (at 50/60 Hz)
Lower cutoff frequency (high pass) / time constant	DC for EEG and AUX signals 0 Hz (DC)	0.016 Hz / 10s	0 Hz in DC mode, 0.016 Hz / 10s in AC mode. Switchable between AC and DC mode (in software)
Upper cutoff frequency (low pass)	EEG channels: 20 kHz (without label) or 8 kHz (with 8 kHz label or imprint on EEG module) AUX channels: Rev 01: 0.3 V to 4 V, as of Rev 02: Bipolar -4.8 V to +4.8 V	1,000 Hz	1,000 / 250 Hz (switchable for resolutions 0.1 µV / 0.5 µV per bit)
Resolution	EEG: ≈0.0487 µV per bit; AUX: Rev. 01: ≈0.298 µV per bit as of Rev. 02: ≈0.596 µV per bit	0.1 µV per bit	switchable: 0.1 µV; 0.5 µV; 10.0 µV per bit
Sampling rate in combination with BrainVision PyCorder (Python-based open source recording software)	16ch + 8 AUX: 100 kHz 32ch + 8 AUX: 50 kHz 64ch + 8 AUX: 25 kHz 96ch + 8 AUX: 10 kHz 128ch + 8 AUX: 10 kHz 160ch + 8 AUX: 10 kHz	combination not possible	combination not possible
Sampling Rate in combination with BrainVision Recorder 1.20 and higher (commercial license)	16ch + 8 AUX: 100 kHz 32ch + 8 AUX: 100 kHz 64ch + 8 AUX: 50 kHz 96ch + 8 AUX: 25 kHz 128ch + 8 AUX: 25 kHz 160ch + 8 AUX: 25 kHz	5 kHz per channel	5 kHz per channel
Bit width of A/D converter	24 bit for EEG and AUX channels	16 bit	16 bit
Deblocking function	no	present	present
Power supply	rechargeable battery („actiPOWER")	rechargeable battery (PowerPack)	rechargeable battery (PowerPack)
Computer interface	direct via USB 2.0	USB 2 Adapter (BUA, dualBUA) or PCI Adapter Card	USB 2 Adapter (BUA, dualBUA) or PCI Adapter Card
Trigger input	8 bit, D-Sub, 9 pin, female	16 bit	16 bit
Trigger output	8 bit, D-Sub, 9 pin, male		
Suitable for use in MR scanner room	no, MR unsafe	no, MR unsafe	no, MR unsafe
Medical product	no	no	no
CE marking	Yes, according to EMC directive	CE according to EMC directive	CE
Dimensions (H x W x D)	68 mm x 160 mm x 187 mm	68 mm x 160 mm x 187 mm	68 mm x 160 mm x 187 mm
Weight (approx.)	1.1 kg	1.1 kg	1.1 kg

Figure A6. Information leaflet for different Brain Products Amplifier, with the amplifier used in this experiment circled.

Following the specification of the equipment and the program, came the specification of the study design. To do this, three possible study designs were devised and the requirements for each were specified.

Scenario 1 with an 'Intelligent' car (following specific car)

This scenario is where the driver (the participant) would follow an 'intelligent' car. The driver will be asked to maintain the 2 second rule when following the lead car. This would mean that they need to maintain enough distance reaction time (1s) and braking time (1s). Visually, participants would be asked to maintain a distance so that they always see the back tires of the car in front of them.

Requirements

- Use 'intelligent' car
- Set speed to maximum of 50km/hr

Scenario

- Take the exit (make a right)
- Go straight
- Maintain 2 second rule

Triggers

- Triggers for the scenarios
- Triggers for when the scenarios are executed (desired)
- Triggers for when the scenarios are not executed (undesired)

Scenario		Outcome		Trigger Symbol	
Cue	Trigger Symbol	Desired	Undesired	Desired	Undesired
Take the exit (make a right)	1	Driver makes a right	Driver goes straight Driver does not take the exit Driver stays in the right lane Driver shifts to the left lane Driver speeds up Driver slows down	01	11

Go straight	2	Driver goes straight	Driver makes a right turn	02	22
Maintain 2-second rule	-	Driver maintains distance from leading vehicle, observing the 2 second rule	Driver does not maintain distance from leading vehicle, observing the 2 second rule	03	33

Table A1. Description of Scenario cues and trigger symbol, outcomes and trigger symbol

Scenario 2 with smart cars (no following specific car)

This scenario will make use of 'intelligent' cars. The driver (the participant) will not be following any car in specific. However, the driver will be given scenario prompts to do certain actions. The driver will be asked to maintain the 2 second rule when driving behind a car. This would mean that they need to maintain enough distance reaction time (1s) and braking time (1s). Visually, participants would be asked to maintain a distance so that they always see the back tires of the car in front of them.

Requirements

- Scenarios provided in the environment
    - *Would be great if it is possible to use auditory cues rather than visual*
- Trigger and outcome information fed to the amplifier
- Trigger symbol should be used as input to the amplifier
- Use 'intelligent' cars in the driving environment
- Set speed to maximum of 50km/hr

Scenario

- Take the exit (make a right)
- Go straight
- Maintain 2-second rule

Triggers

- Triggers for the scenarios are prompted (appear on screen)
- Triggers for when the scenarios are executed (desired)
- Triggers for when the scenarios are not executed (undesired)

Scenario	Outcome	Trigger Symbol

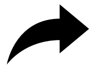
Cues	Trigger Symbol	Symbol (On the screen in the car)	Desired	Undesired	Desired	Undesired
Take the exit (make a right)	1	  	Driver makes a right	Driver goes straight Driver does not take the exit Driver stays in the right lane Driver shifts to the left lane Driver speeds up Driver slows down	01	11
Go straight	2	 	Driver goes straight	Driver makes a right turn	02	22
Maintain 2-second rule	-	There will be no symbol for this scenario. Participant will be instructed at the start of the experiment about this scenario	Driver maintains distance from leading vehicle, observing the 2 second rule	Driver does not maintain distance from leading vehicle, observing the 2 second rule	03	33

Table A2. Description of Scenario cues and trigger symbol, outcomes and trigger symbol

Scenario 3 using a predetermined route (using GPS to navigate)

In this scenario, the driver (the participant) would have to follow a predetermined route. This would replicate using GPS in the car to get to your destination. The driver will be asked to maintain the 2 second rule when following the lead car. This would mean that they need to maintain enough distance reaction time (1s) and braking time (1s). Visually, participants would be asked to maintain a distance so that they always see the back tires of the car in front of them.

Requirements

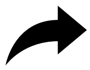
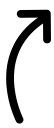
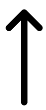
- Visual and auditory cues for the route the driver must take
- Trigger and outcome information fed to the amplifier
- Trigger symbol should be used as input to the amplifier
- Set speed to maximum of 50km/hr

Scenario

- Take the exit (make a right)
- Go straight
- Maintain 2-second rule

Triggers

- Triggers for the scenarios are prompted (appear on screen)
- Triggers for when the scenarios are executed (desired)
- Triggers for when the scenarios are not executed (undesired)

Scenario			Outcome		Trigger Symbol	
Cues	Trigger Symbol	Symbol (On the screen in the car)	Desired	Undesired	Desired	Undesired
Take the exit (make a right)	1	  	Driver makes a right	Driver goes straight Driver does not take the exit Driver stays in the right lane Driver shifts to the left lane Driver speeds up Driver slows down	01	11
Go straight	2		Driver goes straight	Driver makes a right turn	02	22

		^				
Maintain 2-second rule	-	There will be no symbol for this scenario. Participant will be instructed at the start of the experiment about this scenario	Driver maintains distance from leading vehicle, observing the 2 second rule	Driver does not maintain distance from leading vehicle, observing the 2 second rule	03	33

Table A3. Description of Scenario cues and trigger symbol, outcomes and trigger symbol

After providing the development team with this information, a redesign of the study was needed to accommodate the time limit allotted to the student researcher and of the limitations of the Unity program. Scenario 2 served as the basis and modifications were made to redesign the study. The requirements that could not be used were:

- Use of an 'intelligent' car
  - This was no longer possible due to its complexity and the time restraint
- Participant observing the 2 second rule
  - This would be difficult for participants to gauge in the driving environment
- Auditory cues of the instruction prompt
  - No longer possible due to time restraints
- Accurate measure of speed
  - Not possible due to the limitations of Unity

Scenario

The driver (the participant) will drive in the driving environment and will be given instruction prompts to do certain actions. There will be other cars driving in the driving environment as well. These cars will spawn outside the view of the driver. Because these other cars cannot be controlled, they could possibly act as obstacles.

Requirements

- Scenarios provided in the environment
- Trigger and outcome information fed to the amplifier
- Trigger symbol should be used as input to the amplifier

Scenario

- Take the exit (make a right)
- Go straight
- Switch lanes

Triggers

- Triggers for the scenarios are prompted (appear on screen)
- Triggers for when the scenarios are executed (desired)
- Triggers for when the scenarios are not executed (undesired)

Scenario			Outcome		Trigger Symbol (Sent to EEG)
Auditory Cues	Trigger Symbol (Sent to EEG)	Symbol (On the screen in the car)	Desired	Undesired	
Take the exit (make a right)	2	↱	Driver makes a right	Driver goes straight Driver does not take the exit Driver shifts to the left lane	02
Go straight	1	↑	Driver goes straight	Driver makes a right turn	01
Keep Left	3	<	Driver maintains driving in the left lane	Driver does not keep to the left	03
Keep Right	4	>	Driver maintains driving in the right lane	Driver does not keep to the right	04

Table A4. Description of Scenario cues and trigger symbol, outcomes and trigger symbol

Once the design of the track was finalized, a test drive was done to identify points for improvement and ensure the driving environment met the requirements. During the test drive of the driving environment, the student researcher counted how many instructions prompts occurred in the span of 30 minutes. What was discovered was that within 30 minutes, a driver could encounter 20 instruction prompts. This, however, was dependent on how much speed the driver drove with.

Once the track was confirmed with the student researcher and the development team, the next step was working on the triggers that would be placed in the driving environment and act as a marker that would then send information to the EEG. The triggers were created using box colliders. When the driver drove through the box collider, a code would be sent from Unity to a device, which would then send a marker to BrainVision Amplifier. This marker would then appear on the EEG data and give an indication to when certain events occurred in the driving environment.

Figure A7. Track with indications of where the box colliders will be placed

Tasks the driver will have during this experiment:

1. Drive on the inner most lane (left lane)
2. Make a right (make an exit)
3. Switch to the right lane when given the prompt to make a right (make an exit)
4. Go straight (remaining on the left lane)

Figure A7 showed the track designed for the experiment. The red dots indicated the markers that will give the driver instructions to either go straight or make a right on the exit. The orange dots indicated the markers that will relay information on which action the driver performed (did they go straight; did they make a right). The green dots indicate markers that will relay information for which lane the driver is in. The green markers are placed after the red marker to see if the participants shifted lanes and again after the orange dots to see if the participants shift or did not.

After the programming of the box colliders was completed, the student researcher then placed the box colliders in the driving environment. While doing this, further changes occurred. These changes were:

- The instruction to change lane to the right was not included in the driving environment.

There were two types of box colliders, instruction markers and markers. The instruction markers included a timing feature as to how long the image of the instruction would appear on the screen within the driving environment. The time can be adjusted simply by typing into the field the number of seconds desired for the instruction image to remain on the screen. Additionally, a field was present to decide what code would be sent to the amplifier. This code could be a letter or number, but a letter was preferred by the student researcher. This code served as the 'signal' that would be sent to the device which was then relayed to the amplifier and recorded in the EEG data. The markers also had the same field but did not have nor need the time field as the marker box colliders did not prompt instruction image to appear on the screen.

Experiment set-up

The initial experiment set-up called for the use of a projector to display the driving environment to the participant. The projection would be done in the are outlined by the blue box. The driving simulator chair would be placed beside the table where the amplifier was. This positioning was chosen to accommodate the electrodes. This positioning is outlined by the red box.

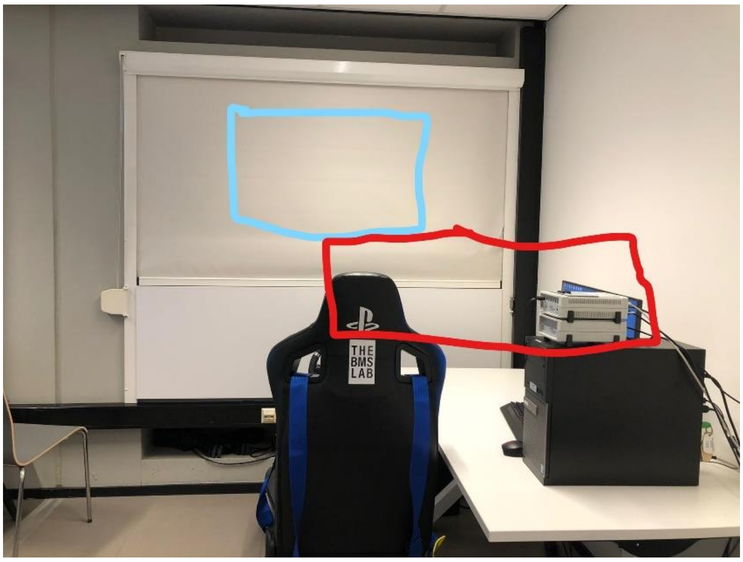


Figure A8. Initial experiment set-up

With this set up, the projector was a limitation as there was no area to place the projector. This prompted an alternative set-up which can be seen in Figure A10. With this new set up, a monitor would be used in place of the projector. This monitor would be situated on a table which would be position directly in front of the driving simulator chair.

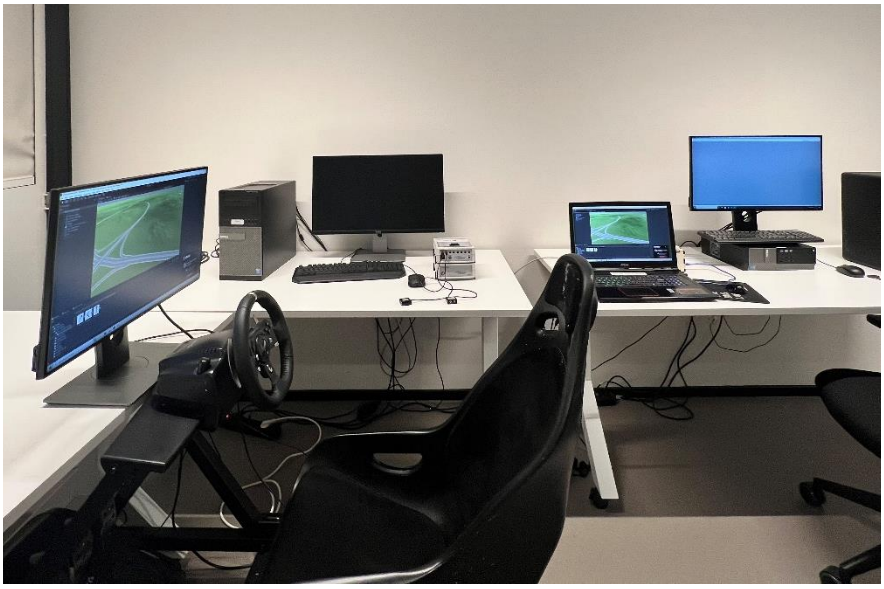


Figure A9. Set up used during the experiments.

After the coding for the communication between Unity and the amplifier was completed and all the box colliders were place, a test was done. This test was done to ensure that the communication between Unity and the amplifier was successful. This meant that if the driver drove through a box collider, the information would be sent to the amplifier through the device (Figure A11) and a marker is recorded in the EEG data.

Figure A10. Device used to facilitate the communication between Unity and the Amplifier

During this testing, there was no driver driving through the box colliders. Instead Test Franky was used which allowed the student researcher to sequentially enter letters and numbers into a typing field on Unity, click the 'Enter' key and that information be sent and recorded in the EEG data. Once all letters in the alphabet, both upper and lower case, and numbers from 0-9 the text file of the EEG recordings were observed to see what marker code was received. This test was repeated three times to ensure that the letter or number corresponded to the same marker code each time.

Cue	INT	Binary	EEG Marker Label
a	97	0110 0001	S135
b	98	0110 0010	S71
c	99	0110 0011	S199
d	100	0110 0100	S39
e	101	0110 0101	S167
f	102	0110 0110	S103
g	103	0110 0111	S231
h	104	0110 1000	S23
i	105	0110 1001	S151
j	106	0110 1010	S87
k	107	0110 1011	S215
l	108	0110 1100	S55
m	109	0110 1101	S183

n	110	0110 1110	S119
o	111	0110 1111	S247
p	112	0111 0000	S15
q	113	0111 0001	S143
r	114	0111 0010	S79
s	115	0111 0011	S207
t	116	0111 0100	S47
u	117	0111 0101	S175
v	118	0111 0110	S111
w	119	0111 0111	S239
x	120	0111 1000	S31
y	121	0111 1001	S159
z	122	0111 1010	S95
0	48	0011 0000	S15
1	49	0011 0001	S143
2	50	0011 0010	S79
3	51	0011 0011	S207
4	52	0011 0100	S47
5	53	0011 0101	S175
6	54	0011 0110	S111
7	55	0011 0111	S239
8	56	0011 1000	S31
9	57	0011 1001	S159
A	65	0100 0001	S131
B	66	0100 0010	S67
C	67	0100 0011	S195
D	68	0100 0100	S35
E	69	0100 0101	S163
F	70	0100 0110	S99
G	71	0100 0111	S227
H	72	0100 1000	S19
I	73	0100 1001	S147
J	74	0100 1010	S83
K	75	0100 1011	S211
L	76	0100 1100	S51
M	77	0100 1101	S179
N	78	0100 1110	S115
O	79	0100 1111	S243
P	80	0101 0000	S11
Q	81	0101 0001	S139
R	82	0101 0010	S75
S	83	0101 0011	S203
T	84	0101 0100	S43
U	85	0101 0101	S171
V	86	0101 0110	S107
W	87	0101 0111	S235
X	88	0101 1000	S27
Y	89	0101 1001	S155
Z	90	0101 1010	S91

Table A5. List containing the Cue, INT, Binary and EEG Marker Label used during testing

The student researcher then selected six letters that be used for the box colliders. Once all the box colliders had the appropriate letter a test was done while driving in the driving environment to see if the markers in the EEG recorded data was still the same.

Next a pilot test of the study design was conducted. This pilot test simulated how the actual experiment would be conducted once started. The participant went through all the steps and drove in the driving environment while being connected to the EEG by electrodes for 40 minutes. The driving behaviour of the participant in this pilot test revealed to the student researcher, that more markers could be added. The new additions included markers at:

- Lamppost
- Dividers
- Junctions

Another test was done by the student researcher and adjustments were made to the markers where necessary.

Appendix B – Experiment Miscellaneous

	Trigger Symbol	EEG Marker Symbol
Instruction to ''Straight'	a	135
Instruction to 'Right Turn'	b	71
Instruction to 'Shift to the left Lane'	c	199
Marker for 'Straight'	s	207
Marker for 'Right Turn'	r	79
Marker for 'Left Lane'	x	31
Marker for 'Right Lane'	y	159
Marker for Dividers/Barriers	d	39
Marker for Lamp posts	p	15
Marker for Junction	j	87

Table B1. Description of Driving Instruction, Trigger Symbol and EEG Marker Symbol

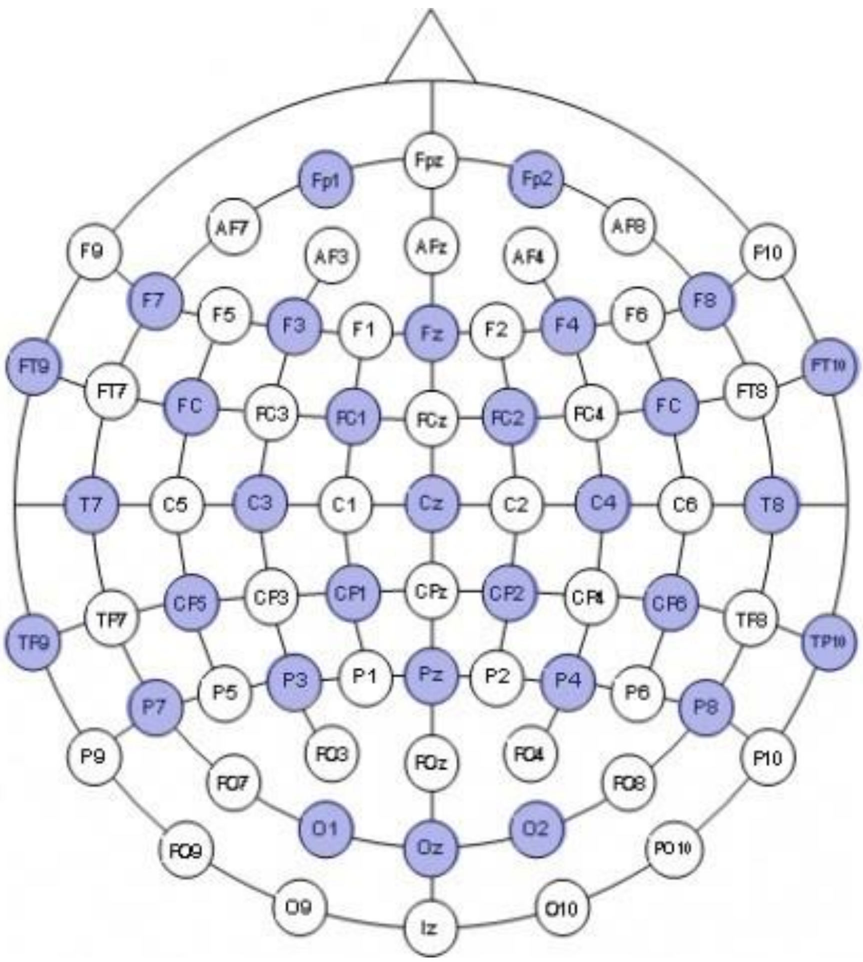


Figure B1. 32 electrode placements.

Appendix C -Additional Results

Alpha

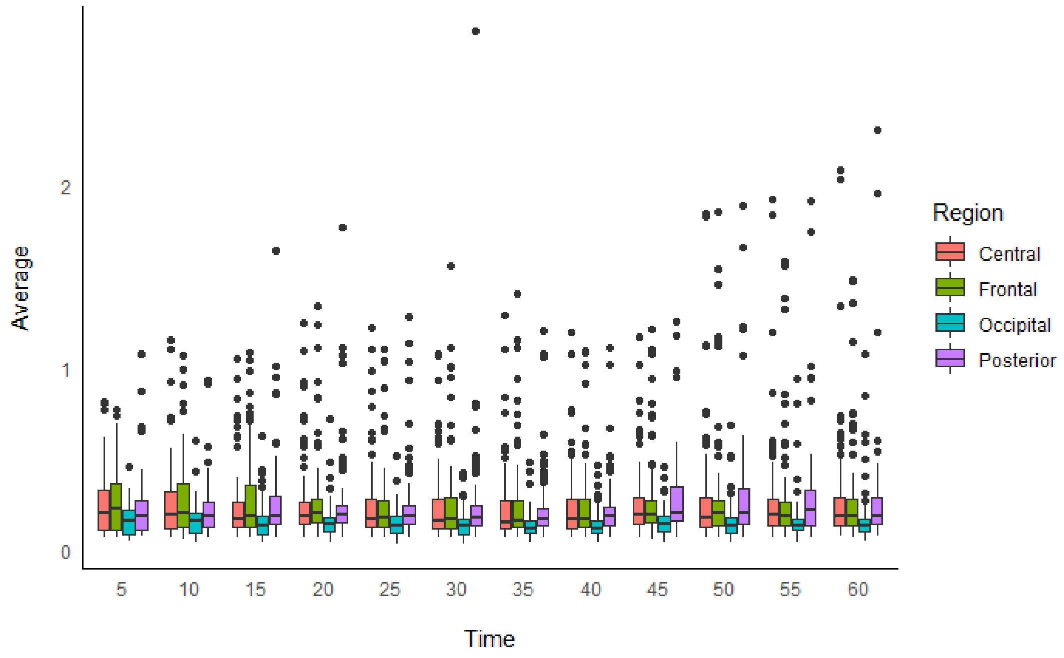


Figure C1. Boxplot of changes in alpha power over time

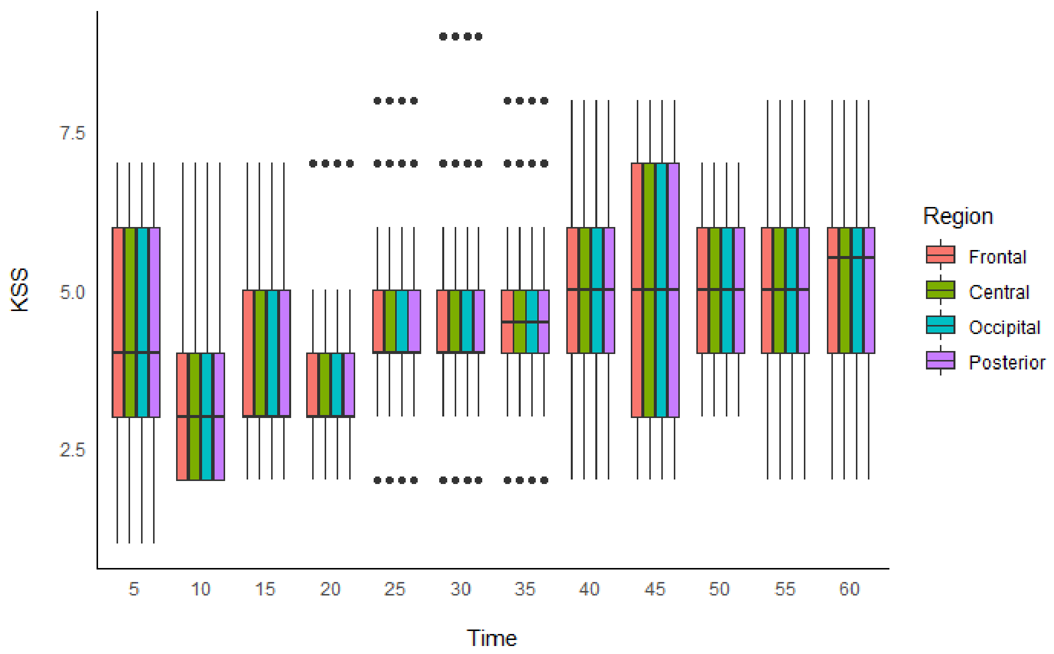


Figure C2: Boxplot of changes in KSS over time in the alpha frequency band

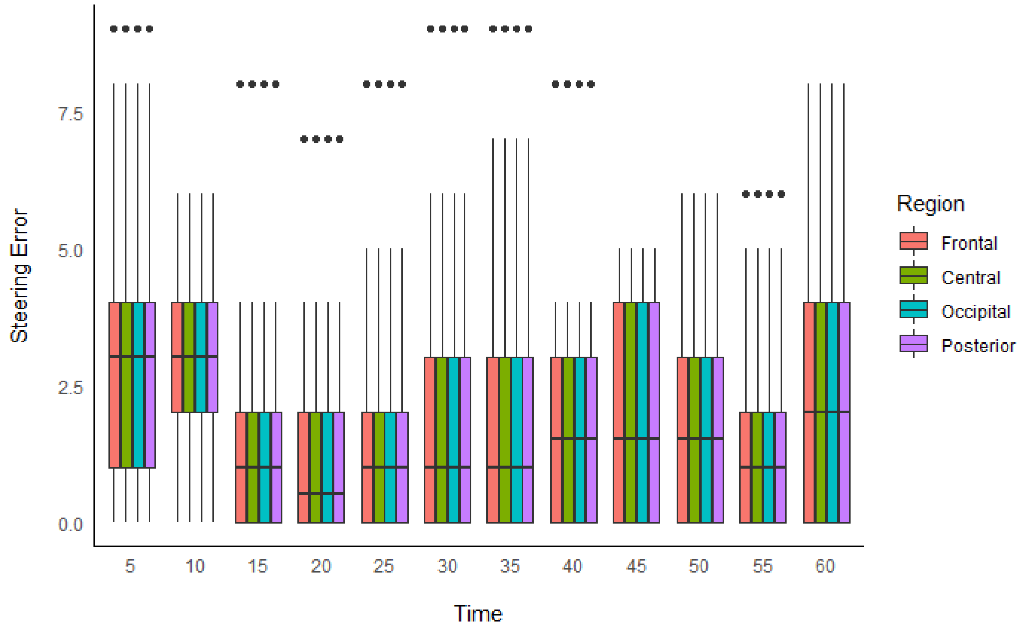


Figure C3: Boxplot of changes in Steering Errors over time in the alpha frequency band

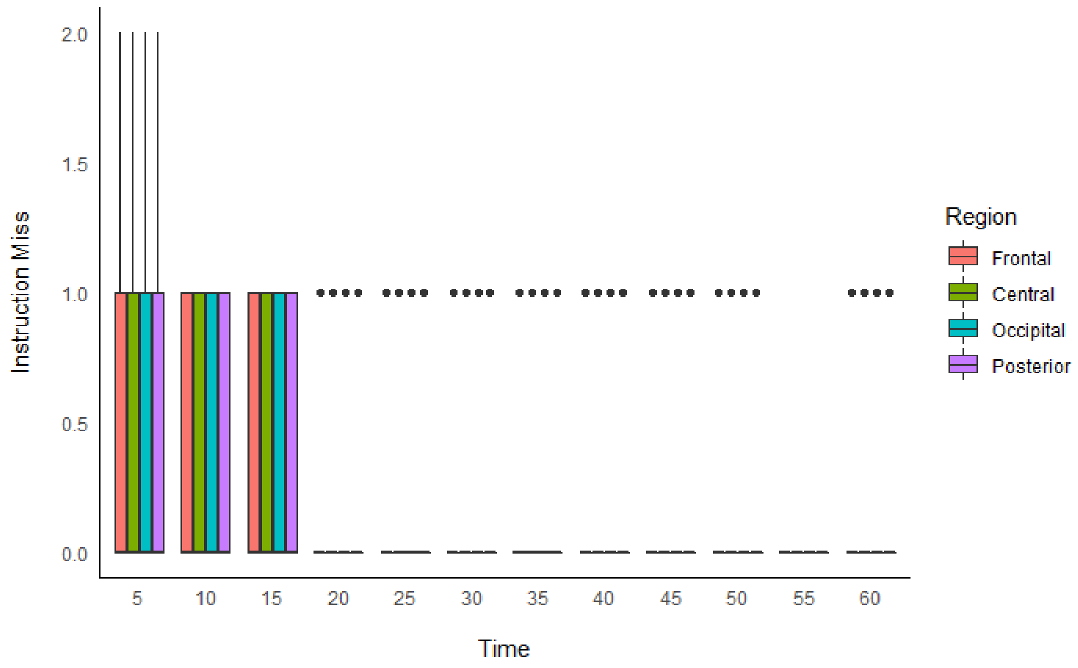


Figure C4: Boxplot of changes in Instruction Miss over time in the alpha frequency band

Theta

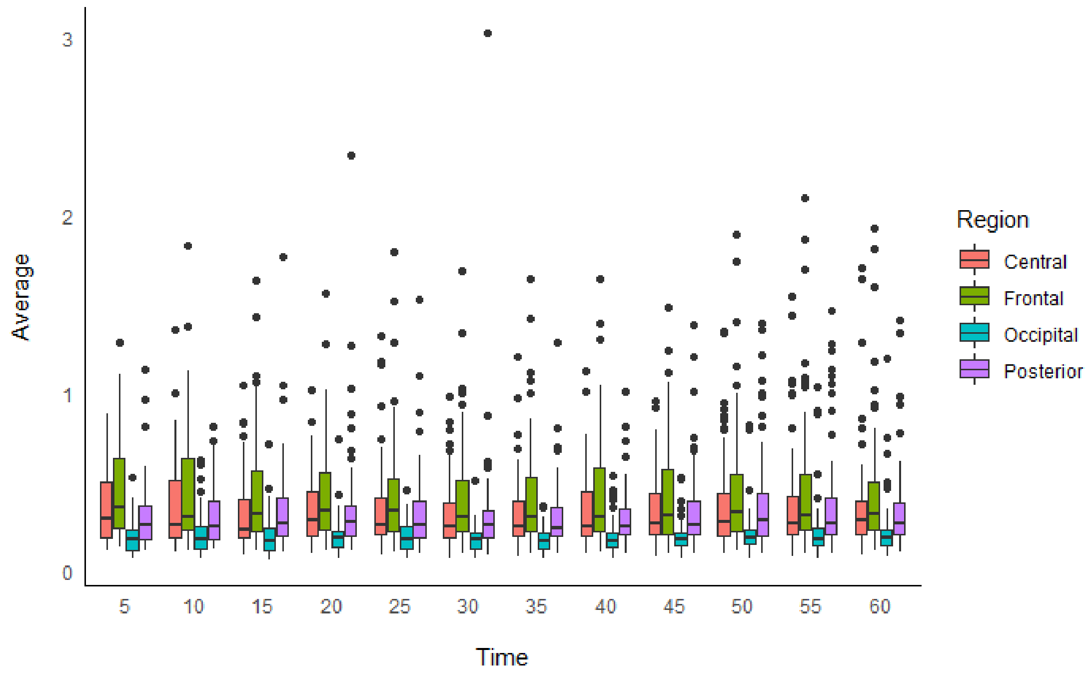


Figure C5: Boxplot of changes in theta power over time

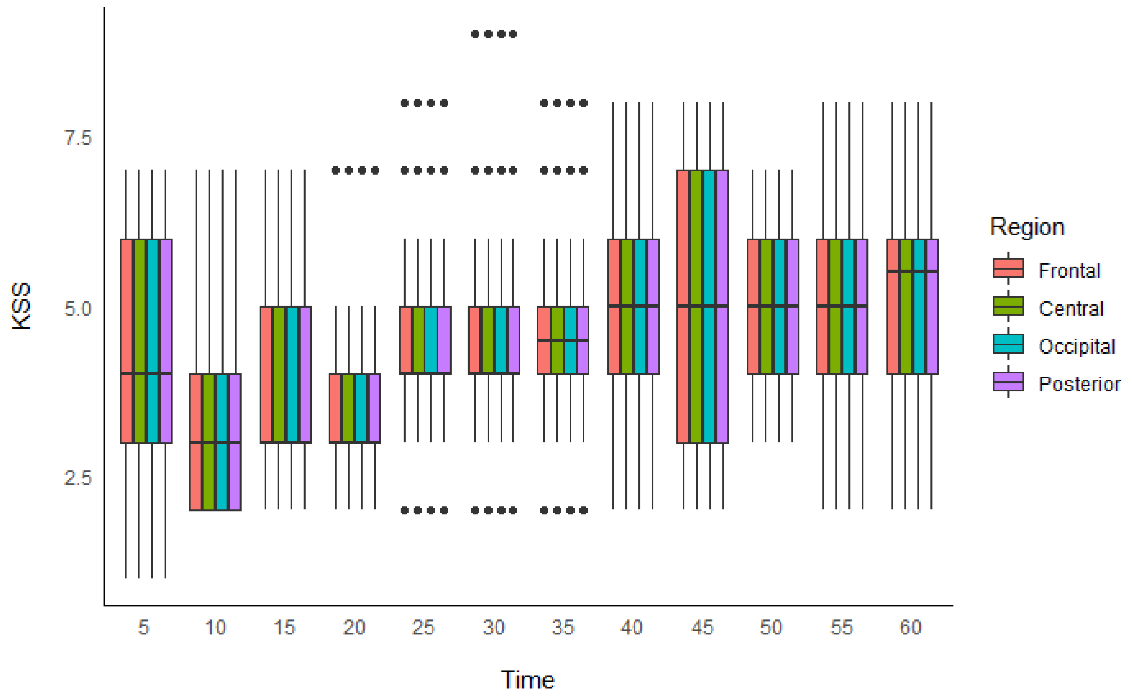


Figure C6: Boxplot of changes in KSS over time in the theta frequency band

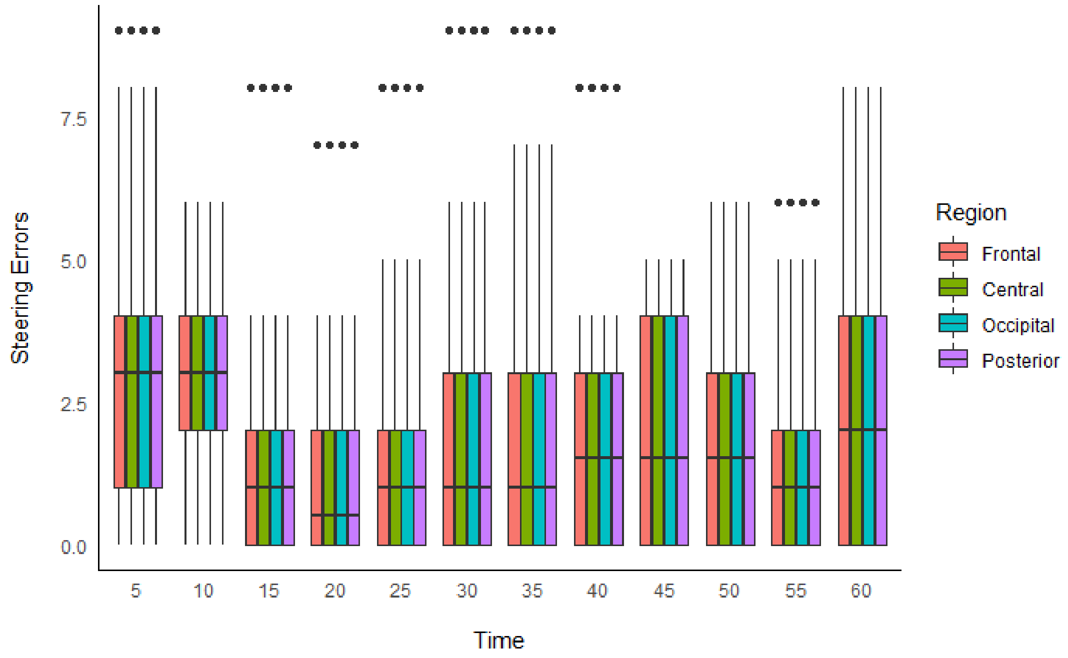


Figure C7: Boxplot of changes in Steering Errors over time in the theta frequency band

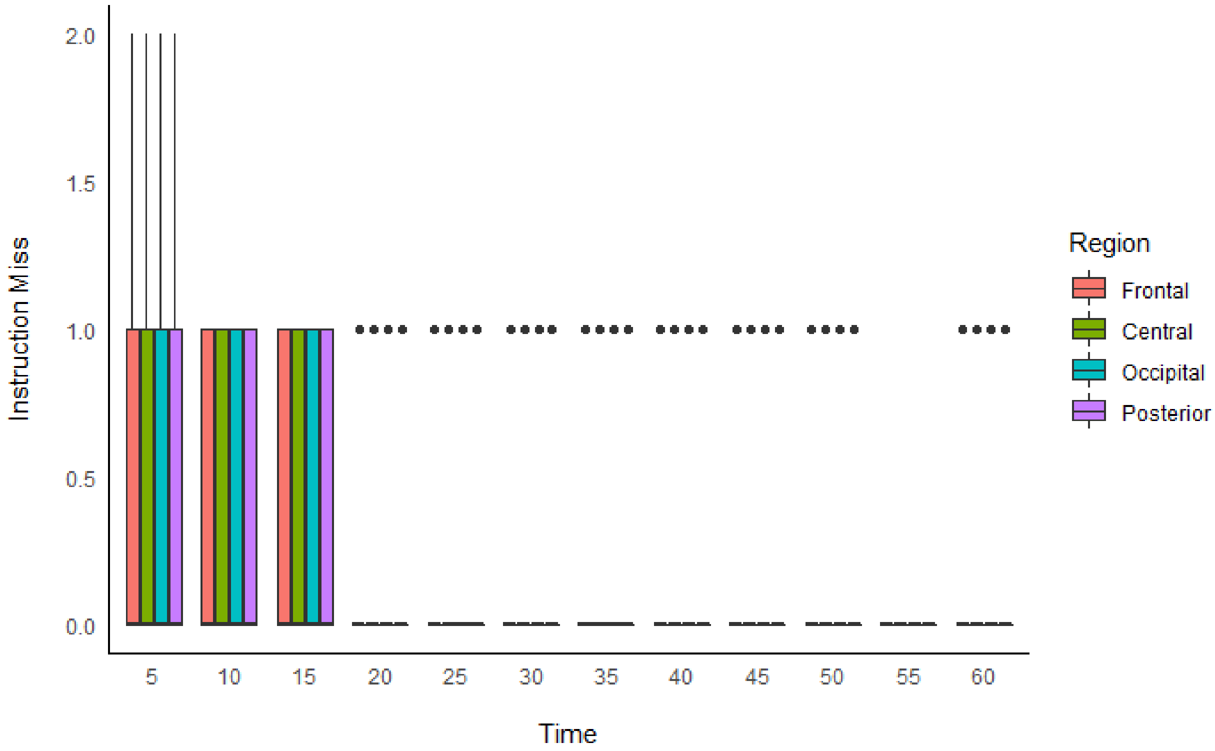


Figure C8: Boxplot of changes in Instruction Miss over time in the theta frequency band

Appendix D – R Script

```
---
title: "The Vigilant Brain"
author: "Dorvanique Cocks"
date: "2022-07-27"
output:
  word_document: default
  pdf_document: default
---

```{r setup, include=FALSE}
knitr::opts_chunk$set(echo = TRUE)

library(tidyverse)
library(printr)
library(rstanarm)
library(dplyr)
library(brms)
library(scales)
library(devtools)
install_github("schmettow/mascutils")
install_github("schmettow/bayr")
library(GGally)
library("ggpubr")

if (!require("pacman")) install.packages("pacman")
pacman::p_load(tidyverse, car,sjPlot,gridExtra,knitr,
               psych,kableExtra,tableone,sjlabelled,
               lmerTest,lme4,countreg)

opts_chunk$set(message=FALSE, warning=FALSE)
```
```

```
##READ AND CLEAN DATA##
```{r, Load data.frames}
Alpha <- read.csv("C:/Users/Dove/Documents/Psychology/Masters/Master Thesis/Data
Analysis/The Vigilant Brain - Alpha R.csv",
                header = TRUE)

Theta <- read.csv("C:/Users/Dove/Documents/Psychology/Masters/Master Thesis/Data
Analysis/The Vigilant Brain - Theta R.csv",
              header = TRUE)

data<- rbind(Alpha, Theta)

AlphaL <- read.csv("C:/Users/Dove/Documents/Psychology/Masters/Master Thesis/Data
Analysis/The Vigilant Brain - AlphaLog.csv",
                header = TRUE)
Alpha$Region <- as.factor(Alpha$Region)

ThetaL <- read.csv("C:/Users/Dove/Documents/Psychology/Masters/Master Thesis/Data
Analysis/The Vigilant Brain - ThetaLog.csv",
              header = TRUE)
Theta$Region <- as.factor(Theta$Region)

dataL<- rbind(AlphaL, ThetaL)

#Data set with the first 10 minutes removed#
AlphaLE <- read.csv("C:/Users/Dove/Documents/Psychology/Masters/Master Thesis/Data
Analysis/The Vigilant Brain - AlphaLE.csv",
                header = TRUE)

ThetaLE <- read.csv("C:/Users/Dove/Documents/Psychology/Masters/Master Thesis/Data
Analysis/The Vigilant Brain - ThetaLE.csv",
                header = TRUE)
```
```

~~~~
```


##DATA EXPLORATION##
```{r}
library(tidyverse)
```


```{r}
apa_theme <- theme(
  plot.margin = unit(c(1, 1, 1, 1), "cm"),
  plot.background = element_rect(fill = "white", color = NA),
  plot.title = element_text(size = 11, face = "bold",
                            hjust = 0.5,
                            margin = margin(b = 15)),
  axis.line = element_line(color = "black", size = .5),
  axis.title = element_text(size = 11, color = "black"),
  axis.text = element_text(size = 11, color = "black"),
  axis.text.x = element_text(margin = margin(t = 10)),
  axis.title.y = element_text(margin = margin(r = 10)),
  axis.ticks = element_line(size = .5),
  panel.grid = element_blank(),
  legend.position = "right",
  legend.text = element_text(size = 11),
  legend.margin = margin(t = 5, l = 5, r = 5, b = 5),
  legend.key = element_rect(color = NA, fill = NA)
 )

 theme_set(theme_minimal(base_size = 11) +
           apa_theme)
```


```{r}
~~~~

````
T1 <- CreateTableOne(
  vars = names(data[,-c(1,16)]),
  data = data,
  strata = "Frequency",
  test=F,
  addOverall = T
) %>% print(showAllLevels =T)

kable(T1[,1:4],
      caption = 'Table 1: Descriptives by Frequency',
      align = 'cccc',booktabs = TRUE)%>%
  kable_styling(latex_options = "HOLD_position",
                font_size = 12)
```


```{r}
summary(Alpha)
```


```{r}
summary(Theta)
```


```{r}
data %>%
  ggplot(aes(Time, Average, color=Region, fill=Region))  +
  facet_wrap(~Frequency) +
  stat_summary(fun.data = mean_se, alpha=1, position=position_dodge(width=.5)) +
  stat_summary(fun.y = mean, geom="line", position=position_dodge(width=.5)) +
  labs(x="\nTime", y = "Average Power \n",
       color="Region", fill="Region")
ggsave("plot1.tiff", units="in", width=6, height=3, dpi=300, compression = 'lzw')
```
````
````

````
```{r}
Alpha %>%
    ggplot(aes(Time, Steering.Errors))  +
  stat_summary(fun.data = mean_se, alpha=1, position=position_dodge(width=.5)) +
  stat_summary(fun.y = mean, geom="line", position=position_dodge(width=.5)) +
  labs(x="\nTime", y = "Steering Errors \n")
ggsave("plot2.tiff", units="in", width=6, height=3, dpi=300, compression = 'lzw')
```

```{r}
Alpha %>%
  ggplot(aes(Time, Instruction.Miss))  +
  stat_summary(fun.data = mean_se, alpha=1, position=position_dodge(width=.5)) +
  stat_summary(fun.y = mean, geom="line", position=position_dodge(width=.5)) +
  labs(x="\nTime", y = "Instruction Miss \n")
ggsave("plot3.tiff", units="in", width=6, height=3, dpi=300, compression = 'lzw')
```

```{r}
Alpha %>%
  ggplot(aes(Time, KSS))  +
  stat_summary(fun.data = mean_se, alpha=1, position=position_dodge(width=.5)) +
  stat_summary(fun.y = mean, geom="line", position=position_dodge(width=.5)) +
  labs(x="\nTime", y = "KSS \n")
ggsave("plot3.tiff", units="in", width=6, height=3, dpi=300, compression = 'lzw')
```

```{r}
Alpha %>%
ggplot(aes(x = factor(Time), y = Average, fill = Region))  +
  geom_boxplot() +
  labs(x = "\nTime", y = "Average\n") +
````
````

~~~
  theme_minimal() +
  labs(color="Region")+
  theme(legend.position = "right") +
  theme(axis.line = element_line(colour = "black")) +
  theme(panel.grid.major = element_blank(), panel.grid.minor = element_blank())
ggsave("plot4.tiff", units="in", width=6, height=3, dpi=300, compression = 'lzw')
```


```{r}
Alpha %>%
ggplot(aes(x = factor(Time), y = KSS, fill = Region))  +
  geom_boxplot() +
  labs(x = "\nTime", y = "KSS\n") +
  theme_minimal() +
  labs(color="Region")+
  theme(legend.position = "right")+
  theme(axis.line = element_line(colour = "black")) +
  theme(panel.grid.major = element_blank(), panel.grid.minor = element_blank())
ggsave("plot6.tiff", units="in", width=6, height=3, dpi=300, compression = 'lzw')
```


```{r}
Alpha %>%
ggplot(aes(x = factor(Time), y = Steering.Errors, fill = Region))  +
  geom_boxplot() +
  labs(x = "\nTime", y = "Steering Error\n") +
  theme_minimal() +
  labs(color="Region")+
  theme(legend.position = "right")+
  theme(axis.line = element_line(colour = "black")) +
  theme(panel.grid.major = element_blank(), panel.grid.minor = element_blank())
ggsave("plot7.tiff", units="in", width=6, height=3, dpi=300, compression = 'lzw')
```
~~~

```{r}
Alpha %>%
ggplot(aes(x = factor(Time), y = Instruction.Miss, fill = Region))  +
  geom_boxplot() +
  labs(x = "\nTime", y = "Instruction Miss\n") +
  theme_minimal() +
  labs(color="Region")+
  theme(legend.position = "right")+
  theme(axis.line = element_line(colour = "black")) +
  theme(panel.grid.major = element_blank(), panel.grid.minor = element_blank())
ggsave("plot8.tiff", units="in", width=6, height=3, dpi=300, compression = 'lzw')
```

#Theta#

```{r}
Theta %>%
ggplot(aes(x = factor(Time), y = Average, fill = Region))  +
  geom_boxplot() +
  labs(x = "\nTime", y = "Average\n") +
  theme_minimal() +
  labs(color="Region")+
  theme(legend.position = "right") +
  theme(axis.line = element_line(colour = "black")) +
  theme(panel.grid.major = element_blank(), panel.grid.minor = element_blank())
ggsave("plot9.tiff", units="in", width=6, height=3, dpi=300, compression = 'lzw')
```

```{r}
Theta %>%
ggplot(aes(x = factor(Time), y = KSS, fill = Region))  +
  geom_boxplot() +
  labs(x = "\nTime", y = "KSS\n") +
```

```
  theme_minimal() +
  labs(color="Region")+
  theme(legend.position = "right")+
  theme(axis.line = element_line(colour = "black")) +
  theme(panel.grid.major = element_blank(), panel.grid.minor = element_blank())
ggsave("plot10.tiff", units="in", width=6, height=3, dpi=300, compression = 'lzw')
```

```{r}
Theta %>%
ggplot(aes(x = factor(Time), y = Steering.Errors, fill = Region))  +
  geom_boxplot() +
  labs(x = "\nTime", y = "Steering Errors\n") +
  theme_minimal() +
  labs(color="Region")+
  theme(legend.position = "right")+
  theme(axis.line = element_line(colour = "black")) +
  theme(panel.grid.major = element_blank(), panel.grid.minor = element_blank())
ggsave("plot11.tiff", units="in", width=6, height=3, dpi=300, compression = 'lzw')
```

```{r}
Theta %>%
ggplot(aes(x = factor(Time), y = Instruction.Miss, fill = Region))  +
  geom_boxplot() +
  labs(x = "\nTime", y = "Instruction Miss\n") +
  theme_minimal() +
  labs(color="Region")+
  theme(legend.position = "right")+
  theme(axis.line = element_line(colour = "black")) +
  theme(panel.grid.major = element_blank(), panel.grid.minor = element_blank())
ggsave("plot12.tiff", units="in", width=6, height=3, dpi=300, compression = 'lzw')
```

````
##CORRELATION##
#Alpha#
```{r}
cor.test(Alpha$Average, Alpha$KSS,  method = "spearman")
```
```{r}
cor.test(Alpha$Average, Alpha$Steering.Errors,  method = "spearman")
```
```{r}
cor.test(Alpha$Average, Alpha$Instruction.Miss,  method = "spearman")
```
```{r}
cor.test(Alpha$KSS, Alpha$Steering.Errors,  method = "spearman")
```
```{r}
cor.test(Alpha$KSS, Alpha$Instruction.Miss,  method = "spearman")
```
```{r}
cor.test(Alpha$Steering.Errors, Alpha$Instruction.Miss,  method = "spearman")
```


#Theta#
```{r}
cor.test(Theta$Average, Theta$KSS,  method = "spearman")
```
```{r}
cor.test(Theta$Average, Theta$Steering.Errors,  method = "spearman")
```
```{r}
cor.test(Theta$Average, Theta$Instruction.Miss,  method = "spearman")
```
```{r}
````
````

```
cor.test(Theta$KSS, Theta$Steering.Errors,  method = "spearman")
```

```{r}
cor.test(Theta$KSS, Theta$Instruction.Miss,  method = "spearman")
```

```{r}
cor.test(Theta$Steering.Errors, Theta$Instruction.Miss,  method = "spearman")
```

##MULITILEVEL ANALYSIS##

First step in Multi-level modeling is making sure the modeling is appropriate. The unconditional model is done with the dependent variable only and no predictors. The dependent variable is the 'Average power of each frequency band'.No predictor variables are added. The predictor values are Regions, Time, KSS scores, Instruction Misses and Steering Errors.

```{r}
M1 <- lmer(Average ~ 1 + (1|Participant),data=AlphaL)

tab_model(M1,show.se=T,digits = 4,
        title="Table: Unconditional Model for Alpha")
```

```{r}
M2 <- lmer(Average ~ 1 + (1|Participant),data=ThetaL)

tab_model(M2,show.se=T,digits = 4,
        title="Table: Unconditional Model for Theta")
```

After determining that a multilevel model is appropriate, the next step is to begin to add the level-1 predictors.

```{r}
M3 <- lmer(Average ~ KSS+Steering.Errors+Instruction.Miss + (1|Participant),data=AlphaL)
```

```
tab_model(M3,show.se=T,digits = 4,
        title="Table: Model for the Relationship of Average Power in the Alpha Frequency with KSS scores, Steering Errors, Instruction Miss")

summary(M3)
```