Exploring the Potential of Functional Near-Infrared Spectroscopy (fNIRS) in Detecting Driver Vigilance

Decrement: A Study on Prolonged Highway Driving

Ilkyaz Caggul Armagan Arslankaya

Master Thesis – Human Factors and Engineering Psychology

Department of Cognitive Psychology and Ergonomics

Faculty of Behavioural, Management and Social Science (BMS)

University of Twente, Enschede

Supervisors

1st Supervisor: Dr. Rob H.J. van der Lubbe

2nd Supervisor: Dr. Simone Borsci

Date: 07/07/2023

Acknowledgements

I would like to sincerely thank the following individuals for their invaluable support in completing my master's thesis:

Lucia Rabago Mayer, Feline Waardenburg, Melina Marie Kowalski, and especially Adrian Fagarasanu from The BMS Lab. Adrian's tireless efforts in building the Unity driving simulator were crucial in making this project a reality.

My supervisors, Rob and Simone, for entrusting me with the opportunity to grow as a researcher and providing valuable guidance.

Max Slutter for his expertise in fNIRS and Dorvanique Cocks for her being there when I have a question about experimental design. Your suggestions greatly improved the quality of my research.

My dear friends Ilter and Laura for the countless hours of emotional support talks.

My loving family, especially my parents and my sibling Alden Doga, for their unconditional love and belief in my abilities. This thesis reflects the values you instilled in me.

Lastly, I want to express my deepest gratitude to my husband, Alp. Your unwavering support, patience, and understanding have been my constant source of strength. I am truly blessed to have you by my side.

Abstract

Traffic accidents resulting from a vigilance decrement contribute to a significant proportion of road incidents in Europe, with an estimated occurrence rate of 10% to 20%. To mitigate such accidents, it is crucial to detect the moments of vigilance decrement. This exploratory study investigated the potential utility of functional Near-Infrared Spectroscopy (fNIRS) in detecting vigilance decrement during prolonged highway driving. Grounded in cognitive resource theory and mindlessness theory, the research hypothesized correlations between fNIRS measures, subjective sleepiness measured by the Karolinska Sleepiness Scale (KSS), and specific driving performance indices, such as steering errors and instruction misses. However, multilevel models used for data analysis revealed no significant associations between these variables, thus not supporting the initial hypotheses. The results implied that the fNIRS measures employed in this study might not be adequate for detecting vigilance decrement in real-world driving scenarios. The research emphasized the need for a more comprehensive exploration, incorporating detailed assessments of driving experience and consistent instructional design between participants to enhance the relevance of fNIRS in predicting vigilance decrement. This study enriched the understanding of vigilance decrement and illuminated challenges and future research paths for the effective application of neuroimaging tools like fNIRS in assessing driver vigilance.

Exploring the Potential of Functional Near-Infrared Spectroscopy (fNIRS) in Detecting Vigilance

Decrement: A Study on Prolonged Highway Driving

Introduction

The growing number of road accidents has raised public concern about driving safety in the last decades. It is stated that most accidents caused by a decline in vigilance occur in road conditions that are meant to be safe, and this decline is strongly linked to the monotony of the road (Thiffault and Bergeron, 2003). The decrease in vigilance alternatively has been attributed to reduced attentional capacity, making it difficult to sustain mental effort (Pattyn et al., 2008). This study aims to investigate the effectiveness of fNIRS measures to detect vigilance decrement in prolonged highway driving.

Vigilance is generally defined as the ability to sustain attention and remain alert over extended periods of time (Warm et al., 2008). However, vigilance decrement, which refers to the decrease in attention and alertness over time while performing attention-requiring tasks (Oken et al., 2006), adds a nuanced perspective to our understanding of vigilance. Different groups of scientists have defined vigilance in various ways, leading to variations in its conceptualization (Oken et al., 2006). For instance, clinical neuropsychologists often consider vigilance as the level of sleepiness on a sleep-wake axis, while psychologists view it as a cognitive performance level, and animal behaviorists focus on being alert specifically to potential dangers (Oken et al., 2006). Despite these differences, vigilance can generally be understood as sustained attention.

Two main theories, namely cognitive resource theory (CRT) and mindlessness theory (MT), have been proposed to explain vigilance decrement and its underlying mechanisms (Flanagan & Nathan-Roberts, 2019). CRT, closely related to Wickens' Multiple Resources Theory (2008), posits that our brains possess diverse resources that are independent of each other, and different tasks may utilize different resources (Wickens, 2008). When two tasks share overlapping resources, depletion of those resources occurs more rapidly compared to a single task utilizing the same resource. According to CRT, the amount

of resources required is determined by task difficulty, and prolonged time spent on a demanding task leads to resource depletion. On the other hand, MT suggests that vigilance decrement is primarily a result of task monotony and the cognitive disengagement it engenders (Helton & Russell, 2015). In this view, cognitive resources are considered fixed and do not deplete over time. Instead, resources may be allocated to other tasks or mind wandering, which is the default state of the mind when the current task lacks sufficient stimulation (Flanagan & Nathan-Roberts, 2019). Consequently, vigilance decrement is observed in the task at hand.

The importance of vigilance in real-world tasks such as driving cannot be understated. Prolonged driving, particularly during long-distance trips between cities or countries, necessitates sustained vigilance for hours. While previous studies on vigilance and driving have predominantly focused on the complex nature of driving tasks, it is worth considering that some driving conditions, particularly on highways in rural areas, lack the unpredictability and variability required to maintain vigilance (Larue et al., 2011). Thiffault and Bergeron (2003) argued that most crashes resulting from vigilance decrement occur on roads specifically designed to enhance road safety. Fell and Black (1997) found that in rural areas characterized by highly monotonous road geometry, 45% of drivers involved in crashes reported not feeling tired before the incident. This suggests that in rural highway settings, vigilance decrement is closely related to the monotony of the road.

Within the driving literature, terms such as fatigue, sleepiness, arousal, and vigilance are frequently associated with performance decline and accidents. Dinges (1995) posited that vigilance decrement is an effect of fatigue and sleepiness. Fatigue encompasses physiological and psychological processes that decrease an individual's capacity to perform by altering their alertness and vigilance (Thiffault & Bergeron, 2003). Sleepiness, on the other hand, refers to the inability to stay awake (Shen et al., 2006). Factors such as the time of day, extended hours of driving, and sleep-related issues have been identified as contributing to driver sleepiness. Time-of-day is related to the 24-hour circadian rhythm of

the body. Lengthy periods of driving, also known as the time-on-task effect, are known to cause fatigue and a decrease in driving performance. Spending extensive time on a task which in turn resulted in a depletion of mental resources is related to active fatigue, which is related to the CRT. The fatigue caused by task monotony is named passive fatigue and it is connected to the MT (Körber et al., 2015). Philip et al. (2005), found out in the study they conducted on a French highway, that duration of driving is not the main factor to explain driving impairment due to vigilance decrement, while time awake (time-of-day effect) and previous sleep duration has a significant impact. Their results indicated individual subjective measures of sleepiness have a negative connection with driving performance, whereas individual subjective measures of fatigue were discovered to be an ineffective predictor of driving performance. This result indicated that fatigue may not be an equally precise indicator as sleepiness when it comes to vigilance decrement, particularly in a highway environment. As Cocks (2022) mentioned, sleepiness appears to be a more significant factor in the link between driving performance and vigilance. One of the reliable methods to measure subjective sleepiness is Karolinska Sleepiness Scale (KSS; Shahid et al., 2011; Kaida et al., 2006) which is widely used in driving vigilance studies (Philip et al., 2005; Bartolacci et al., 2020; Freire & Freire, 2018). Kaida et al. (2007) indicated that KSS scores could be used to predict performance errors due to vigilance decrement. Shoaib et al. (2023) conducted an experiment where they divided participants into two groups: well-rested and sleep deprived. They used KSS and fNIRS measures in a driving environment. Their results indicated that sleep deprivation and fatigue have a noticeable impact on brain activity during driving.

Fatigue and sleepiness result in decrement of driving performance. Lane change, steering wheel reversal, accelerator pedal release time, accelerator to brake transition time and, brake reaction time are some of the most used performance measures in driving research (Savino, 2009). Papantoniou et al. (2017) pointed out in their review, for the distracted driving research that conducted with driving simulators, lateral control measures such as lane keeping, and steering wheel control are very

commonly used. Driver distraction can arise from various sources and is divided into physical distraction, visual distraction, auditory distraction, and cognitive distraction. Vigilance decrement due to boredom and allocation of mental resources to mind-wandering instead of the task at hand can be considered as cognitive distraction. Mixed findings have emerged in lane keeping research, potentially stemming from distinct impacts of visual, manual, and cognitive distraction on the performance of lane keeping. Cognitive distraction was found to increase steering wheel manipulation by Ranney et al. (2005) and Seppelt and Wickens (2003). However, there are also mixed findings for steering wheel manipulation. For example, Feng et al. (2009) found out that fatigued drivers tended to perform fewer steering micro-corrections. Besides these, reaction time and eye-movement measures are becoming increasingly common (Papantoniou et al., 2017). Reaction time increases when an individual fatigues (Li et al., 2009). Fixations, saccades, and smooth pursuits represent three types of eye movements that can be used to help identify cognitive distractions. There are some other methods to measure vigilance such as Psychomotor Vigilance Task (PVT), however, Theresia et al. (2018) argued that one of its limitations is that PVT is not suitable for real-time measurement while driving.

Maintaining vigilance requires maintaining attention over time and this causes fluctuations in neural activity. For measuring neural activity, there are different methods benefiting from; 1) the electrical activity due to the synchronous firing of the neurons (Light et al., 2010), 2) mapping brain activity by recording magnetic fields produced by electrical currents (Singh, 2014) or 3) measuring the blood oxygenation level (Bogler et al., 2014). These methods are 1) electroencephalography (EEG), 2) magnetoencephalography (MEG) and 3) functional magnetic resonance imaging (fMRI) and functional near-infrared spectroscopy (fNIRS) respectively. The comparison of fMRI, EEG and NIRS can be seen in Table 1 (Liu et al., 2015).

Table 1

Comparison of three brain imaging techniques of fMRI, EEG and NIRS.

Items	fMRI	EEG	NIRS
Spatial resolution	+	-	~
Temporal resolution	-	+	~
Constraints on body movement	-	~	+
Continuous, long-time measurement	-	~	+
Application cost	-	+	+

Note. '+', '~' and '–' represent good, moderate, and poor, respectively.

To investigate vigilance, EEG has been used in many studies (Cocks, 2022; Campagne et al., 2004; Formentin et al., 2019). This study builds upon the foundation established by Cocks (2022). In their study, Cocks conducted a driving simulator experiment using similar closed-loop road conditions and EEG to evaluate the effectiveness of EEG in detecting driver vigilance. However, although EEG is capable of high temporal and spatial resolution, it is less immune to ambient electrical noise (Siddique, 2020), and to noise artifacts caused by movement (Palendeng, 2011). Therefore, this study seeks to investigate whether fNIRS could serve as a viable alternative to EEG in effectively detecting driver vigilance.

Functional MRI studies have shown that attentional performance related to vigilance is correlated with blood-oxygen-level-dependent (BOLD)-signals, especially in parietal and prefrontal cortical regions (Bogler et al., 2014). It is important to note that fNIRS differs from fMRI because fNIRS relies upon the intrinsic optical absorption of blood to form its signals, as opposed to fMRI, which utilizes the paramagnetic properties of deoxygenated hemoglobin (HbR). Consequently, fNIRS is capable of simultaneously recording changes in oxygenated hemoglobin (HbO) and deoxygenated hemoglobin (HbR). (Basso Moro et al., 2013). Also, fNIRS measures are limited to the surface of the brain (Bogler et al., 2014). fNIRS is a less expensive non-invasive technique with higher portability and temporal

resolution but a comparable outcome to fMRI, despite fMRI being frequently used in brain imaging research (Siddique, 2020).

Li et al. (2009), studied cerebral oxygenation during prolonged driving using fNIRS. They divided participants into two groups: task and control groups. The task group was required to perform the driving task for 3 hours while the control group was merely required to watch the driving simulation video for 3 hours. According to their results, when driving began HbO increase was observed with a decrease in HbR in the frontal cortex. However, as time on task increased, a decrease in HbO and an increase in HbR started to appear. At the end of the 3-hour study, the cerebral oxygen saturation was significantly lower in the task group, and participants exhibited symptoms of fatigue. However, it is important to note that there was no significant difference in oxygen saturation between the groups before the 180-minute mark, and the significantly higher levels of HbO for the task group remained valid until the 120-minute mark. Another study (Helton et al., 2010) also focused on the cerebral oxygenation levels of participants during vigilance tasks lasting 12 minutes. The participants were divided into three groups: easy vigilance task, hard vigilance task, and control group. In both vigilance tasks, the regional oxygen saturation, calculated using the relative amounts of HbO and HbR, was significantly higher than that of the control group throughout the experiment. Bogler et al (2014), studied vigilance using fNIRS with a vigilance task. Results of the vigilance task (variations in reaction times) were correlated with the oxygenation changes in frontal and parietal regions as expected. Further analysis showed that effects were more prominent in HbO than in HbR. Maintaining vigilance caused an increase in oxygen demand in the cerebral cortex. While HbO concentrations rose following cortical activation due to increased blood flow, HbR concentrations fell. However, during extended periods of specific neuronal activity, the energy requirement might exceed the energy available, causing a disparity in the activated areas of the brain (Rupp & Perrey, 2007). Consequently, there might be an inverse reaction, such as an increase in HbR and a decrease in HbO towards the conclusion of the driving task. As a result, fNIRS may be able to

detect attention-related BOLD signals at the brain's surface, notably in the parietal and prefrontal cortex.

Although vigilance is affected by several neural and functional systems and therefore is not unidimensional as suggested by Oken et al (2006), it is not possible within the scope of this research to experimentally control all different specific physiologic or performance measurements. Therefore, self-reported subjective sleepiness with KSS, steering control and instruction misses, and fNIRS data will be the identifying measures of vigilance in this study. Given the established theories and measures related to vigilance and its decrement, the aim of this study is to investigate the relationship between fNIRS measures, subjective sleepiness (as measured by KSS), and driving performance measures (e.g., steering errors, instruction misses) during prolonged highway driving.

The hypotheses of the current study are as follows:

Based on cognitive resource theory (CRT), it is hypothesized that changes in subjective sleepiness, as indicated by Karolinska Sleepiness Scale (KSS) scores, will be correlated with changes in fNIRS measures in the frontal cortex. Specifically, increased subjective sleepiness will be associated with decreased oxygenated hemoglobin (HbO) levels and increased deoxygenated hemoglobin (HbR) levels in the frontal cortex, indicating resource depletion during vigilance decrement. This effect is predicted because as the brain becomes more fatigued and resources are depleted according to the CRT, there is an increase in oxygen demand and utilization to perform the task, leading to changes in the hemoglobin levels measured by fNIRS.

Building on mindlessness theory (MT), it is hypothesized that fNIRS measures in the frontal cortex will be able to predict individual changes in driving performance measures, such as steering errors and instruction misses. Specifically, increased cognitive disengagement and mind-wandering due to boredom, as reflected by the decrease in HbO and increase in HbR, will be associated with a higher frequency of steering errors and instruction misses during prolonged highway driving. This effect occurs

because as the brain becomes disengaged and bored with the task, the measured changes in fNIRS levels indicate a shift in attention away from the driving task, leading to poorer performance in terms of steering control and following instructions.

Although EEG data is not recorded in this study, based on previous research (Cocks, 2022), it is hypothesized that EEG and fNIRS measures would show complementary predictive abilities for subjective sleepiness and individual changes in driving performance. Specifically, it is hypothesized that fNIRS measures in the frontal cortex would provide additional predictive value beyond what can be captured by EEG, indicating that fNIRS measures can account for a significant portion of the variance in subjective sleepiness and driving performance measures.

Method

Participants

A total of 30 participants took part in the experiment. However, only 23 participants' data could be used in the end. Data files from 4 participants were corrupted due to a computer shutdown during the recording with Oxysoft. Data from 3 participants could not be used due to low signal quality. Among the remained participants, 13 were men and 10 were women, ranging in age from 19 to 37 years old (*M* = 22.7). They were recruited from The University of Twente Faculty of Behavioural, Management, and Social Sciences (BMS) Test Subject Pool system SONA or by the researcher. A post hoc power analysis conducted using GPower software (Faul et al., 2007) revealed that with a total sample size of 23 participants and an effect size of 0.1, the achieved power was 0.445, indicating a 44.5% chance of detecting a significant effect (Mayr et al., 2007). The critical range of R^2 values for rejecting the null hypothesis was 0.011 to 0.381 according to the power analysis.

The study obtained ethical approval from the BMS Ethical Committee with project number 220975. All participants were adults, university students, or staff from the University of Twente. They all had driver's licenses. Participants were verbally informed that their participation was voluntary and that

they could withdraw at any time without any consequences. Before the start of the experiment, they were provided with a written consent form containing complete information about the study and asked to confirm their voluntary participation.

Materials

Participants filled out a demographic questionnaire along with some questions to understand if there were any other factors that could affect their vigilance and fNIRS data before the experiment. The questions can be found in Appendix A. Qualtrics was used to collect answers for the questionnaire. Additionally, participants completed a visual acuity test to assess whether they had normal vision or corrected-to-normal vision as self-reported.

Changes in the concentration of oxyhemoglobin (HbO) and deoxyhemoglobin (HbR) in the frontal cerebral cortex were measured using a continuous wave optical system called Brite 24 (Artinis Medical Systems, Elst, The Netherlands). The system generated two wavelengths of near-infrared light at 760 and 840 nm, which were sampled at a rate of 10 Hz. The system included 10 transmitters and 8 receivers. The optode template used for this study allowed for a total of 27 channels with an inter-optode distance of 3 cm (see Figure 1).

Figure 1

Artinis Optode Template Guide
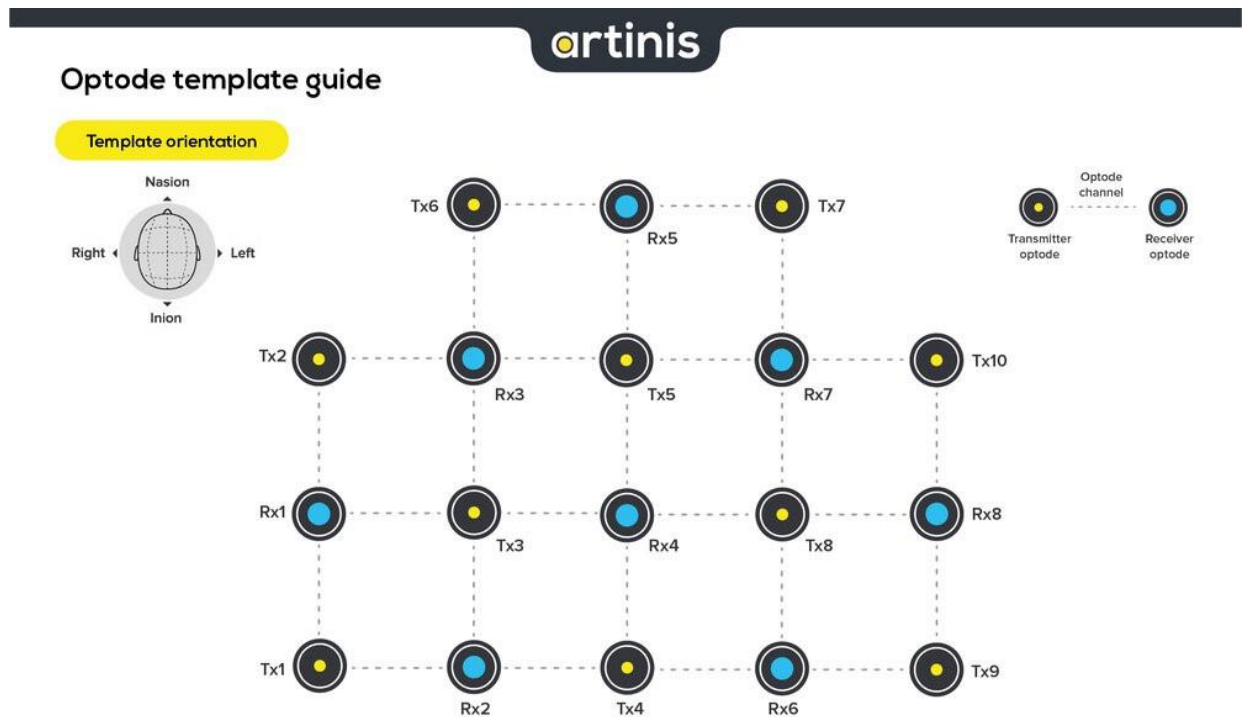
The fNIRS technique relies on NIR light to measure concentration changes in oxygenated and deoxygenated hemoglobin concentrations in the brain. It utilizes the Hemodynamic Response Function (HRF) to effectively monitor cognitive activity. Hemodynamic response functions refer to the physiological changes in blood flow, oxygenation, and volume that occur in response to neural activity in the brain. HRFs are typically modeled as a series of time-dependent functions that describe the temporal dynamics of the hemodynamic response.

OxySoft (version 3.2.51.4, Artinis Medical Systems, Netherlands) was used for data collection. The spatial arrangement slightly differs from the international 10–20 system used in EEG studies. Therefore, the manual digitization option in Oxysoft was used to determine the positions of the optodes (see Figure 2).

Figure 2

Manual Optode Digitization Using Oxysoft
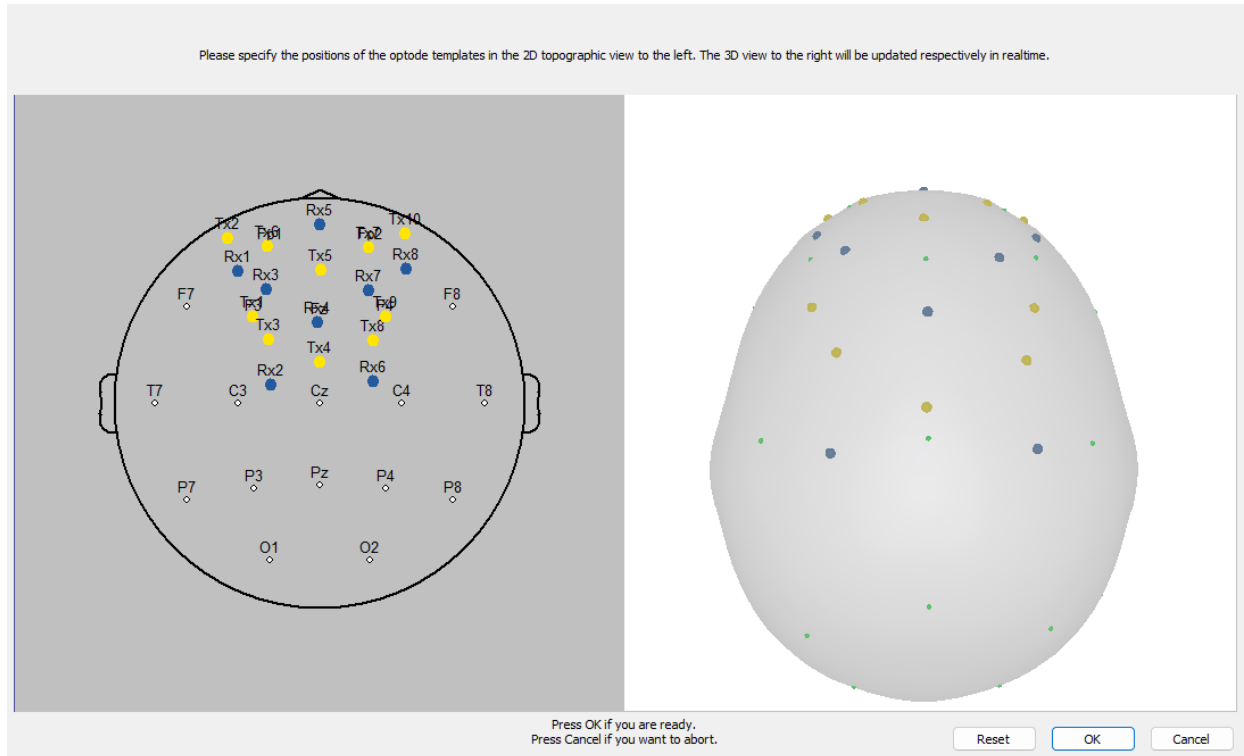
The road and traffic in the driving simulation were built in Unity (Version 2021.3.8.f1) by the

BMS Lab at the University of Twente. The environment was created by me and fellow master student

Abbas Kerem Dogan using assets. The driving environment represented a closed highway system (see

Figure 3) with cloudy weather conditions and traffic. The traffic in the environment included other cars,

but there were no pedestrians or bikes.

Figure 3

Driving Track

The connection between Oxysoft and Unity was established using the Lab Streaming Layer (LSL) protocol, which allows for real-time data and triggering streaming, as well as multi-modal time synchronization.

The setup included a Logitech steering wheel, shift stick, pedals, and a Next Level motion and traction platform. However, only the steering wheel and pedals were used in this experiment. The visual simulation projected onto the wall covered by a 2×3-meter screen. Participants used the gas pedal to accelerate, the brake pedal to stop when the car was moving, and the brake pedal again to reverse when the car was already stopped. The driving simulator room setup can be seen in Figure 3.

Figure 3

Driving Simulator Room

Procedure

After filling out the questionnaire, the researcher placed a properly sized fNIRS cap on each

participant's head. Optodes were positioned according to the template, and the experiment

commenced with a 2-minute baseline measurement. Following the measurement, participants drove in

the driving simulator for 1 hour. They were instructed not to exceed 120 km/h to minimize differences

in steering errors due to speed. During the driving task, participants encountered several visual

instructions. The driving instructions included driving straight, turning right, and keeping the left lane

(see Figure 4 for an example). When participants approached a junction, a visual cue was given,

instructing them to make a right turn or continue driving straight ahead. Participants also received

another driving instruction that instructed them to keep to the left lane. Failure to follow the

instructions correctly resulted in an instruction miss. Please refer to the Appendix B for information on

triggers in Unity and their corresponding marker symbols received by Oxysoft using the LSL connection.

Figure 4

Go Straight Instruction That Was Seen by The Participants

Every five minutes, participants were asked to verbally rate their sleepiness levels on a scale of 1 to 9 using the Karolinska Sleepiness Scale.

During the experiment, the Recforth screen recorder was used to record the screen. These recordings were then used to determine steering errors. Steering errors were identified by observing instances where participants failed to stay in the driving lane or respond appropriately to directional changes in the driving environment. Collisions with the divider, lampposts, and junction points within the driving environment were counted as steering errors.

Data Analysis

The fNIRS data was transferred to Matlab using the oxysoft2matlab script provided by Artinis Medical Systems. The .oxy4 files were converted into .snirf files (Shared Near InfraRed File Format). After conversion, the snirf files were imported into Homer3 (Huppert et al., 2009), a MATLAB application used for analyzing fNIRS data to obtain estimates and maps of brain activation. In Homer3, the data was divided into 12 equal 5-minute blocks and one 2-minute baseline measurement block using events. Basic preprocessing steps were applied. First, the data was converted from intensity to optical density (OD).

Then, to remove motion artifacts, Targeted Principle Component Analysis (tCPA) was applied. tCPA was chosen over other motion artifact correction methods because it is applied only to pre-identified MA segments to avoid over-correction (Yücel et al., 2014). After that, low-pass filtering was applied to the data. To annihilate heart-rate artifacts (~ 1 Hz) but to conserve human respiration frequency component (0.2–0.4 Hz) or Mayer waves (0.1 Hz) during the hemodynamic measurement, a low-pass filter was designed for fNIRS at a 0.5 Hz cutoff frequency. The OD was then converted to concentration. Finally, block averaging was applied to the concentration data (see Appendix C for details).

After preprocessing, the mean HRF values were exported as a text file from Homer3 and added to the datasets. Two datasets were created: one for oxygenated hemoglobin (HbO) HRF means and another for deoxygenated hemoglobin (HbR) HRF means. Each dataset included participant number, acuity score for the left and right eye, age, gender, nationality, education level, handedness, hours slept the night before, drug use, alcohol use, caffeine use, time, KSS score, channel, HRF means, steering errors, and instruction misses for the 23 participants. In the dataset files, the "steering errors" variable represents the number of instances in which a participant made steering errors during a specific 5-minute period. Similarly, the "instruction misses" variable indicates the number of times a participant failed to follow the driving instructions correctly within a specific 5-minute interval.

RStudio was used to conduct statistical analysis using the R programming language (RStudio Team, 2022). In R, the HRF value of the baseline condition was subtracted from the HRF values of each block for every channel and every participant to isolate the activity created by the experimental manipulation (Chuang et al., 2018). Descriptive statistics were estimated for HRF, KSS scores, steering errors, and instruction misses. Line graphs were created to visualize the changes over time for each variable of interest in both the HbO and HbR datasets. Two boxplots were created to examine the changes in HRF over time for HbO and HbR.

Correlation analysis was applied to explore the relationship between fNIRS measures (HRF for HbO and HbR), and sleepiness scores (KSS), instruction miss, and steering errors. Additionally, the correlation coefficients between KSS and steering errors, KSS and instruction miss, and steering errors and instruction miss were calculated to observe the relationship between these variables. The type of correlation analysis conducted was Pearson correlation coefficient analysis. Pearson correlation coefficient analysis is chosen for this analysis because it is a commonly used method to measure the linear relationship between two continuous variables. It assesses the strength and direction of the linear association between variables, indicating how closely the data points align to a straight line. Correlation analysis between fNIRS measures (HRF for HbO and HbR) and subjective sleepiness (KSS) scores examined whether changes in subjective sleepiness are correlated with changes in fNIRS measures in the frontal cortex, as predicted by the first hypothesis. Correlation analysis between fNIRS measures (HRF for HbO and HbR) and driving performance measured (steering errors and instruction misses) investigates whether fNIRS measures in the frontal cortex can predict individual changes in driving performance measures, as proposed by the second hypotheses. To further investigate these relationships, several linear regression analyses were conducted on the same variable pairs. While the correlation analysis provides information about the strength and direction of the linear relationship between variables, linear regression analysis allows for a more comprehensive understanding of the nature, significance, and predictive value of these relationships.

The Multilevel Linear Models (MLMs) were used to examine the relationship between HRF means (dependent variable), KSS scores, steering errors, and instruction misses (independent variables) in separate models for HbO and HbR. MLM is chosen because it is very effective for analyzing data with nested structure, where observations are nested within higher-level units. In this study, HRF means are nested into channels and channels are nested into time blocks for each participant. MLMs allow for the estimation of both fixed effects (population-level effects) and random effects (group-level effects)

simultaneously and can handle unbalanced or missing data. With MLMs random intercepts and slopes

for participants and channels can be estimated, which can help understand the variability in HRF and its

relationships with predictors across different participants and channels.

Two separate models were conducted for HbO and HbR with participants as a random intercept.

HRF was added to the models as a dependent variable, while KSS scores, steering errors, and instruction

misses were included as independent variables. MLM for HbO model examined whether changes in

subjective sleepiness (KSS scores) predict changes in HRF (oxygenated hemoglobin - HbO) levels in the

frontal cortex. It tested the hypothesis that increased subjective sleepiness is associated with decreased

HbO levels, indicating resource depletion during vigilance decrement, as predicted by the CRT. MLM for

HbO model also explored whether HRF (HbO) levels in the frontal cortex can predict individual changes

in driving performance measures (steering errors and instruction misses). It tested the hypothesis that

decreased HbO levels, indicating cognitive disengagement and mind-wandering due to boredom, are

associated with a higher frequency of steering errors and instruction misses during prolonged highway

driving, as suggested by the MT. MLM for HbR model investigated whether changes in subjective

sleepiness (KSS scores) predict changes in HRF (deoxygenated hemoglobin - HbR) levels in the frontal

cortex. It tested the hypothesis that increased subjective sleepiness is associated with increased HbR

levels, indicating resource depletion during vigilance decrement, as proposed by the CRT. MLM for HbR

model also investigated whether HRF (HbR) levels in the frontal cortex can predict individual changes in

driving performance measures (steering errors and instruction misses). It tested the hypothesis that

increased HbR levels, reflecting cognitive disengagement and mind-wandering due to boredom, are

associated with a higher frequency of steering errors and instruction misses during prolonged highway

driving, as proposed by the MT.

After the multilevel analysis, variation partitioning analysis was performed to assess the

proportion of variance in the HRF outcome accounted for by participant-level variation and group-level

variation. Random effects analysis was also performed to estimate random effects for each participant in the models. Considering a possible learning effect in the first 10 minutes as Cocks (2022) observed, data is rearranged to remove the first 10 minutes of observation. First 10 minutes is chosen because Cocks (2022) found out a large decrease in both steering errors and instruction miss after 10 minutes which indicates the learning effect is assumed to be occurred in the first 10 minutes. The aforementioned analyses were also carried out on the new dataset, which will be referred to as the adjusted dataset from this point onward.

Two additional multilevel models were fitted for HbO and HbR with the addition of the channels. These models considered the nested structure of the data, with random intercepts for both Participant and Channel:Participant. These models examined the relationship between HRF and the predictors (KSS, Steering Errors, and Instruction Miss) while considering the channel-specific effects. After that, interaction between HRF and the predictors (KSS, Steering Errors, and Instruction Miss) were added in the multilevel linear regression models. Interaction analysis explored whether the relationship between HRF and the predictors differs depending on the channel.

<div align="center">Results</div>

Descriptive Statistics

Descriptive statistics for the variables HRF, KSS, Steering Errors, and Instruction Miss are presented in Table 1. For oxygenated hemoglobin, the HRF ranged from -0.00013 to 0.00012, with a mean of 0.00000033 (SD = 0.000013). For deoxygenated hemoglobin, the HRF ranged from -0.00010 to 0.000093, with a mean of -0.00000011 (SD = 0.0000093). Karolinska Sleepiness Score ranged from 2 to 9, with a mean of 4.6 (SD = 1.7) which indicates participants were on the more alert side of the scale in general. Steering errors ranged from 0 to 10, with a mean of 1.7 (SD = 1.7) while instruction misses ranged from 0 to 5, with a mean of 0.29 (SD = 0.69). Overall, participants exhibited good driving performance with few instruction misses and steering errors (see Table 1).

Table 2

Descriptive Statistics of Hemodynamic Response Function (HRF) for oxygenated (HbO) and deoxygenated

(HbR) hemoglobin, Karolinska Sleepiness Scale (KSS), Steering Errors and Instruction Miss

Variable	Min	Max	Mean	SD
HRF for HbO	-0.00048	0.00043	0.0000086	0.000054
HRF for HbR	-0.00031	0.00028	-0.0000042	0.000039
KSS	2	9	4.6	1.7
Steering Errors	0	10	1.7	1.7
Instruction Miss	0	5	0.29	0.69

Figure 5 depicts the changes in KSS scores over time. A small decrease in sleepiness can be

observed after five minutes and after 30 minutes of driving. However, participants' sleepiness levels

increased over time during the majority of the driving task in the simulated environment.

Figure 5

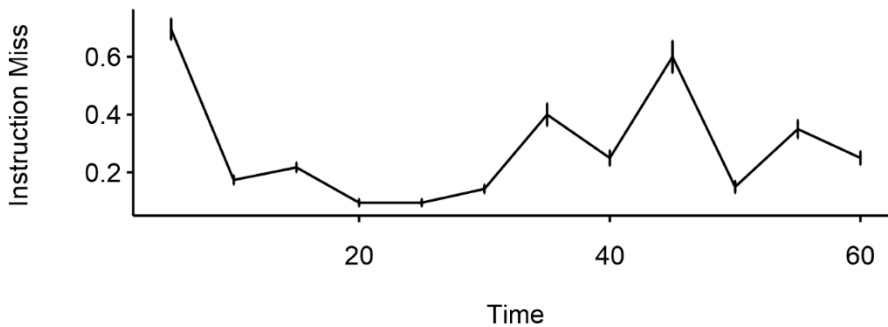*Line graph depicting changes in Karolinska Sleepiness Scale (KSS) over Time*
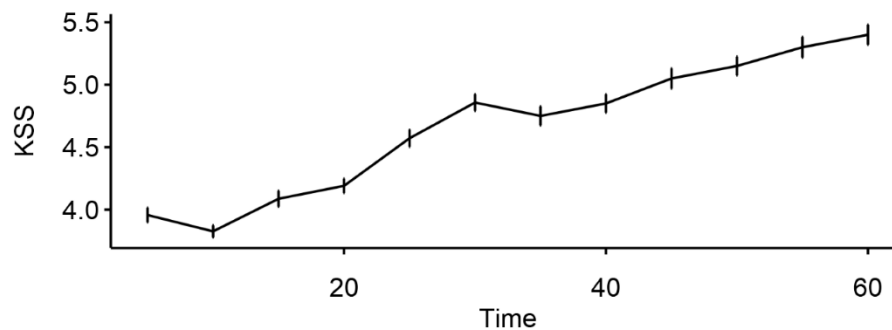
Note: Vertical bars represents the standard error of the mean. The y-axis represents the mean KSS at

each time period for all participants. Time is represented in minutes.

Figure 6 illustrates the changes in instruction misses over time. There is a notable decrease in

instruction misses after five minutes, which may be attributed to a learning effect as participants

familiarized themselves with the driving environment and equipment. Additionally, a sharp fluctuation

in instruction misses can be observed at 45 minutes, potentially indicating an increase in sleepiness levels.

Figure 6

Line graph depicting changes in Instruction Miss over Time
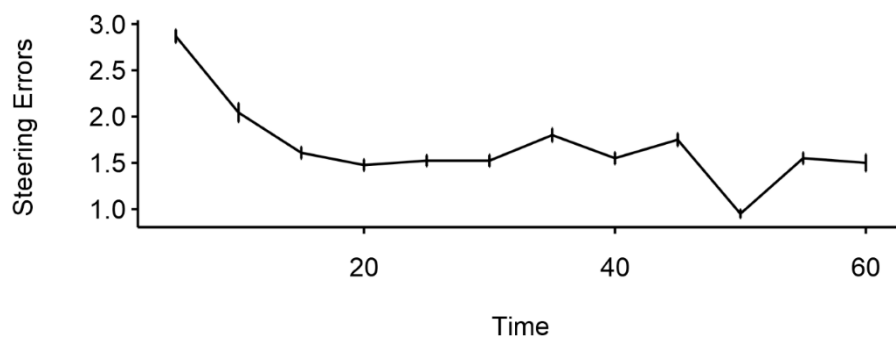

Note: Vertical bars represents the standard error of the mean. The y-axis represents the mean instruction miss at each time period for all participants. Time is represented in minutes.

Figure 7 presents the changes in steering errors over time. Similar to instruction misses, a significant decrease in steering errors can be observed after five minutes, potentially indicating a learning effect. There is a slight increase in steering errors at 45 minutes, followed by a sharp decrease at 50 minutes. The increase in errors at 45 minutes may have prompted participants to make more conscious efforts to avoid mistakes, leading to the subsequent decrease at 50 minutes. The unexpected decrease in steering errors for all participants at exactly 50 minutes raises concerns regarding the experimental setup or other factors. The researcher examined the screen recordings to identify any anomalies in the road design that could cause this effect, but no visible problems were found.

Figure 7

Line graph depicting changes in Steering Errors over Time

Note: Vertical bars represents the standard error of the mean. The y-axis represents the mean steering errors at each time period for all participants. Time is represented in minutes.

Correlations & Regressions

For both the complete dataset and adjusted dataset, all correlations were negligible except for the correlation between steering errors and instruction miss, which indicates a moderate positive correlation (coefficient for the complete dataset: 0.36, coefficient for the adjusted dataset: 0.39). This suggests that as the number of steering errors increases, the number of instruction misses also tends to increase, with a slightly stronger correlation for the adjusted dataset.

The regression analysis between HRF values for HbR and self-reported sleepiness scores (KSS) indicates a small negative relationship between KSS and HRF, which is statistically significant (β = -0.0015, p = .001). However, the R^2 value is 0.0015, indicating that HRF explains only a very small portion of the variability in KSS. The regression analysis of HRF for HbR and steering errors shows a small negative significant relationship (β = -0.15, p = .06). Nonetheless, the R^2 value is very low (i.e. 0.0045), indicating that HRF explain only a small portion of the variability in steering errors. The coefficient for steering errors is -0.15, suggesting a negative relationship between steering errors and KSS, which is statistically significant (β = -0.15, p < .001). The R^2 value is again low (i.e. 0.02), indicating that KSS explain only a small portion of the variability in steering errors. The coefficient for instruction miss is 0.90, suggesting a positive relationship between instruction miss and steering errors, which is statistically significant (β = 0.90, p < .001). The R^2 value is 0.13, indicating that instruction miss explains a

small portion of the variability in steering errors. The regression analysis is performed using the

individual values of instruction miss and steering errors for each time period for each participant. All

other pairs of variables were not statistically significant. In summary, the regression analyses reveal

some relationships between the different variables, but overall, the models have limited explanatory

power, as indicated by the low R^2 values. The significance of the coefficients also varies, with some

relationships being statistically significant while others are not. The regression analysis for the adjusted

dataset did not yield different results.

Multilevel Linear Model

Two multilevel linear regression models were conducted to examine the relationships between

the predictors (KSS, Instruction Miss, and Steering Errors) and the dependent variable HRF, for HbO and

HbR respectively. The models included a random intercept for the variable "Participant" to account for

the nested structure of the data.

For Model 1 (HbO) which used the complete dataset, the predictors (KSS, Instruction Miss, and

Steering Errors) did not have statistically significant associations with HRF for HbO. The fixed effects

estimate for the predictors were close to zero, indicating weak or non-significant associations. The

random effects analysis showed that the participant-level variance was very small, suggesting minimal

variation in HRF levels between participants. The residual variance represented unexplained variation in

HRF after accounting for the fixed and random effects. See Table 3 for values.

Table 3

Model 1: Multilevel Linear Model for oxygenated (HbO) hemoglobin for complete dataset

Predictor	HbO		
	Estimate	*Standard Error*	*t-value*
(Intercept)	0.00000668	0.00000482	1.39
KSS	0.000000234	0.000000692	0.34
Instruction Miss	-0.000000438	0.00000109	-0.40
Steering Errors	-0.000000136	0.000000542	-0.25
Random Effects			

	Variance	Standard Deviation
Participant	0.000000000242	0.0000156
Residual	0.00000000273	0.0000522

N $_{Participant}$ 23

REML Criterion at Convergence -114694.1

Note: REML stands for Restricted Maximum Likelihood. It is a statistical method used for parameter

estimation in mixed-effects models. In general, a lower REML value indicates a better fit of the model to

the data.

The ICC (Intraclass Correlation Coefficient) is a statistical measure used to assess the proportion

of variance in a dependent variable that can be attributed to the differences between groups or

participants. It is commonly used in multilevel or hierarchical models to quantify the amount of variance

at different levels. For Model 1 (Multilevel Linear Model for oxygenated HbO hemoglobin), the ICC value

is approximately 0.081. This suggests that about 8.1% of the total variance in oxygenated HbO

hemoglobin levels can be attributed to the differences between participants, while the remaining 91.9%

is due to the residual variance or random error within participants. This relatively low ICC indicates that

individual differences between participants contribute only a small portion of the overall variance in

oxygenated HbO levels.

In Model 2 (HbR), also using the complete dataset, none of the predictors (KSS, Instruction Miss,

and Steering Errors) had statistically significant associations with HRF for HbR. The fixed effects estimate

for the predictors was close to zero, indicating weak or non-significant associations. The random effects

analysis revealed a small participant-level variance, indicating minimal variation in HRF levels between

participants. The residual variance represents the unexplained variation in HRF after accounting for the

fixed and random effects. It indicates that there is some residual variability in HRF levels that cannot be

explained by the predictors included in the model (see Table 4).

Table 4

Model 2: Multilevel Linear Model for deoxygenated (HbR) hemoglobin for complete dataset

Predictor	HbR		
	Estimate	*Standard Error*	*t-value*
(Intercept)	-0.00000267	0.00000383	-0.70
KSS	-0.000000216	0.000000498	-0.43
Instruction Miss	0.000000220	0.000000770	0.29
Steering Errors	-0.0000000150	0.000000386	-0.04
Random Effects			
	Variance	Standard Deviation	
Participant	0.000000000186	0.0000136	
Residual	0.00000000136	0.0000369	
N $_{Participant}$	23		

REML Criterion at Convergence -119394.7

For Model 2 (Multilevel Linear Model for deoxygenated HbR hemoglobin), the ICC value is approximately 0.121. This indicates that around 12.1% of the total variance in deoxygenated HbR hemoglobin levels can be attributed to the differences between participants, while the remaining 87.9% is due to the residual variance or random error within participants. Similarly to Model 1, this ICC value suggests that individual differences between participants explain a relatively small proportion of the overall variance in deoxygenated HbR levels.

Overall, neither model does provide strong evidence for a significant relationship between the predictors (KSS, Instruction Miss, Steering Errors) and HRF. The low fixed effects estimates, non-significant t-values, and small participant-level variance suggest that these predictors have limited impact on HRF levels, and other factors may be influencing the observed HRF variability.

Two additional models were also explored (Model 3 HbO and Model 4 HbR) where the adjusted datasets were used, the results were consistent with the previous analysis using the complete dataset. There is no strong evidence of a significant effect of the predictors on HRF levels. The variation in HRF is primarily driven by unexplained residual variation rather than participant-level differences (see Table 5 and Table 6).

Table 5

Model 3: Multilevel Linear Model for oxygenated (HbO) hemoglobin for the adjusted dataset

Predictor	HbO		
	Estimate	*Standard Error*	*t-value*
(Intercept)	0.00000690	0.00000552	1.25
KSS	0.000000182	0.000000848	0.22
Instruction Miss	-0.00000000577	0.00000131	-0.004
Steering Errors	0.0000000405	0.000000732	0.06
Random Effects			
	Variance	Standard Deviation	
Participant	0.000000000238	0.0000154	
Residual	0.00000000271	0.0000520	
N Participant	23		

REML Criterion at Convergence -93772.3

Table 6

Model 4: Multilevel Linear Model for deoxygenated (HbR) hemoglobin for the adjusted dataset

Predictor	HbR		
	Estimate	*Standard Error*	*t-value*
(Intercept)	-0.00000248	0.00000434	-0.57
KSS	-0.000000223	0.000000619	-0.36
Instruction Miss	-0.000000138	0.000000932	-0.15
Steering Errors	-0.000000124	0.000000525	-0.24
Random Effects			
	Variance	Standard Deviation	
Participant	0.000000000188	0.0000137	
Residual	0.00000000136	0.0000369	
N Participant	23		

REML Criterion at Convergence -97589.2

Two additional multilevel models were fitted for HbO and HbR with random intercepts for both the Participant and Channel, nested within Participant. Additionally, an interaction term was added to the models to investigate potential moderating effects. The interaction terms included in the models were KSS * steering errors, KSS * instruction miss, and steering errors * instruction miss.

The fixed effects results for Model HbO are as follows: The intercept was estimated to be 0.00000664 (SE = 0.00000345, t(6800) = 1.93, p = .05). The predictor KSS showed a non-significant effect on HRF (estimate = 0.000000217, SE = 0.000000177, t(6800) = 1.23, p = .22). Similarly, steering errors also had a non-significant effect on HRF (estimate = -0.000000165, SE = 0.000000135, t(6800) = -1.22, p = .22). Instruction miss had a non-significant effect on HRF as well (estimate = -0.00000039, SE = 0.000000266, t(6800) = -1.46, p = .14). The correlation of fixed effects in Model HbO indicated a negative correlation between KSS and steering errors (r = -0.25) and a weak negative correlation between KSS and instruction miss (r = -0.01). There was also a weak negative correlation between steering errors and instruction miss (r = -0.15). The details of the HbO model can be seen in Table 7.

Table 7

Model 5: Multilevel Linear Model for oxygenated (HbO) hemoglobin (Channel included)

Predictor	HbO		
	Estimate	*Standard Error*	*t-value*
(Intercept)	0.00000664	0.00000345	1.93
KSS	0.000000217	0.000000177	1.23
Instruction Miss	-0.000000164	0.000000134	-1.22
Steering Errors	-0.000000390	0.000000266	-1.46
Random Effects			
	Variance	Standard Deviation	
Channel:Participant	0.00000000278	0.0000527	
Participant	0.000000000152	0.0000123	
Residual	0.000000000162	0.0000127	
N $_{Participant}$	23		

REML Criterion at Convergence -130727.9

When interaction term was added to the Model HbO, none of the interaction terms reached statistical significance (all p > .05). The interaction between KSS and steering errors (Estimate = -0.0000000914, SE = 0.0000000855, t = -1.07), KSS and instruction miss (Estimate = 0.000000296, SE = 0.00000032, t = 0.93), steering errors and instruction miss (Estimate = 0.000000103, SE = 0.000000408, t = 0.25), and the three-way interaction of KSS, steering errors, and instruction miss (Estimate = -

0.00000011, SE = 0.0000000863, t = -1.28) were not statistically significant. The random effects results

indicated that a considerable portion of the variance in HRF could be attributed to the between-

Participant level (Participant: Channel random intercept variance = 0.00000000278, SD = 0.0000527;

Participant random intercept variance = 0.000000000151, SD = 0.0000123) and the within-Participant

level (residual variance = 0.000000000162, SD = 0.0000127).

For the Model HbR, the intercept was not significantly different from zero (β = -0.00000326, SE =

0.00000296, t = -1.10, p > .05). None of the predictors, including KSS (β = -0.00000011, SE =

0.000000128, t = -0.86, p > .05), steering errors (β = 0.0000000769, SE = 0.0000000975, t = 0.79, p > .05),

and instruction miss (β = 0.000000242, SE = 0.000000193, t = 1.25, p > .05), showed a significant

association with HRF. The random effects analysis revealed that the participant-level variance was very

small (Variance = 0.000000000141, SD = 0.0000119), indicating little variability across participants. The

random effects results indicate that there is variability in HbR levels at the between-Participant level and

the within-Participant level across different channels. The residual variance was also small (Variance =

0.0000000000851, SD = 0.00000922). The details can be found in Table 8.

Table 8

Multilevel Linear Model for deoxygenated (HbR) hemoglobin (Channel included)

Predictor	HbO		
	Estimate	*Standard Error*	*t-value*
(Intercept)	-0.00000327	0.00000296	-1.10
KSS	-0.000000110	0.000000128	-0.86
Instruction Miss	0.0000000769	0.0000000975	0.79
Steering Errors	0.000000242	0.000000193	1.25
Random Effects			
	Variance	Standard Deviation	
Channel:Participant	0.00000000136	0.0000369	
Participant	0.000000000141	0.0000119	
Residual	0.0000000000851	0.00000922	
N $_{Participant}$	23		

REML Criterion at Convergence -135142.6

Interaction term showed that the intercept was not significantly different from zero (β = -0.00000286, SE = 0.00000299, t = -0.96, p > .05). The interaction between KSS and steering errors (Estimate = 0.000000054, SE = 0.000000062, t = 0.87), KSS and instruction miss (Estimate = -0.000000212, SE = 0.000000232, t = -0.91), steering errors and instruction miss (Estimate = -0.0000000467, SE = 0.000000296, t = -0.16), and the three-way interaction of KSS, steering errors, and instruction miss (Estimate = 0.0000000655, SE = 0.0000000626, t = 1.05) were not statistically significant. The random effects analysis revealed that both the participant-level variance (Variance = 0.000000000142, SD = 0.0000119) and the channel-level variance (Variance = 0.00000000136, SD = 0.0000369) were small. The residual variance was 0.0000000000851 (SD = 0.00000922).

Discussion

The present study aimed to examine the relationships between fNIRS measures, subjective sleepiness (as measured by the Karolinska Sleepiness Scale) and driving performance measures (steering errors and instruction misses) during prolonged highway driving. The investigation of these relationships was motivated by the need to better understand the underlying mechanisms of vigilance decrement and its impact on driving safety. With the emergence of automated vehicles, another important consideration is the ability of drivers to maintain alertness and promptly take over control when necessary. With the current level of automation (SAE Level 2; SAE, 2018) drivers must monitor the autonomous vehicle operations and its surroundings and, if possible, anticipate failures of the automated vehicle, and respond quickly to potential take-over events (Balters et al., 2021). To fulfill these requirements, drivers must maintain vigilance and be prepared to take over from the vehicle. Mindlessness theory, as discussed in the introduction, suggests that cognitive disengagement due to task monotony can contribute to vigilance decrement. This notion becomes particularly relevant in the context of automated vehicles, as mind-wandering resulting from boredom may hinder drivers' ability to promptly respond and regain timely focus when taking over control.

Given the importance of vigilance in driving, it is crucial to identify reliable measures that can capture changes in cognitive states and predict performance decline. By exploring the associations between fNIRS measures, subjective sleepiness, and driving performance, this study sought to contribute to our understanding of vigilance decrement and provide insights into the potential utility of fNIRS as a complementary measure to assess driver vigilance. The conceptual framework guiding this investigation was informed by two prominent theories: cognitive resource theory and mindlessness theory. These theories offer distinct perspectives on the mechanisms underlying vigilance decrement, emphasizing either resource depletion or cognitive disengagement, respectively. Building upon these theoretical foundations, the hypotheses of this study aimed to investigate the relationships between fNIRS measures, subjective sleepiness as measured by the Karolinska Sleepiness Scale (KSS), and driving performance measures, such as steering errors and instruction misses. By exploring these relationships, the study sought to shed light on the potential of fNIRS as a reliable tool for assessing vigilance in real-world driving scenarios and comparing its effectiveness to EEG.

In this study, it is hypothesized that changes in subjective sleepiness will correspond to changes in fNIRS measures, particularly in the frontal cortex, indicating resource depletion during vigilance decrement. However, the results did not support these hypotheses, as no significant associations were found between the Karolinska Sleepiness Scale (KSS) predictor and HRF levels using multilevel models.

Although the overall findings did not support this hypothesis, the regression analysis revealed a statistically significant small negative relationship between self-reported sleepiness scores (KSS) and the HRF for HbR. This finding aligns with previous research by Chen et al. (2021), which explored the relationship between fNIRS measures and sleepiness levels during N-back tasks and subsequent rest periods. Chen et al. (2021) reported that individuals with higher levels of sleepiness during the N-back task exhibited a higher HRF for HbR in the frontal cortex, indicating increased oxygen consumption in the brain to complete cognitive tasks. Additionally, during the rest periods, subjects with higher

sleepiness levels showed greater variation in HbO levels in the dorsolateral prefrontal and frontal

cortices, suggesting a need for increased oxygen supply to compensate for the oxygen consumed during

the tasks. However, it is important to note that the low R^2 value in our regression analysis indicates that

KSS explains only a small portion of the variability in HRF.

Even though there is a relationship between KSS and HRF for HbR based on regression analysis,

multilevel models show a nonsignificant relationship between them. The lack of significant relationships

between subjective sleepiness, fNIRS measures, and driving performance as indicated by the multilevel

models may be attributed to several factors. Firstly, the small participant-level variance observed

suggests that individual differences between participants had minimal impact on HRF levels. Instead, the

unexplained residual variance indicates the presence of other unidentified factors contributing to the

variability in HRF. Multilevel models account for the dependency and correlation within each level of the

hierarchy. By explicitly modeling the random effects and capturing the variation between higher-level

units and the correlation among observations within the same higher-level unit, multilevel models

provide more accurate standard errors and avoid biased parameter estimates that may arise from

disregarding the dependency or correlation. Additionally, multilevel models can enhance statistical

power compared to single-level models by effectively utilizing the variability within and between higher-

level units, leading to more precise estimates. These considerations may explain the lack of a significant

relationship between KSS and HRF for HbR in the multilevel model.

The non-significant relationships between KSS and fNIRS measures in the frontal cortex, as

indicated by the multilevel model, conflict with findings from the literature (Philip et al., 2005).

Descriptive statistics presented in the results indicate that participants demonstrated overall good

driving performance, with low levels of steering errors and instruction misses. The KSS scores also

suggest that participants were generally on the more alert side of the sleepiness scale. These findings

may partially explain the lack of significant associations between sleepiness, driving performance, and

HRF in the multilevel model. It is possible that the study sample consisted of individuals who were generally attentive and alert, resulting in limited variability in sleepiness levels and driving performance. However, it is also important to note that Cocks (2022) observed an increase in alpha and theta power in EEG when there was an increase in sleepiness, while the mean and standard deviation of the KSS scores ($M = 4.56$, $SD = 1.68$) were very similar to this study ($M = 4.6$, $SD = 1.7$).

One potential reason for the non-significant relationship between sleepiness and HRF could be the complex nature of the physiological responses involved. Although it was hypothesized that higher sleepiness would lead to changes in HRF values, the brain's response to sleepiness may not have manifested straightforwardly within the specific measures used in this study. Other factors, such as cognitive load and contextual variables (simulator fidelity, scenario complexity, experimental instructions and so on) could have influenced the fNIRS measures and masked the effects of sleepiness.

Another potential factor that may have influenced the lack of significant results is the difference in sleep deprivation levels among participants. A study by Shoaib et al. (2023) observed significant differences in frontal brain region activation for the oxygenated hemoglobin (HbO) measure between awake participants and sleep-deprived/fatigued participants. For the awake group they ensured that the subjects had a good night's sleep of 7.9 h ± 0.5 and for the sleep-deprived group it was ensured that each participant underwent continuous sleep deprivation for 22 ± 0.5 h. The experimental periods were chosen to best match the experimental needs, incorporating the times with the lowest risk of sleepiness (in the morning) for the awake-state experiments and times with the highest risk of sleepiness (middle of the night) for the sleep deprived-state experiments. The awake group, which had sufficient sleep, exhibited higher brain activity, oxygen consumption, and cerebral blood flow, leading to higher levels of HbO. Conversely, the sleep-deprived or fatigued group showed diminished brain activity, resulting in reduced HbO levels. In the current study, participants were not divided into groups, and they were invited to the experiment randomly either in the morning (between 09:30-12:00) or in the afternoon

(between 13:30-16:00). This might be the reason why their HRF responses are different during the experiment.

Alternatively, the reason why there is no significant relationship between sleepiness and fNIRS measures can be the speed range was too high (with no lower limit and 120 km/h as a higher limit) in this study. Liu (2014) examined the relationship between prefrontal activation, mental state of drowsiness, and driving performance in a simulated speed-control driving task using fNIRS. The study divided participants into two groups: a speed-free group and a speed-control group with a speed limit of 30-40 km/h. The results revealed a positive correlation between left prefrontal activation (indicated by an increase in HbO concentration) and subjective drowsiness level in the speed-control group, but not in the speed-free group. Considering the findings of Liu (2014), it is plausible to speculate that the lack of significant associations between subjective sleepiness (as measured by KSS) and fNIRS measures in the current study could be attributed, in part, to the relatively large speed range (0-120 km/h) employed during the driving task. The speed of the drivers may be a confounding factor for depletion of the resources as suggested by CRT and the wide speed range might be preventing the changes in HRF levels as expected.

The second hypothesis stated that participants driving on a monotonous highway will experience boredom, leading to a mind-wandering state, resulting in more instruction misses and steering errors, while changes in fNIRS measures will be observed. However, the results failed to prove this hypothesis.

A possible explanation for this could be the level of effort participants invested in the simulator driving is different than real-world driving. Li et al. (2009) investigated prolonged driving with fNIRS and reaction time as a performance measure. They had a task group which drove 3 hours in a simulated environment and a control group which just watched the driving in the same set-up. They observed an increase in frontal cortex oxygenation at the start of a 3-hour driving task and a decrease at the end in

the task group while there was no significant difference for the control group. The significant difference in the cerebral oxygen saturation was observed between the task and control groups during the post-task periods. In the current study, the complexity of the simulated task may not be stimulative enough to see the effects that Li et al. (2009) saw with their task group.

One possible explanation for the lack of significant findings could be related to the participants' driving experience, which was not thoroughly assessed in this study. While participants in the current study possessed a valid driver's license, their driving experience in terms of kilometers driven per day or overall driving expertise was not explicitly measured. This omission may have influenced the ability to detect meaningful relationships between driving performance and fNIRS measures. In contrast, Larue et al. (2011) implemented specific criteria when selecting their participants, which included having a minimum of two years of driving experience, driving a minimum of three days per week, and covering a minimum of 100 kilometers per week. By implementing these criteria, the authors aimed to minimize potential confounding factors related to age and inexperience. Given the absence of comprehensive information on participants' driving experience in the current study, it becomes difficult to ascertain whether driving expertise played a role in the observed results. It is possible that individuals with varying levels of driving experience may exhibit differential driving performance and neural activation patterns during the task. Factors such as accumulated driving hours, exposure to diverse driving conditions, and familiarity with driving techniques could potentially influence driving performance and associated neural activity. Participants who are used to drive more may experience boredom but maintain better control, which might lead to better steering than participants who drive less even though they experience mind-wandering.

Another potential factor that could have influenced the lack of significant results in relation to instruction miss and fNIRS measures is the design of the instructions given to participants. It was observed that participants were exposed to different numbers of instructions based on their driving

speed. Those driving at faster speeds received more instructions, while those driving at slower speeds received fewer instructions. This variability in the number of instructions might have introduced confounding effects on the outcomes and limited the comparability of the data. Driving speed of participants could also affect their stimulation levels and participants who drove with a higher speed could experience less boredom, in turn less mind-wandering. This may hinder abilities of fNIRS to observe changes in HRF for HbO and HbR.

The multilevel linear models confirmed the lack of significant associations between the predictors and HRF. The small participant-level variance observed suggests that individual differences between participants had minimal impact on HRF levels. Instead, the unexplained residual variance indicated the presence of other unidentified factors contributing to the variability in HRF. Other unidentified factors could be blood flow, oxygen consumption, arterial saturation, and arterial and venous volume which could affect the cerebral tissue oxygenation signal (Tachtsidis et al. 2008). These findings suggest that the EEG and fNIRS measures also did not relate in terms of predicting the subjective level of sleepiness and individual changes in driving performance.

While the hypotheses failed to find support in the results, an interesting observation was made regarding the correlation between the number of steering errors and instruction misses. Results indicate that an increase in the occurrence of steering errors is accompanied by a corresponding increase in the number of instruction misses. This pattern suggests that drivers experiencing a higher number of steering errors also exhibit a higher frequency of errors in following instructions. Such a relationship between steering errors and instruction misses is indicative of a potential vigilance decrement occurring during the driving task.

Limitations and Recommendations

This study has several limitations that should be acknowledged.

Firstly, the use of a simulated driving environment may not fully replicate the complexities and conditions of real-world driving. This could potentially limit the ecological validity of the results. Future studies could benefit from incorporating real-world driving conditions or utilizing more advanced driving simulators that can better mimic real-world driving scenarios. However, it is important to consider the safety of the drivers and capabilities of fNIRS measurement while designing the real-world driving studies. If real-world driving would not be possible due to increased sleepiness could be a threat to driver safety, more advanced equipment for the driving simulator such as a moving base that replicates movements felt in real life driving or speakers and lights to replicate traffic sounds and lighting could be integrated into the study. This will ensure a more realistic experience which stimulates actual driving behavior.

Secondly, future researchers could consider administering black coverage over the optodes to counteract artifact due to light and maintain a light level close to the natural light in the experiment room. In this study, the lights were always dimmed to get better signal, but this could also affect the sleepiness level of the participants and it is different from how they drive in the real-world under the sunlight.

Another limitation of the study is the use of a single Brite 24 device, which has a limited number of channels for data acquisition. This limited spatial coverage and resolution of the fNIRS measurements in the frontal cortex. To overcome this limitation, future studies could consider using a Dual Brite system, which offers increased channel coverage of up to 54 channels and allows for the inclusion of short-separation channels. The inclusion of short-separation channels improves the accuracy of recorded fNIRS data by measuring signals originating from shallow tissue layers. This would improve the accuracy of the data and lead to better results.

In this study, participant recruitment was largely conducted through the SONA system, which may have resulted in participants with varying levels of driving experience. To better understand the

relationship between driving performance and fNIRS measures, future studies should assess participants' driving experience. This can be achieved by collecting data on the number of years participants have held a driver's license, their frequency of driving, and the average distance covered. Gathering such information would provide valuable insights into the potential influence of driving experience on driving performance and its neural correlates.

To investigate the relationship between sleepiness and hemodynamic response function (HRF), future studies should recruit participants with a wider range of sleepiness levels. This could be accomplished by including individuals with different sleep schedules or testing participants at different times of the day when sleepiness levels vary. Additionally, dividing participants into awake and sleep-deprived groups could help isolate the effects of sleep deprivation on fNIRS measures. It is also recommended to consider additional measures of driving performance, such as reaction time and lane deviation, in combination with subjective ratings, instruction miss, and steering errors. Advanced computer vision techniques and machine learning algorithms can be employed to enhance the evaluation of steering errors, providing a more comprehensive analysis without relying solely on manual screen recording.

In this study, there was a higher speed limit of 120 km/h, but no lower speed limit was implemented. Future studies should consider using a standardized number of instructions for all participants, regardless of their driving speed. This approach would ensure that each participant receives a similar number of instructions during the driving task, facilitating more meaningful comparisons across individuals. Additionally, implementing a lower speed limit in addition to the existing higher speed limit could help maintain a consistent level of instruction exposure across participants. By controlling the number of instructions received, researchers can more accurately assess the impact of these instructions on driving performance and the activation of the frontal cortex.

Additionally, future researchers could consider choosing a small range for the speed limit. By using a narrower speed range, such as 30-40 km/h as in Liu's study (2014), it is possible that the effects of sleepiness on prefrontal activation captured by fNIRS could have been more pronounced and detectable. While the high speed of the drivers may be a confounding factor for resource depletion, as suggested by Cognitive Resource Theory (CRT); lower speeds can potentially induce boredom, leading to increased mind-wandering, as proposed by Mindlessness Theory (MT). To investigate the effects suggested by MT and CRT, future studies could consider determining different speed limits in higher and lower ranges. For instance, one group of participants could drive at speeds ranging from 40-50 km/h, while the other group could drive at speeds ranging from 120-130 km/h. By manipulating speed limits ranges, researchers can examine how different speed contexts influence the effects predicted by MT and CRT, potentially shedding light on the interplay between cognitive resources, mind-wandering, and driving performance.

Although the overall impact was minimal, the line graphs clearly indicate the presence of a learning effect among participants during the initial five-minute period. To mitigate or eliminate steering errors and missed instructions resulting from this learning effect, future studies should allocate a trial period for participants to familiarize themselves with the driving environment before data collection begins. This familiarization period would help participants adapt to the driving task and minimize the confounding effects of the learning curve on the measured variables.

While this study considered the results of an EEG study and fNIRS provides valuable insights into cerebral hemodynamic responses, future studies could consider integrating these two neurophysiological measures simultaneously to provide a more comprehensive understanding of vigilance decrement. The combination of fNIRS and EEG could help capture both the hemodynamic and electrophysiological aspects of brain activity, enhancing our understanding of the underlying mechanisms involved in vigilance decrement.

The findings of this study, although not supporting the initial hypotheses, have important theoretical implications for approaches to vigilance decrement. The lack of significant associations between subjective sleepiness, fNIRS measures, and driving performance suggests that vigilance decrement is a complex phenomenon that might be influenced by various factors beyond resource depletion or cognitive disengagement alone. Future research should continue to explore theoretical frameworks and develop comprehensive models that can capture the multifaceted nature of vigilance decrement and its underlying mechanisms.

Finally, it would be good to consider the sample size was relatively small, which may have limited the ability to detect significant associations between variables. To address this limitation, future studies should consider increasing the sample size to improve the statistical power and enhance the generalizability of the findings. A larger and more diverse sample would allow for a more robust examination of the relationships under investigation.

References

Balters, S., Baker, J., Geeseman, J. W., & Reiss, A. L. (2021). A Methodological Review of fNIRS in Driving Research: Relevance to the Future of Autonomous Vehicles. *Frontiers in Human Neuroscience*, *15*. https://doi.org/10.3389/fnhum.2021.637589

Bartolacci, C., Scarpelli, S., D'Atri, A., Gorgoni, M., Annarumma, L., Cloos, C., Giannini, A. M., & De Gennaro, L. (2020). The influence of sleep quality, vigilance, and sleepiness on Driving-Related cognitive abilities: A comparison between young and older adults. *Brain Sciences*, *10*(6), 327. https://doi.org/10.3390/brainsci10060327

Basso Moro, S., Cutini, S., Ursini, M. L., Ferrari, M., & Quaresima, V. (2013). Prefrontal cortex activation during story encoding/retrieval: a multi-channel functional near-infrared spectroscopy study. *Frontiers in Human Neuroscience*, *7*. https://doi.org/10.3389/fnhum.2013.00925

Bogler, C., Mehnert, J., Steinbrink, J., & Haynes, J. D. (2014). Decoding vigilance with NIRS. *PLoS ONE*, *9*(7), e101729. https://doi.org/10.1371/journal.pone.0101729

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. https://doi.org/10.1016/j.physbeh.2003.10.004

Chen, Y., Fang, C., Chen, E. Z., Huang, L., & Sawan, M. (2021). Correlation of sleepiness scale with hemoglobin concentration variation: experimental fNIRS validation. In *2021 Photonics & Electromagnetics Research Symposium (PIERS)*. https://doi.org/10.1109/piers53385.2021.9694881

Chuang, C., Cao, Z., King, J., Wu, B., Wang, Y., & Lin, C. (2018). Brain Electrodynamic and Hemodynamic Signatures Against Fatigue During Driving. *Frontiers in Neuroscience*, *12*. https://doi.org/10.3389/fnins.2018.00181

Cocks, D. (2022). *Monitoring vigilance: Using EEG to assess changes in drivers' vigilant state* [MA Thesis]. University of Twente.

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

Faul, F., Erdfelder, E., Lang, A., & Buchner, A. (2007). G*Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior Research Methods*, *39*(2), 175–191. https://doi.org/10.3758/bf03193146

Fell, D. L., & Black, B. (1997). Driver fatigue in the city. *Accident Analysis & Prevention*, *29*(4), 463–469. https://doi.org/10.1016/s0001-4575(97)00025-0

Feng, R., Zhang, G., & Cheng, B. (2009). An on-board system for detecting driver drowsiness based on multi-sensor data fusion using Dempster-Shafer theory. *2009 International Conference on Networking, Sensing and Control*. https://doi.org/10.1109/icnsc.2009.4919399

Flanagan, J., & Nathan-Roberts, D. (2019). Theories of vigilance and the prospect of cognitive restoration. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, *63*(1), 1639–1643. https://doi.org/10.1177/1071181319631506

Formentin, C., De Rui, M., Zoncapè, M., Ceccato, S., Zarantonello, L., Senzolo, M., Burra, P., Angeli, P., Amodio, P., & Montagnese, S. (2019). The psychomotor vigilance task: Role in the diagnosis of hepatic encephalopathy and relationship with driving ability. *Journal of Hepatology*, *70*(4), 648–657. https://doi.org/10.1016/j.jhep.2018.12.031

Freire, A. X., & Freire, X. A. (2018). 0151 Karolinska sleepiness scale pilot correlation with Psycho-Vigilance test and driving response failures - in a "Sleepy" healthy youth. *Sleep*, *41*(suppl_1), A58–A59. https://doi.org/10.1093/sleep/zsy061.150

Helton, W. S., & Russell, P. N. (2015). Rest is best: The role of rest and task interruptions on vigilance. *Cognition*, *134*, 165–173. https://doi.org/10.1016/j.cognition.2014.10.001

Helton, W. S., Warm, J. S., Tripp, L. D., Matthews, G., Parasuraman, R., & Hancock, P. A. (2010). Cerebral

    lateralization of vigilance: A function of task difficulty. *Neuropsychologia*, *48*(6), 1683–1688.

    https://doi.org/10.1016/j.neuropsychologia.2010.02.014

Huppert, T. J., Diamond, S. G., Franceschini, M. A., & Boas, D. A. (2009). HomER: a review of time-series

    analysis methods for near-infrared spectroscopy of the brain. *Applied Optics*, *48*(10), D280.

    https://doi.org/10.1364/ao.48.00d280

Kaida, K., Åkerstedt, T., Kecklund, G., Nilsson, J., & Axelsson, J. (2007). Use of subjective and

    physiological indicators of sleepiness to predict performance during a vigilance task. *Industrial

    Health*, *45*(4), 520–526. https://doi.org/10.2486/indhealth.45.520

Kaida, K., Takahashi, M., Åkerstedt, T., Nakata, A., Otsuka, Y., Haratani, T., & Fukasawa, K. (2006).

    Validation of the Karolinska sleepiness scale against performance and EEG variables. *Clinical

    Neurophysiology*, *117*(7), 1574–1581. https://doi.org/10.1016/j.clinph.2006.03.011

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.

    https://doi.org/10.1016/j.promfg.2015.07.499

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.

    https://doi.org/10.1016/j.aap.2011.05.023

Li, Z., Zhang, M., Zhang, X., Dai, S., Yu, X., & Wang, Y. (2009). Assessment of cerebral oxygenation during

    prolonged simulated driving using near infrared spectroscopy: its implications for fatigue

    development. *European Journal of Applied Physiology*, *107*(3), 281–287.

    https://doi.org/10.1007/s00421-009-1122-6

Light, G. A., Williams, L. E., Minow, F., Sprock, J., Rissling, A., Sharp, R., Swerdlow, N. R., & Braff, D. L.

    (2010). Electroencephalography (EEG) and event-related potentials (ERPs) with human

participants. *Current Protocols in Neuroscience*, *52*(1).

https://doi.org/10.1002/0471142301.ns0625s52

Liu, T. (2014). Positive correlation between drowsiness and prefrontal activation during a simulated

speed-control driving task. *Neuroreport*, *25*(16), 1316–1319.

https://doi.org/10.1097/wnr.0000000000000265

Liu, T., Pelowski, M., Pang, C., Zhou, Y., & Cai, J. (2015). Near-infrared spectroscopy as a tool for driving

research. *Ergonomics*, *59*(3), 368–379. https://doi.org/10.1080/00140139.2015.1076057

Mayr, S., Erdfelder, E., Buchner, A., & Faul, F. (2007). A short tutorial of GPower. *Tutorials in*

Quantitative Methods for Psychology, *3*(2), 51–59. https://doi.org/10.20982/tqmp.03.2.p051

Oken, B., Salinsky, M., & Elsas, S. (2006). Vigilance, alertness, or sustained attention: physiological basis

and measurement. *Clinical Neurophysiology*, *117*(9), 1885–1901.

https://doi.org/10.1016/j.clinph.2006.01.017

Palendeng, M. E. (2011). *Removing noise from electroencephalogram signals for BIS based depth of*

anaesthesia monitors [Master Dissertation]. University of Southern Queensland.

Papantoniou, P., Papadimitriou, E., & Yannis, G. (2017). Review of driving performance parameters

critical for distracted driving research. *Transportation Research Procedia*, *25*, 1796–1805.

https://doi.org/10.1016/j.trpro.2017.05.148

Pattyn, N., Neyt, X., Henderickx, D., & Soetens, E. (2008). Psychophysiological investigation of vigilance

decrement: Boredom or cognitive fatigue? *Physiology & Behavior*, *93*(1–2), 369–378.

https://doi.org/10.1016/j.physbeh.2007.09.016

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.

https://doi.org/10.1016/j.aap.2004.07.007

Qualtrics. (n.d.). [Software]. https://www.qualtrics.com/

Ranney, T. A., Harbluk, J. L., & Noy, Y. I. (2005). Effects of voice technology on test track driving performance: Implications for driver distraction. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *47*(2), 439–454. https://doi.org/10.1518/0018720054679515

RStudio Team (2023). R: a language and environment for statistical computing. *R Foundation for Statistical Computing*, Vienna, Austria. https://www.R-project.org

SAE (2018). Taxonomy and definitions for terms related to driving automation systems for on-road motor vehicles. https://www.sae.org/standards/content/j3016_202104/

Savino, M. R. (2009). *Standardized names and definitions for driving performance measures* [MS Thesis]. Tufts University.

Seppelt, B., & Wickens, C. D. (2003). *In-vehicle tasks: Effects of modality, driving relevance, and redundancy* (AHFD-03-16/GM-03-2). Aviation Human Factors Division, University of Illinois at Urbana-Champaign.

Shahid, A., Wilkinson, K., Marcu, S., & Shapiro, C. M. (2011). Karolinska sleepiness scale (KSS). *STOP, THAT and One Hundred Other Sleep Scales*, 209–210. https://doi.org/10.1007/978-1-4419-9893-4_47

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

Shoaib, Z., Akbar, A., Kim, E. S., Kamran, M. A., Kim, J. H., & Jeong, M. Y. (2023). Utilizing EEG and fNIRS for the detection of sleep-deprivation-induced fatigue and its inhibition using colored light stimulation. *Scientific Reports*, *13*(1). https://doi.org/10.1038/s41598-023-33426-2

Siddique, M. R. (2020). *Detection of human vigilance state during locomotion using wearable FNIRS* [PhD Dissertation]. Florida International University.

Singh, S. (2014). Magnetoencephalography: Basic principles. *Annals of Indian Academy of Neurology*, *17*(5), 107. https://doi.org/10.4103/0972-2327.128676

Smiley, A. (1998). Fatigue management: Lessons from research. *International Conference on Fatigue and Transportation, 3rd, 1998, Fremantle, Western Australia*.

Tachtsidis, I., Tisdall, M., Delpy, D. T., Smith, M. D., & Elwell, C. E. (2008). Measurement of Cerebral Tissue Oxygenation in Young Healthy Volunteers During Acetazolamide Provocation: A Transcranial Doppler and Near-Infrared Spectroscopy Investigation. In *Springer eBooks* (pp. 389–396). https://doi.org/10.1007/978-0-387-74911-2_43

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

Thiffault, P., & Bergeron, J. (2003). Monotony of road environment and driver fatigue: a simulator study. *Accident Analysis & Prevention*, *35*(3), 381–391. https://doi.org/10.1016/s0001-4575(02)00014-3

Warm, J. S., Parasuraman, R., & Matthews, G. (2008). Vigilance requires hard mental work and is stressful. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *50*(3), 433–441. https://doi.org/10.1518/001872008x312152

Wickens, C. D. (2008). Multiple resources and mental workload. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *50*(3), 449–455. https://doi.org/10.1518/001872008x288394

Yücel, M. A., Selb, J., Cooper, R. G., & Boas, D. A. (2014). Targeted principle component analysis: A new motion artifact correction approach for near-infrared spectroscopy. *Journal of Innovative Optical Health Sciences*, *07*(02), 1350066. https://doi.org/10.1142/s1793545813500661

Appendix A – Informed Consent and Qualtrics Questionnaire

You are being invited to participate in a research study titled The Vigilant Brain of Drivers in Driving Simulator: an fNIRS Study. This study is being conducted by Yaz Armagan from the Faculty of Behavioural, Management and Social Sciences at the University of Twente. Supervisor of this master Psychology thesis is Assoc. Prof. Dr. Rob van der Lubbe.

The purpose of this research study is to understand if fNIRS is effective in predicting lapses of attention in a driving simulator, which in real-life driving conditions may lead to serious accidents. This experiment lasts for 2-3 hours in total. You will fill in a questionnaire after signing the informed consent. Then, you will be driving for an hour in a simulated environment, and this might be stressful or might create nausea. If you begin to feel uncomfortable, you have every right to stop the experiment at any point. Your participation in this study is entirely voluntary and you can withdraw at any time. You are free to omit any question.

You will gain 3 credits if you are joining the experiment through SONA test subject pool. Your data will be used for research purposes only and will be stored completely anonymous. You will not be asked any identifying personal data and your data will be further anonymized by giving you a participant number.

Contact Information of Researcher

If you have any questions about the study or your privacy rights, such as accessing, changing, deleting, or updating your data, please contact me, Yaz Armagan by i.c.armagan@student.utwente.nl

Contact Information for Questions about Your Rights as a Research Participant

If you have questions about your rights as a research participant, or wish to obtain information, ask questions, or discuss any concerns about this study with someone other than the researcher(s), please contact the Secretary of the Ethics Committee/domain Humanities & Social Sciences of the

Faculty of Behavioural, Management and Social Sciences at the University of Twente by

ethicscommittee-hss@utwente.nl

I have read and understood the study information. I have been able to ask questions about the study and my questions have been answered to my satisfaction. – Yes/No

I consent voluntarily to be a participant in this study and understand that I can refuse to answer questions and I can withdraw from the study at any time, without having to give a reason. – Yes/No

I understand that taking part in the study involves a survey questionnaire and an experiment with fNIRS and driving simulator. – Yes/No

I understand that information I provide will only be used for research purposes. – Yes/No

1. For the next question, you will have to go the following link and complete visual acuity test.

   https://michaelbach.de/fract/FrACT10/capp/index.html

Left eye (write with a comma between two values):

Right eye (write with a comma between two values):

2. Please enter your age.

3. Please select your gender. – Male/Female/Non-binary,third gender/Prefer not to say

4. Please enter your nationality.

5. Do you have normal vision? – Yes/No

If yes, survey continues from question Q6

If no, survey continues from question Q7

6. Are you using any vision correction? (glasses, contact lenses) – Yes/No

7. Please select your highest level of education. - High school graduate/ HBO (Profession-oriented higher education)/ WO (Research-oriented higher education)/ Master graduate/Doctorate

8. Please select your handedness. - Left-handed/ Right-handed/ Ambidextrous (both)

9. Have you taken any mind altering drugs in the last two weeks? – Yes/No

10. Have you had alcohol over the last 24 hours? – Yes/No

11. Have you had caffeinated drinks over the last 24 hours? Yes/No

12. How many hours have you slept last night? – More than 8 hours/ 5 to 8 hours/ Less than 5 hours

13. Please report your level of sleepiness. – According to the Karolinska Sleepiness Scale

Appendix B – Driver Simulator Requirements

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 oxysoft

- Trigger symbol should be used as input to the oxysoft

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 fNIRS using LSL)	
Meanings of the cues	Trigger Symbol (sent to fNIRS)	Symbol (On the screen in the car)	Desired	Undesired	Desired	Undesired

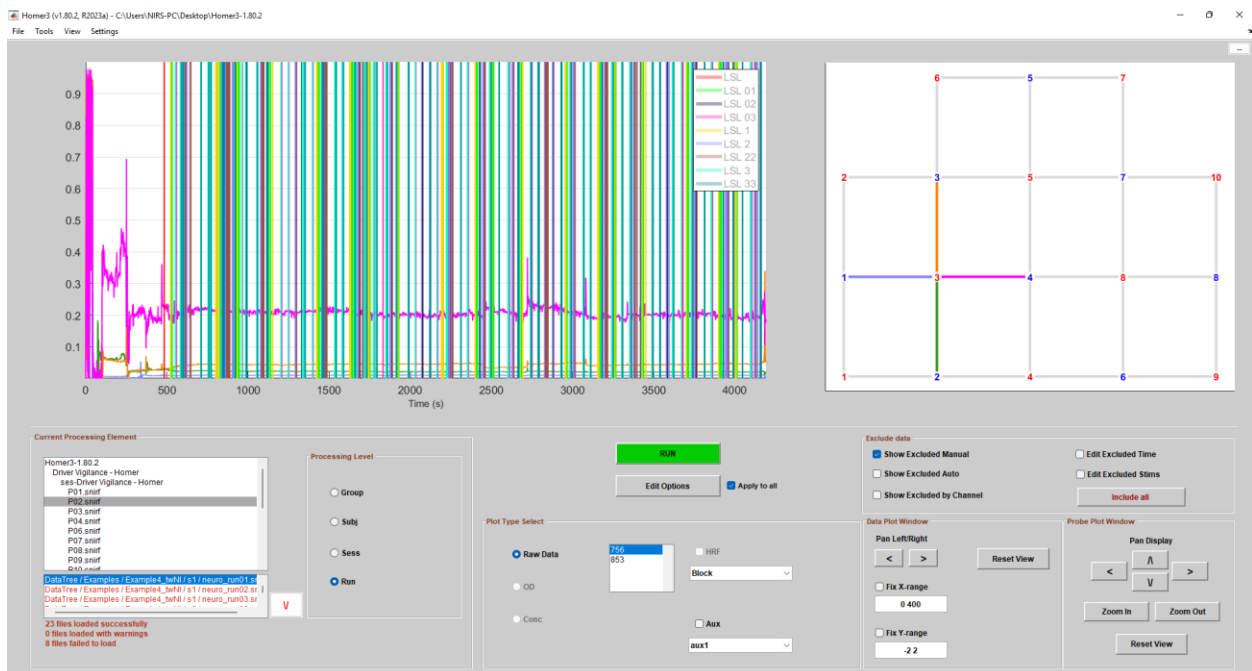|						
Take the exit (make a right)	2		Driver makes a right exit	Driver does not take the exit	02	22
Go straight	1		Driver goes straight	Driver makes a right exit	01	11
Keep Left	3		Driver maintains driving in the left lane	Driver does not keep to the left	03	33

Appendix C – Preprocessing with Homer

● Convert the .oxy4 files from Oxysoft to Matlab format using the oxysoft2matlab script (provided

   by Artinis Medical Systems). Choose both project file and individual oxy4file to make sure output

   will include the template information.
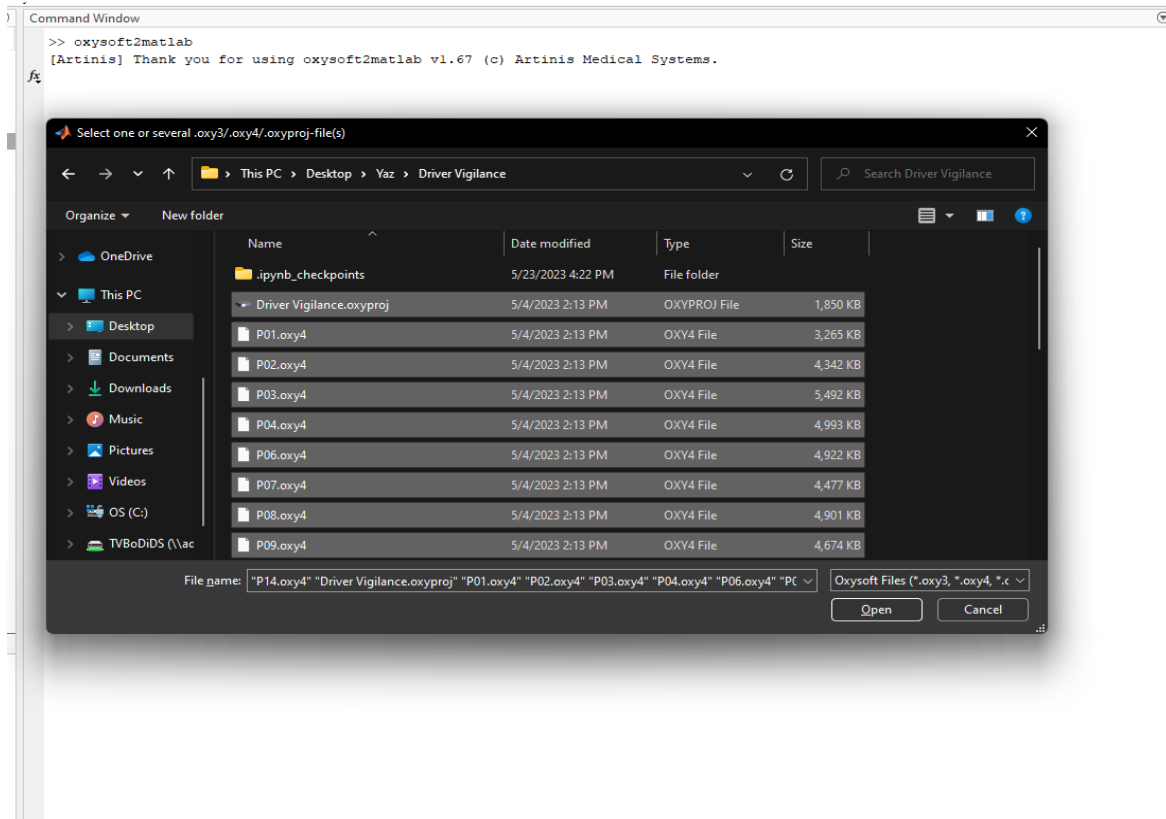
● Choose the .snirf data type as the output format.
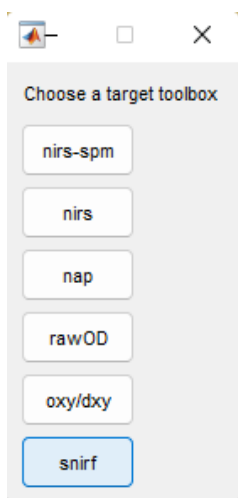
- Place the .snirf file in a folder within the Homer3 directory for Homer3 to read it.

- Don't forget to install the required toolboxes for Homer3 in Matlab, including the Signal Processing Toolbox, Image Processing Toolbox, Curve Fitting Toolbox, Statistics and Machine Learning Toolbox, Wavelet Toolbox, and Symbolic Math Toolbox.

- Open Homer3 and access the Edit Events TSV file tool to modify the event triggers. LSL triggers from Oxysoft is not needed here. For this study, data needs to be divided into 12 5-minute intervals.

- Go to Tools>Edit Events TSV file.
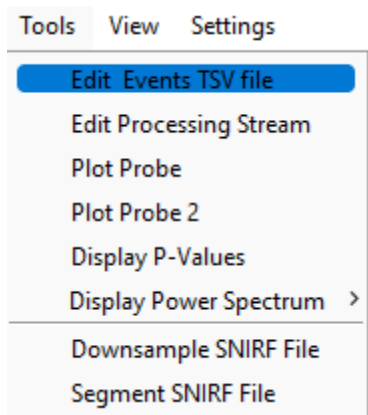
```
Editor - C:\Users\NIRS-PC\Desktop\Homer3-1.80.2\Driver Vigilance - Homer\P02_events.tsv
  P02_events.tsv  ✕   +
  1    Onset    Duration    Amplitude    trial_type
  2    483.5    5    1    LSL
  3    523.1    5    1    LSL 01
  4    523.2    5    1    LSL 1
  5    526.1    5    1    LSL 01
  6    526.3    5    1    LSL 01
  7    529.6    5    1    LSL 01
  8    532.2    5    1    LSL 01
  9    553.8    5    1    LSL 3
 10    558.7    5    1    LSL 03
 11    582.7    5    1    LSL 3
 12    586.3    5    1    LSL 3
 13    591.5    5    1    LSL 3
 14    591.6    5    1    LSL 03
 15    591.6    5    1    LSL 33
 16    592.8    5    1    LSL 3
 17    601.5    5    1    LSL 33
 18    606.9    5    1    LSL 2
 19    608.1    5    1    LSL 2
 20    613.2    5    1    LSL 22
 21    614.5    5    1    LSL 2
 22    615.3    5    1    LSL 22
 23    616 5    1    LSL 2
 24    623.3    5    1    LSL 2
 25    643.7    5    1    LSL 22
 26    647.3    5    1    LSL 02
 27    647.7    5    1    LSL 22
 28    708.6    5    1    LSL 3
 29    712 5    1    LSL 03
 30    712 5    1    LSL 33
```

- In the TSV file, delete the existing events and put events according to the needs of the study.

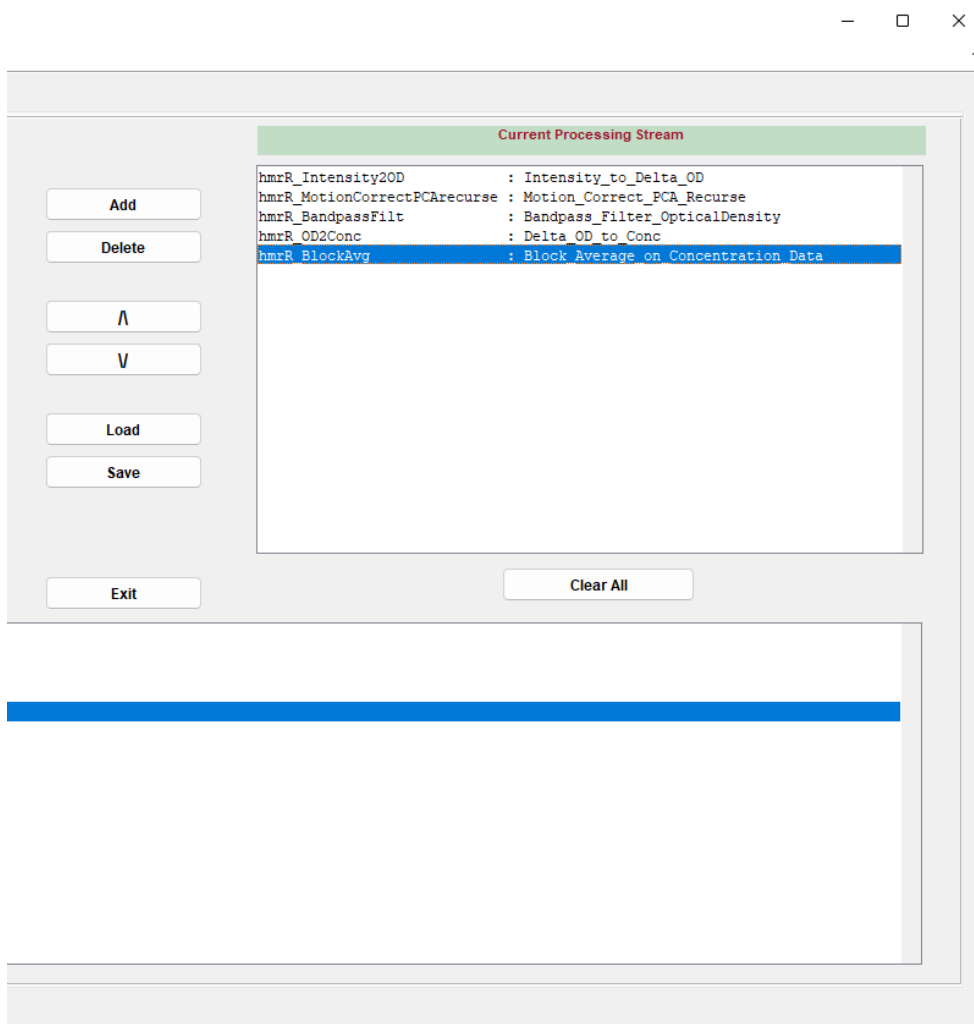- After modifying the events, the data will be divided into the specified intervals and a baseline period.
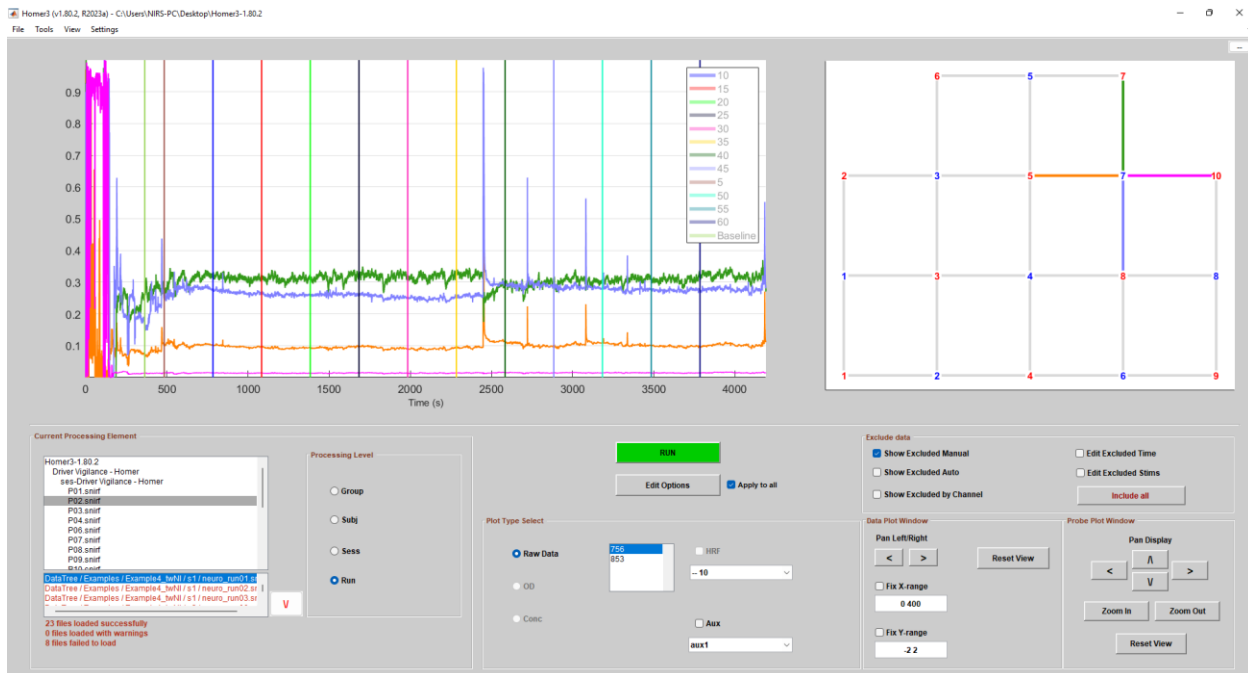
- Proceed to preprocess the data by selecting the Edit Processing Stream option in Homer3's main interface. (Tools > Edit Processing Stream).
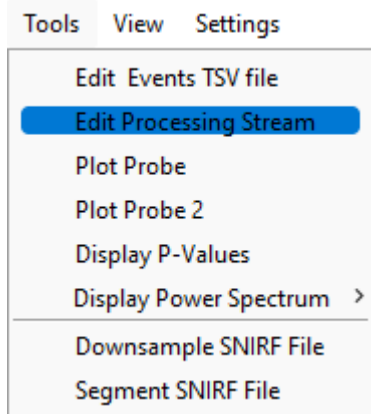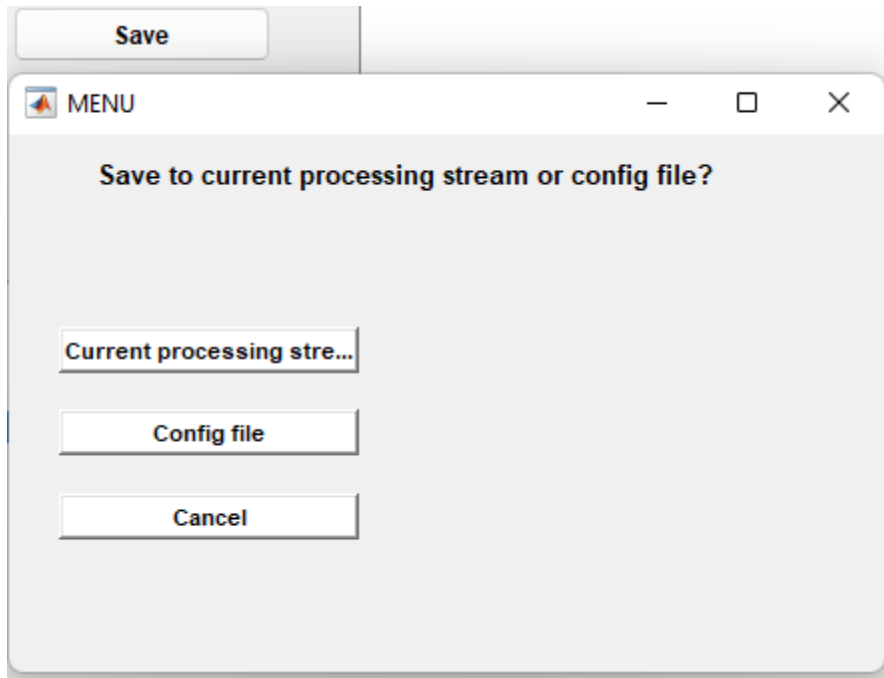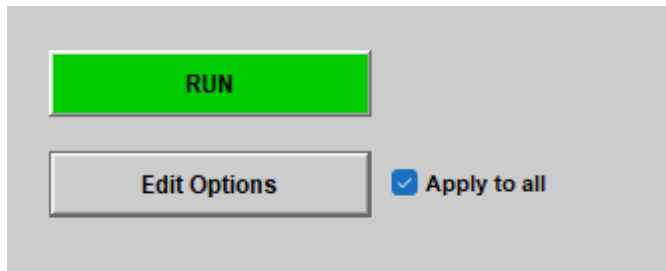
- In the processing screen, choose the desired preprocessing steps.

- It is important to click save after choosing the desired steps and saving the current processing stream.
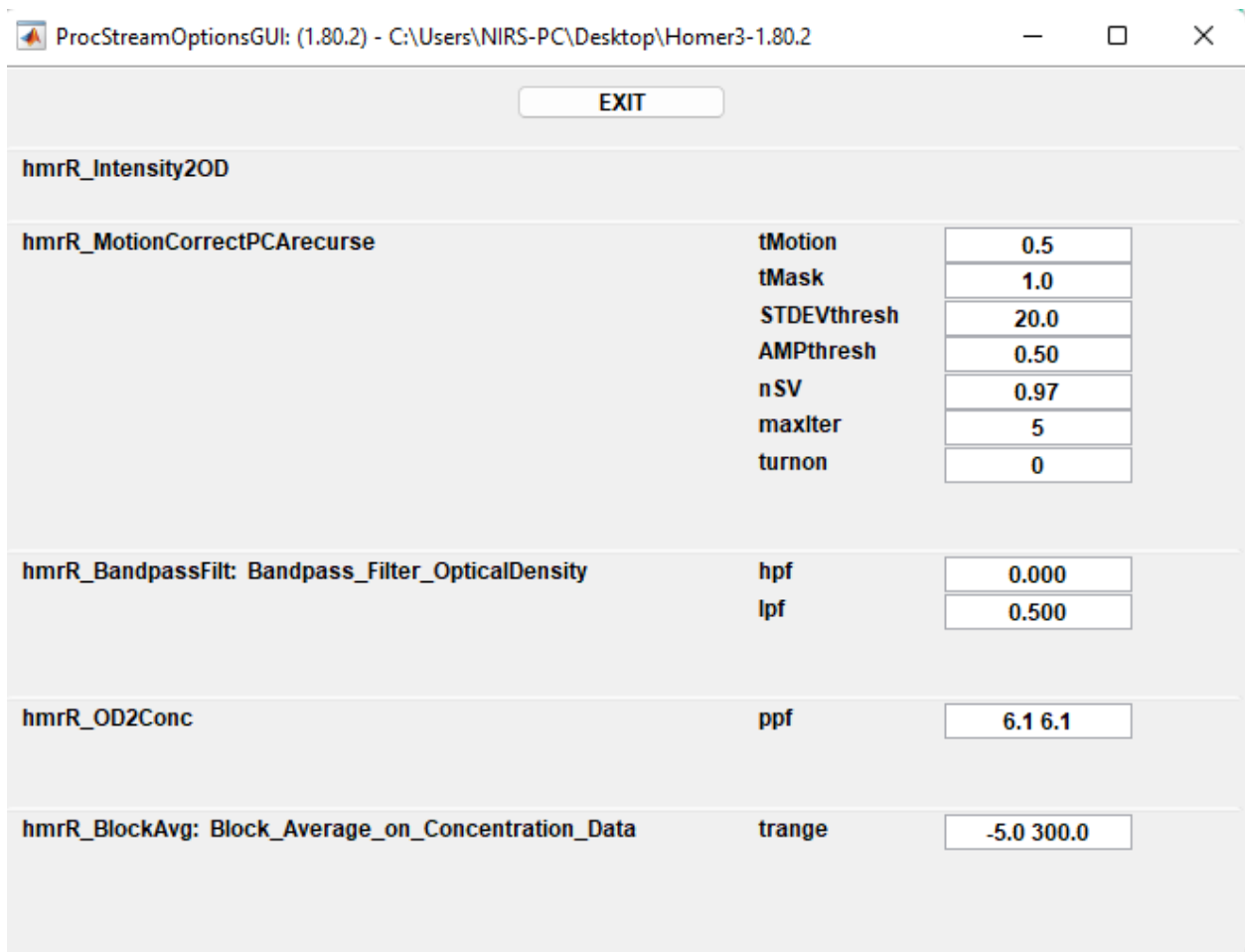
- Close the processing window and click on Edit Options in the Homer3 main GUI.

- Enter the parameter values for each preprocessing step. For this study the steps were:

  1. Convert to optical densities: This step does not require any additional parameters.

  2. Motion artifact correction (tCPA): Apply the tCPA model for efficient motion artifact correction in pre-identified segments. tCPA is applied as motion artifact correction model because it is very efficient when motion is the main source of variance and it is applied only to pre-identified MA segments to avoid over-correction.

  3. Low-pass filtering: Design a low-pass filter with a cutoff frequency of 0.5 Hz to remove heart-rate artifacts (~ 1 Hz) while preserving respiration frequencies (0.2–0.4 Hz) or Mayer waves (0.1 Hz) during the hemodynamic measurement.

4. High-pass filtering: It is not recommended to use high-pass filtering as it may remove important signals, so it can be omitted.

5. OD to concentration: Apply the Modified Beer-Lambert Law with a conversion factor of 6.06 (which appears as 6.1 when entered). This value is the advice from Artinis Medical System from their fNIRS analysis toolbox series – Homer article.

6. Average trials: Determine a sufficiently long tRange to capture the longest trial (e.g., 5 minutes) based on stimulus marks. When Homer3 sees the new stimulus mark, it assumes it is the start of another stimulus.

ProcStreamOptionsGUI: (1.80.2) - C:\Users\NIRS-PC\Desktop\Homer3-1.80.2   —   □   ✕

EXIT

hmrR_Intensity2OD

hmrR_MotionCorrectPCArecurse		
	tMotion	0.5
	tMask	1.0
	STDEVthresh	20.0
	AMPthresh	0.50
	nSV	0.97
	maxIter	5
	turnon	0

hmrR_BandpassFilt: Bandpass_Filter_OpticalDensity		
	hpf	0.000
	lpf	0.500

hmrR_OD2Conc		
	ppf	6.1 6.1

hmrR_BlockAvg: Block_Average_on_Concentration_Data		
	trange	-5.0 300.0

- Manually exclude bad channels and exclude data before or after the experiment using the Exclude Data menu on the right side of the Homer3 GUI.
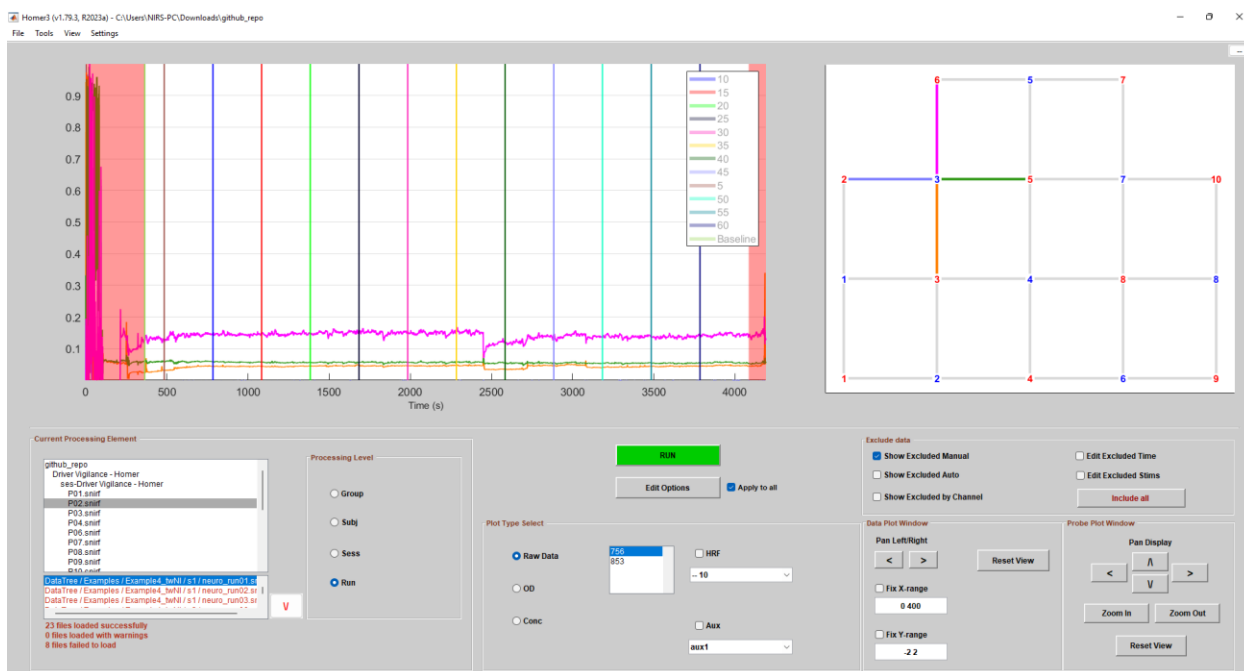
- After applying the preprocessing steps by clicking "Run," the data will be displayed as below, including OD and concentration views.
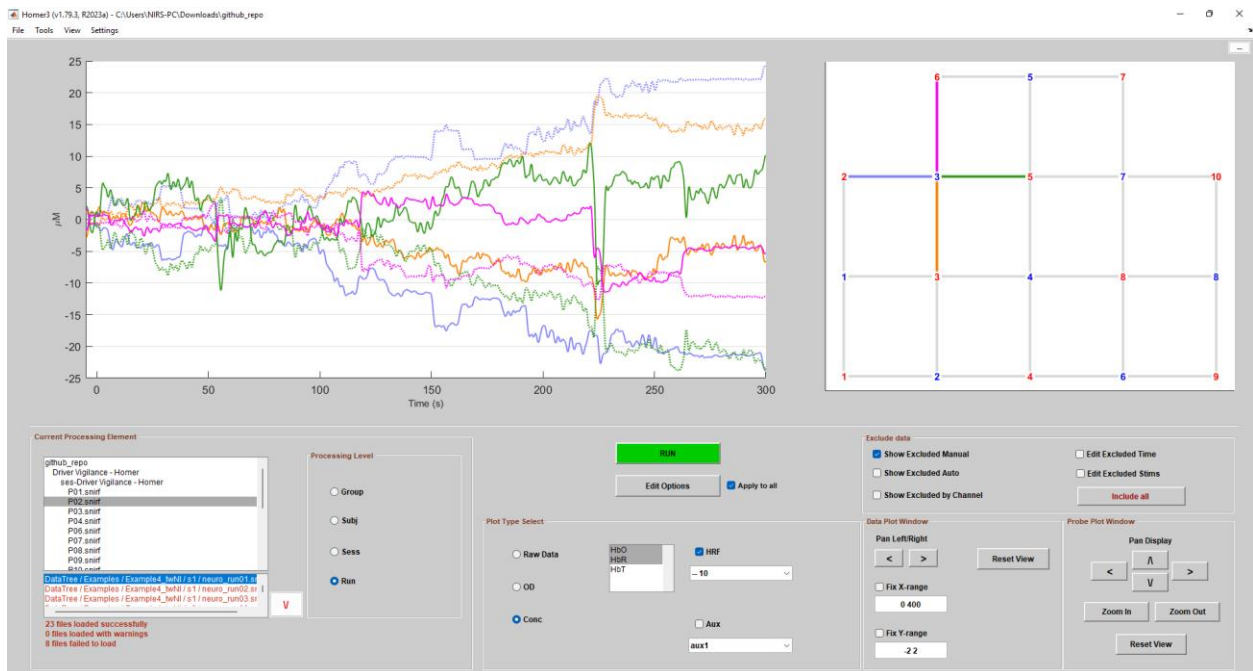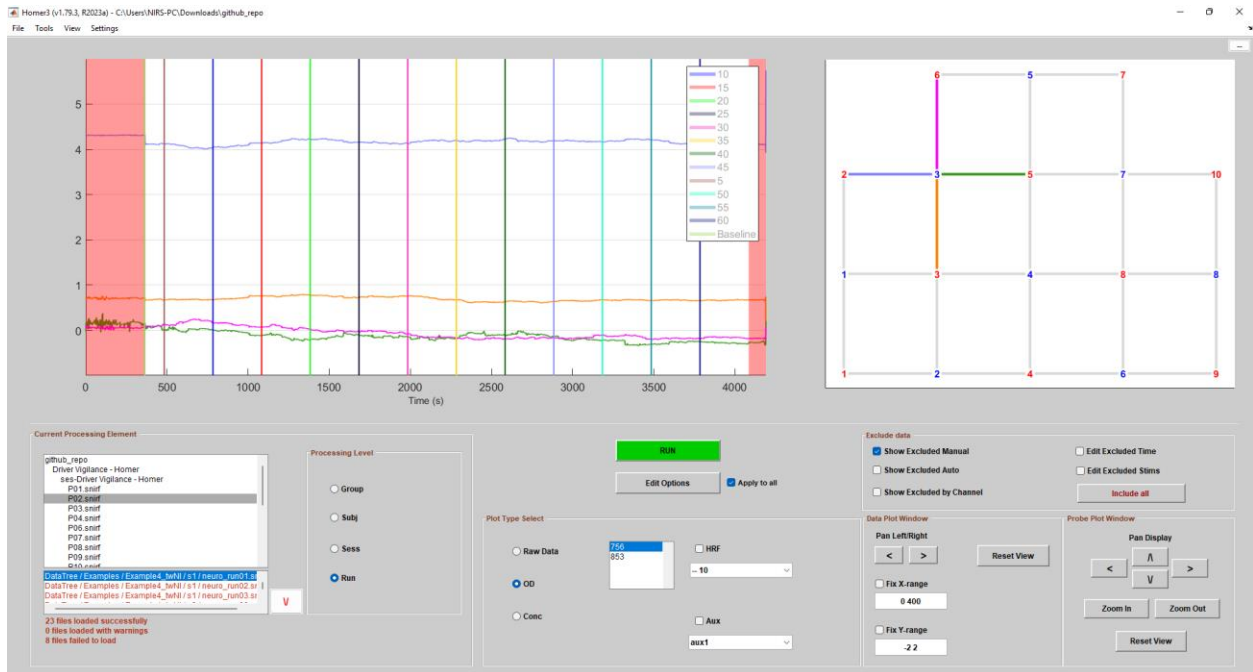
- Export the hemodynamic response function (HRF) means by selecting File > Export HRF Means and save it as a text file.
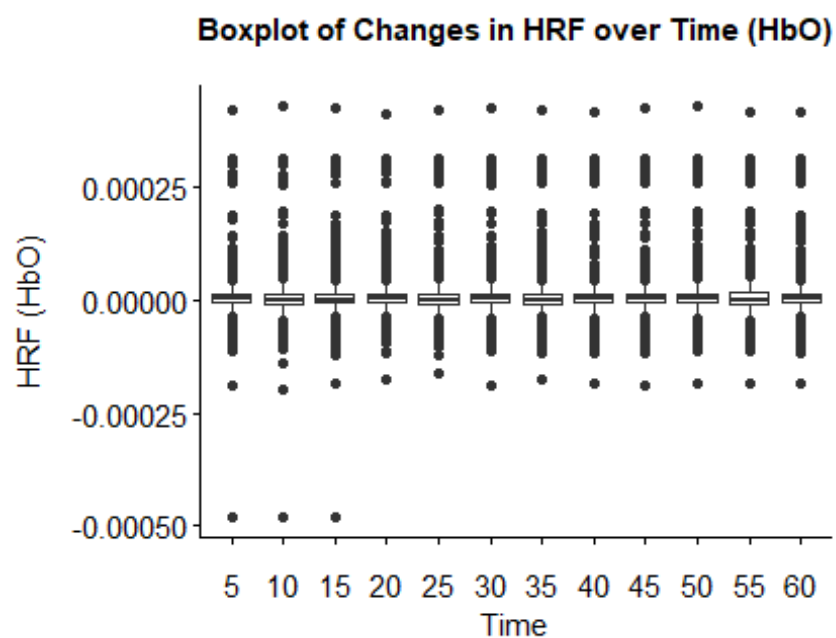
Appendix D – Additional Results

Figure D1.

Boxplot of Changes in HRF over Time for HbO

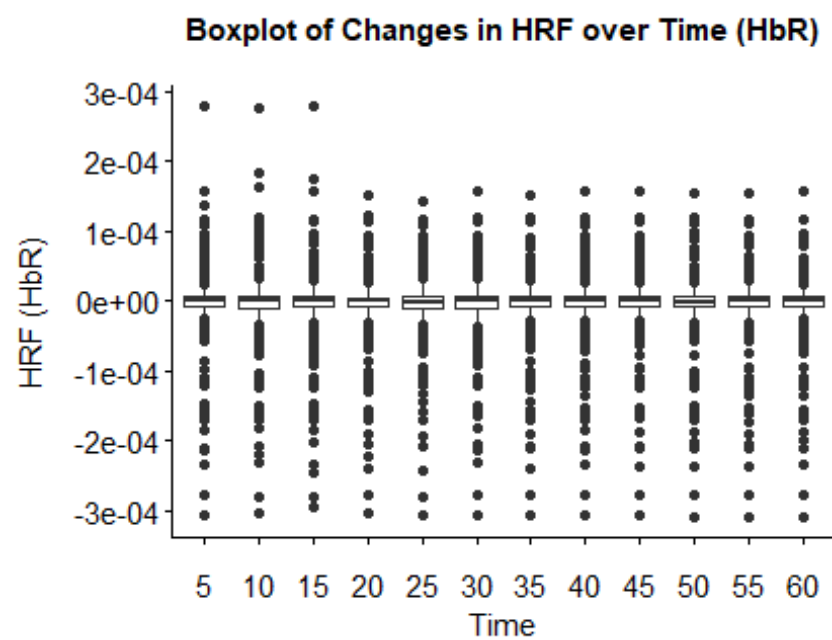**Boxplot of Changes in HRF over Time (HbO)**

Figure D2.

Boxplot of Changes in HRF over Time for HbR

Boxplot of Changes in HRF over Time (HbR)

Figure D3.

Bar plots of changes in HRF over time
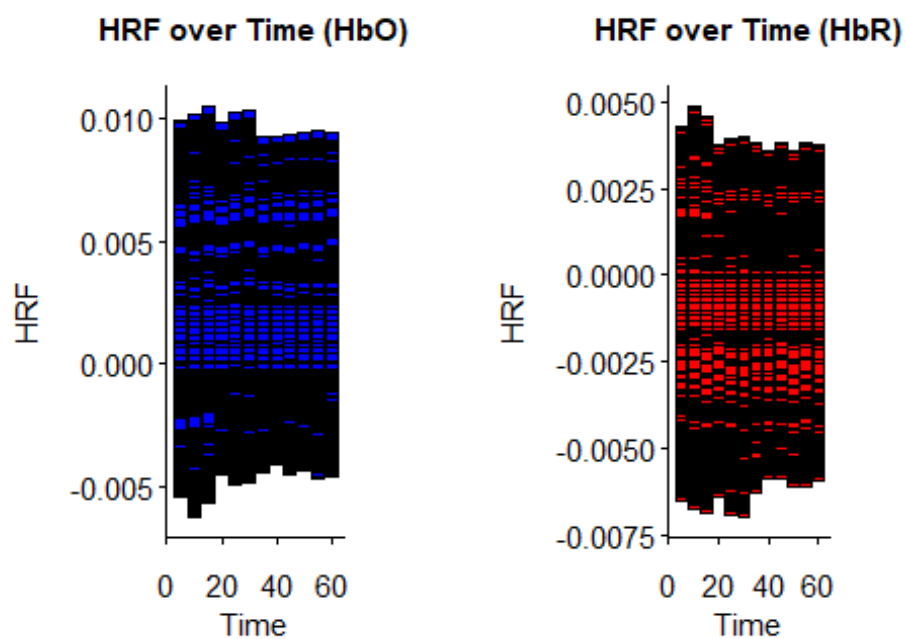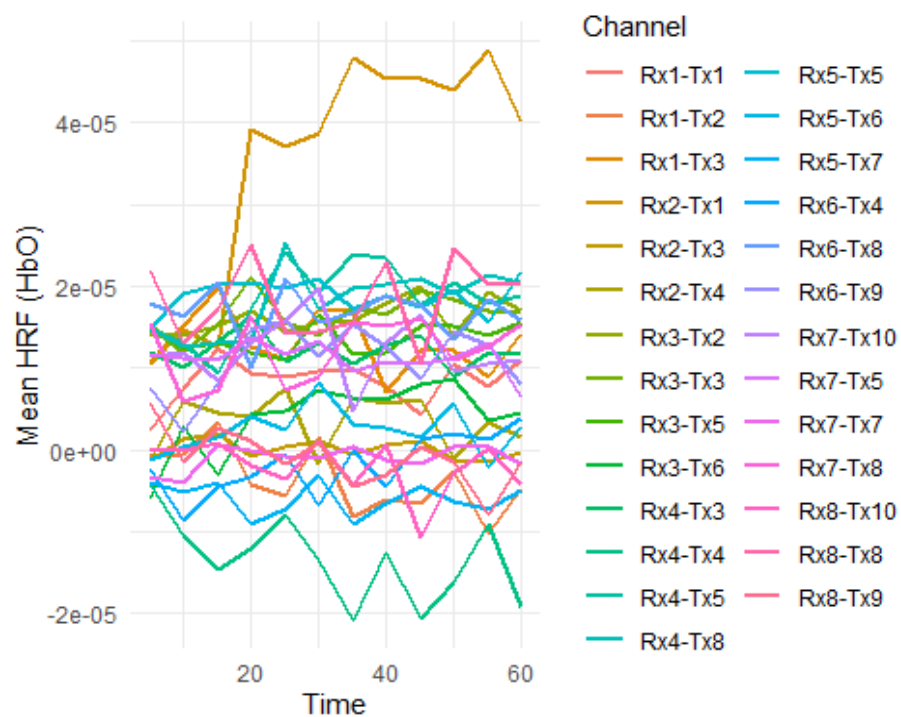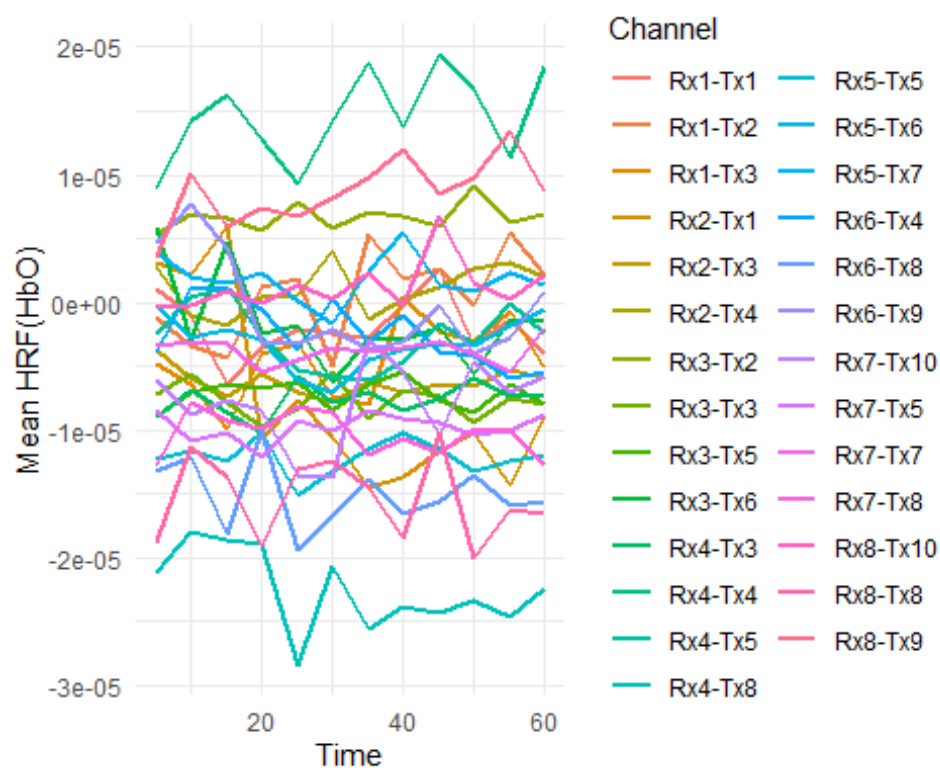
HRF over Time (HbO)

HRF over Time (HbR)

Figure D4.

Line graph depicting mean changes in HRF over time for each channel (for HbO)

Figure D5.

Line graph depicting mean changes in HRF over time for each channel (for HbR)

Appendix E – R Script

```r
```{r setup, include=FALSE}

knitr::opts_chunk$set(echo = TRUE)

# Load required packages

#For reading excel files

library(readxl)

# For data manipulation and visualization

library(tidyverse)

library(dplyr)

library(ggplot2)

#For extending ggplot2 with statistical significance annotations

library(ggsignif)

#For creating American Psychological Association (APA) style tables

library(apaTables)

# For conducting psychological and psychometric research, including descriptive statistics and factor

analysis

library(psych)

#For summarizing and visualizing regression models

library(jtools)

#For implementing linear mixed-effects models

library(lme4)

#For working with statistical models and computing effect sizes

library(sjstats)

#For producing high-quality, anti-aliased graphics output
```

```r
library(Cairo)

```

# Set the option for numeric display format
options(scipen=999)

Code chunk without warning messages

suppressWarnings({

Read the HbO data

baseline_hbo_data <- read_excel("C:/Users/NIRS-PC/Desktop/Yaz/Driver Vigilance-HbO - Baseline.xlsx")

Read the HbR data

baseline_hbr_data <- read_excel("C:/Users/NIRS-PC/Desktop/Yaz/Driver Vigilance-HbR - Baseline.xlsx")

Clean NA values

baseline_hbo_data <- na.omit(baseline_hbo_data)

baseline_hbr_data <- na.omit(baseline_hbr_data)

})
Subtract corresponding 0 HRF values from every other Time HRF values to isolate the activity created

by the experimental manipulation

time_points <- c(5, 10, 15, 20, 25, 30, 35, 40, 45, 50, 55, 60)

subtract_hrf <- function(data) {

  data <- data %>%

    group_by(Participant, Channel) %>%

    mutate(HRF = HRF - HRF[Time == 0])
```

```
  return(data)

}
```

Subtract HRF values for HbO

```
baseline_hbo_data <- subtract_hrf(baseline_hbo_data)
```

Subtract HRF values for HbR

```
baseline_hbr_data <- subtract_hrf(baseline_hbr_data)
```

Verify the updated datasets

```
head(baseline_hbo_data)

head(baseline_hbr_data)
```

Remove rows where Time=0

```
clean_hbO_data <- baseline_hbo_data %>% filter(Time != 0)

clean_hbR_data <- baseline_hbr_data %>% filter(Time != 0)
```

Verify the updated datasets

```
head(clean_hbO_data)

head(clean_hbR_data)
```

Bind the cleaned datasets

```
combined_data <- bind_rows(clean_hbO_data, clean_hbR_data)
```

Remove rows where Time=5 and Time=10

```
clean_hbO_data_r <- clean_hbO_data %>% filter(Time != 5 & Time != 10)
```

```r
clean_hbR_data_r <- clean_hbR_data %>% filter(Time != 5 & Time != 10)


# Verify the removed datasets

head(clean_hbO_data_r)

head(clean_hbR_data_r)

# Bind the cleaned adjusted datasets

combined_data_r <- bind_rows(clean_hbO_data_r, clean_hbR_data_r)

# Get unique participants

unique_participants <- unique(combined_data$Participant)


# Initialize empty lists for age and gender

age_list <- c()

gender_list <- c()


# Loop through unique participants

for (participant in unique_participants) {

  # Extract age and gender for the current participant

  participant_data <- subset(combined_data, Participant == participant)

  age <- participant_data$Age[1]  # Assuming age is the same for all rows of a participant

  gender <- participant_data$Gender[1]  # Assuming gender is the same for all rows of a participant


  # Append age and gender to the respective lists

  age_list <- c(age_list, age)

  gender_list <- c(gender_list, gender)
```

```r
}


# Descriptive statistics for age

age_summary <- summary(age_list)

print(age_summary)

# Descriptive statistics for gender

gender_table <- table(gender_list)

print(gender_table)

#For complete dataset

# Define the variables and statistics to include in the table

variables <- c("HRF", "KSS", "SteeringErrors", "InstructionMiss")

statistics <- c("min", "max", "mean", "sd")


# Function to compute the specified statistics

compute_statistics <- function(x) {

  c(min(x, na.rm = TRUE), max(x, na.rm = TRUE), mean(x, na.rm = TRUE), sd(x, na.rm = TRUE))

}


# Create APA-style descriptive table for HbO

hbO_descriptives <- sapply(clean_hbO_data[, variables], compute_statistics)


# Add row and column names to the table

rownames(hbO_descriptives) <- c("Min", "Max", "Mean", "SD")

colnames(hbO_descriptives) <- c("HRF", "KSS", "Steering Errors", "Instruction Miss")
```

```r
# Print the APA-style descriptive table for HbO

print(hbO_descriptives, format = "html", digits = 2)

# Create APA-style descriptive table for HbR

hbR_descriptives <- sapply(clean_hbR_data[, variables], compute_statistics)


# Add row and column names to the table

rownames(hbR_descriptives) <- c("Min", "Max", "Mean", "SD")

colnames(hbR_descriptives) <- c("HRF", "KSS", "Steering Errors", "Instruction Miss")


# Print the APA-style descriptive table for HbR

print(hbR_descriptives, format = "html", digits = 2)

#For the adjusted dataset

# Define the variables and statistics to include in the table

variables <- c("HRF", "KSS", "SteeringErrors", "InstructionMiss")

statistics <- c("min", "max", "mean", "sd")


# Function to compute the specified statistics

compute_statistics <- function(x) {

  c(min(x, na.rm = TRUE), max(x, na.rm = TRUE), mean(x, na.rm = TRUE), sd(x, na.rm = TRUE))

}


# Create APA-style descriptive table for HbO

hbO_descriptives_removed <- sapply(clean_hbO_data_r[, variables], compute_statistics)
```

```r
# Add row and column names to the table

rownames(hbO_descriptives_removed) <- c("Min", "Max", "Mean", "SD")

colnames(hbO_descriptives_removed) <- c("HRF", "KSS", "Steering Errors", "Instruction Miss")


# Print the APA-style descriptive table for HbO

print(hbO_descriptives_removed, format = "html", digits = 2)

# Create APA-style descriptive table for HbR

hbR_descriptives_removed <- sapply(clean_hbR_data_r[, variables], compute_statistics)


# Add row and column names to the table

rownames(hbR_descriptives_removed) <- c("Min", "Max", "Mean", "SD")

colnames(hbR_descriptives_removed) <- c("HRF", "KSS", "Steering Errors", "Instruction Miss")


# Print the APA-style descriptive table for HbR

print(hbR_descriptives_removed, format = "html", digits = 2)

# Define APA theme

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", linewidth = 0.5),

  axis.title = element_text(size = 11, color = "black"),

  axis.text = element_text(size = 11, color = "black"),
```

```r
  axis.text.x = element_text(margin = margin(t = 10)),

  axis.title.y = element_text(margin = margin(r = 10)),

  axis.ticks = element_line(linewidth = 0.5),

  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)



# Line graph depicting how Karolinska Sleepiness Scale (KSS) changes over time (mean with standard

error bars)

kss_hrf_plot <- ggplot(clean_hbO_data, aes(x = Time, y = KSS)) +

  stat_summary(fun.data = mean_se, geom = "line", fun.args = list(alpha = 1),

        position = position_dodge(width = .5)) +

  stat_summary(fun = mean, geom = "line", position = position_dodge(width = .5)) +

  stat_summary(fun.data = mean_se, geom = "errorbar", width = 0.1, fun.args = list(mult = 1), position =

position_dodge(width = .5)) +

  labs(x = "\nTime", y = "KSS \n") +

  ggtitle("KSS Changes Over Time")
```

```
# Line graph depicting how Steering Errors changes over time (mean with standard error bars)

steering_hrf_plot <- ggplot(clean_hbO_data, aes(x = Time, y = SteeringErrors)) +

  stat_summary(fun.data = mean_se, geom = "line", fun.args = list(alpha = 1),

        position = position_dodge(width = .5)) +

  stat_summary(fun = mean, geom = "line", position = position_dodge(width = .5)) +

  stat_summary(fun.data = mean_se, geom = "errorbar", width = 0.1, fun.args = list(mult = 1), position =

position_dodge(width = .5)) +

  labs(x = "\nTime", y = "Steering Errors \n") +

  ggtitle("Steering Errors Changes Over Time")




# Line graph depicting how Instruction Miss changes over time (mean with standard error bars)

instruction_hrf_plot <- ggplot(clean_hbO_data, aes(x = Time, y = InstructionMiss)) +

  stat_summary(fun.data = mean_se, geom = "line", fun.args = list(alpha = 1),

        position = position_dodge(width = .5)) +

  stat_summary(fun = mean, geom = "line", position = position_dodge(width = .5)) +

  stat_summary(fun.data = mean_se, geom = "errorbar", width = 0.1, fun.args = list(mult = 1), position =

position_dodge(width = .5)) +

  labs(x = "\nTime", y = "Instruction Miss \n") +

  ggtitle("Instruction Miss Changes Over Time")
```

```r
# Line graph depicting changes of HRF for HbO and HRF for HbR over time

hrf_hbo_plot <- ggplot(clean_hbO_data, aes(x = Time, y = HRF)) +

  stat_summary(fun = "mean", geom = "line") +

  labs(x = "Time", y = "HRF") +

  ggtitle("HRF Changes Over Time (HbO)")



hrf_hbr_plot <- ggplot(clean_hbR_data, aes(x = Time, y = HRF)) +

  stat_summary(fun = "mean", geom = "line") +

  labs(x = "Time", y = "HRF") +

  ggtitle("HRF Changes Over Time (HbR)")

# Save line graphs in APA style as TIFF files

ggsave("kss_hrf_plot.tiff", plot = kss_hrf_plot, width = 6, height = 3, dpi = 300, units = "in", type =
"cairo")

ggsave("steering_hrf_plot.tiff", plot = steering_hrf_plot, width = 6, height = 3, dpi = 300, units = "in",
type = "cairo")

ggsave("instruction_hrf_plot.tiff", plot = instruction_hrf_plot, width = 6, height = 3, dpi = 300, units =
"in", type = "cairo")

ggsave("hrf_hbo_plot.tiff", plot = hrf_hbo_plot, width = 6, height = 3, dpi = 300, units = "in", type =
"cairo")

ggsave("hrf_hbr_plot.tiff", plot = hrf_hbr_plot, width = 6, height = 3, dpi = 300, units = "in", type =
"cairo")

# Boxplot of changes in HRF over time for HbO

ggplot(clean_hbO_data, aes(x = factor(Time), y = HRF)) +

  geom_boxplot() +
```

```
  labs(x = "Time", y = "HRF (HbO)") +

  ggtitle("Boxplot of Changes in HRF over Time (HbO)") +

  theme_minimal(base_size = 11) +

  apa_theme

# Boxplot of changes in HRF over time for HbR

ggplot(clean_hbR_data, aes(x = factor(Time), y = HRF)) +

  geom_boxplot() +

  labs(x = "Time", y = "HRF (HbR)") +

  ggtitle("Boxplot of Changes in HRF over Time (HbR)") +

  theme_minimal(base_size = 11) +

  apa_theme


# Calculate the mean HRF over time for each channel

mean_hbO_data <- aggregate(HRF ~ Time + Channel, data = clean_hbO_data, FUN = mean)


# Visualize the mean changes in HRF over time for each channel (HbO)

ggplot(mean_hbO_data, aes(x = Time, y = HRF, group = Channel)) +

  geom_line(aes(color = as.factor(Channel)), linewidth = 1) +

  labs(x = "Time", y = "Mean HRF (HbO)", color = "Channel") +

  theme_minimal()


# Calculate the mean HRF over time for each channel

mean_hbR_data <- aggregate(HRF ~ Time + Channel, data = clean_hbR_data, FUN = mean)
```

```
# Visualize the mean changes in HRF over time for each channel (HbR)

ggplot(mean_hbR_data, aes(x = Time, y = HRF, group = Channel)) +

  geom_line(aes(color = as.factor(Channel)), linewidth = 1) +

  labs(x = "Time", y = "Mean HRF(HbO)", color = "Channel") +

  theme_minimal()



# Compute mean HRF for each time point, channel, and participant (HbO)

mean_hbO_data <- clean_hbO_data %>%

  group_by(Time, Channel, Participant) %>%

  summarize(mean_HRF = mean(HRF), .groups = "drop")



# Create a graph showing the mean changes in HRF over time for each channel and participant (HbO)

ggplot(mean_hbO_data, aes(x = Time, y = mean_HRF, group = Participant)) +

  geom_line(aes(color = as.factor(Channel)), linewidth = 0.5) +

  facet_wrap(~ Channel, nrow = 5) +

  labs(x = "Time", y = "Mean HRF", color = "Channel") +

  theme_minimal()



# Create a bar plot for HbO

plot_hbO <- ggplot(clean_hbO_data, aes(x = Time, y = HRF)) +

  geom_bar(stat = "identity", fill = "blue", color = "black") +

  labs(title = "HRF over Time (HbO)",

     x = "Time",

     y = "HRF") +
```

```
  apa_theme
```

Create a bar plot for HbR

```
plot_hbR <- ggplot(clean_hbR_data, aes(x = Time, y = HRF)) +

  geom_bar(stat = "identity", fill = "red", color = "black") +

  labs(title = "HRF over Time (HbR)",

      x = "Time",

      y = "HRF") +

  apa_theme
```

Arrange the plots side by side

```
gridExtra::grid.arrange(plot_hbO, plot_hbR, ncol = 2)
```

#For the complete dataset

Correlation analysis between HRF and KSS for HbO

```
correlation_hbo_kss <- cor(clean_hbO_data$HRF, clean_hbO_data$KSS)
```

Correlation analysis between HRF and KSS for HbR

```
correlation_hbr_kss <- cor(clean_hbR_data$HRF, clean_hbR_data$KSS)
```

Correlation analysis between HRF and steering errors for HbO

```
correlation_hbo_steering <- cor(clean_hbO_data$HRF, clean_hbO_data$SteeringErrors)
```

Correlation analysis between HRF and steering errors for HbR

```
correlation_hbr_steering <- cor(clean_hbR_data$HRF, clean_hbR_data$SteeringErrors)
```

```r
# Correlation analysis between HRF and instruction miss for HbO

correlation_hbo_instruction <- cor(clean_hbO_data$HRF, clean_hbO_data$InstructionMiss)


# Correlation analysis between HRF and instruction miss for HbR

correlation_hbr_instruction <- cor(clean_hbR_data$HRF, clean_hbR_data$InstructionMiss)


# Correlation analysis between KSS and steering errors

correlation_kss_steering <- cor(combined_data$KSS, combined_data$SteeringErrors)


# Correlation analysis between KSS and instruction miss

correlation_kss_instruction <- cor(combined_data$KSS, combined_data$InstructionMiss)


# Correlation analysis between steering errors and instruction miss

correlation_steering_instruction <- cor(combined_data$SteeringErrors,

combined_data$InstructionMiss)


# Correlation analysis results

cat("Correlation Analysis:\n")

# HRF and KSS for HbO

cat("Correlation between HRF and KSS (HbO): ", correlation_hbo_kss, "\n")

# HRF and KSS for HbR

cat("Correlation between HRF and KSS (HbR): ", correlation_hbr_kss, "\n")
```

```r
# HRF and steering errors for HbO

cat("Correlation between HRF and Steering Errors (HbO): ", correlation_hbo_steering, "\n")

# HRF and steering errors for HbR

cat("Correlation between HRF and Steering Errors (HbR): ", correlation_hbr_steering, "\n")

# HRF and instruction miss for HbO

cat("Correlation between HRF and Instruction Miss (HbO): ", correlation_hbo_instruction, "\n")

# HRF and instruction miss for HbR

cat("Correlation between HRF and Instruction Miss (HbR): ", correlation_hbr_instruction, "\n")

# KSS and steering errors

cat("Correlation between KSS and Steering Errors: ", correlation_kss_steering, "\n")

# KSS and instruction miss

cat("Correlation between KSS and Instruction Miss: ", correlation_kss_instruction, "\n")

# Steering errors and instruction miss

cat("Correlation between Steering Errors and Instruction Miss: ", correlation_steering_instruction, "\n")

#For the adjusted dataset

# Correlation analysis between HRF and KSS for HbO

correlation_hbo_kss_r <- cor(clean_hbO_data_r$HRF, clean_hbO_data_r$KSS)


# Correlation analysis between HRF and KSS for HbR

correlation_hbr_kss_r <- cor(clean_hbR_data_r$HRF, clean_hbR_data_r$KSS)


# Correlation analysis between HRF and steering errors for HbO

correlation_hbo_steering_r <- cor(clean_hbO_data_r$HRF, clean_hbO_data_r$SteeringErrors)
```

```r
# Correlation analysis between HRF and steering errors for HbR

correlation_hbr_steering_r <- cor(clean_hbR_data_r$HRF, clean_hbR_data_r$SteeringErrors)


# Correlation analysis between HRF and instruction miss for HbO

correlation_hbo_instruction_r <- cor(clean_hbO_data_r$HRF, clean_hbO_data_r$InstructionMiss)


# Correlation analysis between HRF and instruction miss for HbR

correlation_hbr_instruction_r <- cor(clean_hbR_data_r$HRF, clean_hbR_data_r$InstructionMiss)


# Correlation analysis between KSS and steering errors

correlation_kss_steering_r <- cor(combined_data_r$KSS, combined_data_r$SteeringErrors)


# Correlation analysis between KSS and instruction miss

correlation_kss_instruction_r <- cor(combined_data_r$KSS, combined_data_r$InstructionMiss)


# Correlation analysis between steering errors and instruction miss

correlation_steering_instruction_r <- cor(combined_data_r$SteeringErrors,

combined_data_r$InstructionMiss)


# Correlation analysis results

cat("Correlation Analysis for adjusted dataset:\n")

# HRF and KSS for HbO

cat("Correlation between HRF and KSS (HbO): ", correlation_hbo_kss_r, "\n")
```

```r
# HRF and KSS for HbR

cat("Correlation between HRF and KSS (HbR): ", correlation_hbr_kss_r, "\n")

# HRF and steering errors for HbO

cat("Correlation between HRF and Steering Errors (HbO): ", correlation_hbo_steering_r, "\n")

# HRF and steering errors for HbR

cat("Correlation between HRF and Steering Errors (HbR): ", correlation_hbr_steering_r, "\n")

# HRF and instruction miss for HbO

cat("Correlation between HRF and Instruction Miss (HbO): ", correlation_hbo_instruction_r, "\n")

# HRF and instruction miss for HbR

cat("Correlation between HRF and Instruction Miss (HbR): ", correlation_hbr_instruction_r, "\n")

# KSS and steering errors

cat("Correlation between KSS and Steering Errors: ", correlation_kss_steering_r, "\n")

# KSS and instruction miss

cat("Correlation between KSS and Instruction Miss: ", correlation_kss_instruction_r, "\n")

# Steering errors and instruction miss

cat("Correlation between Steering Errors and Instruction Miss: ", correlation_steering_instruction_r,

"\n")

cat("\n")

#For the complete dataset

# Regression analysis between HRF and KSS for HbO

regression_hbo_kss <- lm(HRF ~ KSS, data = clean_hbO_data)


# Regression analysis between HRF and KSS for HbR

regression_hbr_kss <- lm(HRF ~ KSS, data = clean_hbR_data)
```

```r
# Regression analysis between HRF and steering errors for HbO

regression_hbo_steering <- lm(HRF ~ SteeringErrors, data = clean_hbO_data)


# Regression analysis between HRF and steering errors for HbR

regression_hbr_steering <- lm(HRF ~ SteeringErrors, data = clean_hbR_data)


# Regression analysis between HRF and instruction miss for HbO

regression_hbo_instruction <- lm(HRF ~ InstructionMiss, data = clean_hbO_data)


# Regression analysis between HRF and instruction miss for HbR

regression_hbr_instruction <- lm(HRF ~ InstructionMiss, data = clean_hbR_data)


# Regression analysis between KSS and steering errors

regression_kss_steering <- lm(KSS ~ SteeringErrors, data = combined_data)


# Regression analysis between KSS and instruction miss

regression_kss_instruction <- lm(KSS ~ InstructionMiss, data = combined_data)


# Regression analysis between steering errors and instruction miss

regression_steering_instruction <- lm(SteeringErrors ~ InstructionMiss, data = combined_data)


# Regression analysis results

cat("Regression Analysis:\n")
```

```r
# HRF and KSS for HbO

cat("Regression analysis: HRF ~ KSS (HbO)\n")

print(summary(regression_hbo_kss))

# HRF and KSS for HbR

cat("Regression analysis: HRF ~ KSS (HbR)\n")

print(summary(regression_hbr_kss))

# HRF and steering errors for HbO

cat("Regression analysis: HRF ~ Steering Errors (HbO)\n")

print(summary(regression_hbo_steering))

# HRF and steering errors for HbR

cat("Regression analysis: HRF ~ Steering Errors (HbR)\n")

print(summary(regression_hbr_steering))

# HRF and instruction miss for HbO

cat("Regression analysis: HRF ~ Instruction Miss (HbO)\n")

print(summary(regression_hbo_instruction))

# HRF and instruction miss for HbR

cat("Regression analysis: HRF ~ Instruction Miss (HbR)\n")

print(summary(regression_hbr_instruction))

# KSS and steering errors

cat("Regression analysis: KSS ~ Steering Errors\n")

print(summary(regression_kss_steering))

# KSS and instruction miss

cat("Regression analysis: KSS ~ Instruction Miss\n")

print(summary(regression_kss_instruction))
```

```r
# Steering errors and instruction miss

cat("Regression analysis: Steering Errors ~ Instruction Miss\n")

print(summary(regression_steering_instruction)) #For the adjusted dataset

# Regression analysis between HRF and KSS for HbO

regression_hbo_kss_r <- lm(HRF ~ KSS, data = clean_hbO_data_r)


# Regression analysis between HRF and KSS for HbR

regression_hbr_kss_r <- lm(HRF ~ KSS, data = clean_hbR_data_r)


# Regression analysis between HRF and steering errors for HbO

regression_hbo_steering_r <- lm(HRF ~ SteeringErrors, data = clean_hbO_data_r)


# Regression analysis between HRF and steering errors for HbR

regression_hbr_steering_r <- lm(HRF ~ SteeringErrors, data = clean_hbR_data_r)


# Regression analysis between HRF and instruction miss for HbO

regression_hbo_instruction_r <- lm(HRF ~ InstructionMiss, data = clean_hbO_data_r)


# Regression analysis between HRF and instruction miss for HbR

regression_hbr_instruction_r <- lm(HRF ~ InstructionMiss, data = clean_hbR_data_r)


# Regression analysis between KSS and steering errors

regression_kss_steering_r <- lm(KSS ~ SteeringErrors, data = combined_data_r)
```

```r
# Regression analysis between KSS and instruction miss

regression_kss_instruction_r <- lm(KSS ~ InstructionMiss, data = combined_data_r)


# Regression analysis between steering errors and instruction miss

regression_steering_instruction_r <- lm(SteeringErrors ~ InstructionMiss, data = combined_data_r)


# Regression analysis results

cat("Regression Analysis for adjusted dataset:\n")

# HRF and KSS for HbO

cat("Regression analysis: HRF ~ KSS (HbO)\n")

print(summary(regression_hbo_kss_r))

# HRF and KSS for HbR

cat("Regression analysis: HRF ~ KSS (HbR)\n")

print(summary(regression_hbr_kss_r))

# HRF and steering errors for HbO

cat("Regression analysis: HRF ~ Steering Errors (HbO)\n")

print(summary(regression_hbo_steering_r))

# HRF and steering errors for HbR

cat("Regression analysis: HRF ~ Steering Errors (HbR)\n")

print(summary(regression_hbr_steering_r))

# HRF and instruction miss for HbO

cat("Regression analysis: HRF ~ Instruction Miss (HbO)\n")

print(summary(regression_hbo_instruction_r))
```

```r
# HRF and instruction miss for HbR

cat("Regression analysis: HRF ~ Instruction Miss (HbR)\n")

print(summary(regression_hbr_instruction_r))

# KSS and steering errors

cat("Regression analysis: KSS ~ Steering Errors\n")

print(summary(regression_kss_steering_r))

# KSS and instruction miss

cat("Regression analysis: KSS ~ Instruction Miss\n")

print(summary(regression_kss_instruction_r))

# Steering errors and instruction miss

cat("Regression analysis: Steering Errors ~ Instruction Miss\n")

print(summary(regression_steering_instruction_r))

#For complete dataset

# Model 1: Multilevel Linear Model for HbO

model_hbO <- lmer(HRF ~ KSS + InstructionMiss + SteeringErrors + (1 | Participant), data =

clean_hbO_data)


# Model 2: Multilevel Linear Model for HbR

model_hbR <- lmer(HRF ~ KSS + InstructionMiss + SteeringErrors + (1 | Participant), data =

clean_hbR_data)


# Extract fixed effects summary

summary_hbO <- summary(model_hbO)

summary_hbR <- summary(model_hbR)
```

```r
# Extract residual variance manually

residual_var_hbO <- summary_hbO$sigma^2

residual_var_hbR <- summary_hbR$sigma^2


# Extract participant-level variance manually

participant_var_hbO <- unlist(lapply(VarCorr(model_hbO), function(x) sum(x^2)))

participant_var_hbR <- unlist(lapply(VarCorr(model_hbR), function(x) sum(x^2)))


# Total variance

total_var_hbO <- participant_var_hbO + residual_var_hbO

total_var_hbR <- participant_var_hbR + residual_var_hbR


# Print the results

cat("Model 1: Multilevel Linear Model for HbO\n")

print(summary_hbO)

cat("Model 2: Multilevel Linear Model for HbR\n")

print(summary_hbR)

#For the adjusted dataset

# Model 1: Multilevel Linear Model for HbO

model_hbO_r <- lmer(HRF ~ KSS + InstructionMiss + SteeringErrors + (1 | Participant), data =

clean_hbO_data_r)


# Model 2: Multilevel Linear Model for HbR
```

```r
model_hbR_r <- lmer(HRF ~ KSS + InstructionMiss + SteeringErrors + (1 | Participant), data =

clean_hbR_data_r)


# Extract fixed effects summary

summary_hbO_r <- summary(model_hbO_r)

summary_hbR_r <- summary(model_hbR_r)


# Extract residual variance manually

residual_var_hbO_r <- summary_hbO_r$sigma^2

residual_var_hbR_r <- summary_hbR_r$sigma^2


# Extract participant-level variance manually

participant_var_hbO_r <- unlist(lapply(VarCorr(model_hbO_r), function(x) sum(x^2)))

participant_var_hbR_r <- unlist(lapply(VarCorr(model_hbR_r), function(x) sum(x^2)))


# Total variance

total_var_hbO_r <- participant_var_hbO_r + residual_var_hbO_r

total_var_hbR_r <- participant_var_hbR_r + residual_var_hbR_r


# Print the results

cat("Model 1: Multilevel Linear Model for HbO for the adjusted dataset\n")

print(summary_hbO_r)

cat("Model 2: Multilevel Linear Model for HbR for the adjusted dataset\n")

print(summary_hbR_r)
```

```
# Multilevel models with Channel included

# Model for HbO dataset

model_hbO_c <- lmer(HRF ~ KSS + SteeringErrors + InstructionMiss + (1 | Participant/Channel), data =

clean_hbO_data)


# Model for HbR dataset

model_hbR_c <- lmer(HRF ~ KSS + SteeringErrors + InstructionMiss + (1 | Participant/Channel), data =

clean_hbR_data)


# Summary of the multilevel models

summary_hbO_c <- summary(model_hbO_c)

summary_hbR_c <- summary(model_hbR_c)


# Extract residual variance manually

residual_var_hbO_c <- summary_hbO_c$sigma^2

residual_var_hbR_c <- summary_hbR_c$sigma^2


# Extract participant-level variance manually

participant_var_hbO_c <- unlist(lapply(VarCorr(model_hbO_c), function(x) sum(x^2)))

participant_var_hbR_c <- unlist(lapply(VarCorr(model_hbR_c), function(x) sum(x^2)))


# Total variance

total_var_hbO_c <- participant_var_hbO_c + residual_var_hbO_c
```

```r
total_var_hbR_c <- participant_var_hbR_c + residual_var_hbR_c


# Print the results

cat("Model 1: Multilevel Linear Model for HbO\n")

print(summary_hbO_c)

cat("Model 2: Multilevel Linear Model for HbR\n")

print(summary_hbR_c)

cat("\n")

cat("Variation Partitioning for HbO:\n")

cat("Total Variance:", total_var_hbO_c, "\n")

cat("Participant-level Variance:", participant_var_hbO_c, "\n")

cat("Residual Variance:", residual_var_hbO_c, "\n")

cat("\n")

cat("Variation Partitioning for HbR:\n")

cat("Total Variance:", total_var_hbR_c, "\n")

cat("Participant-level Variance:", participant_var_hbR_c, "\n")

cat("Residual Variance:", residual_var_hbR_c, "\n")

cat("\n")

# Adding the interaction between HRF and predictors (KSS, SteeringErrors, InstructionMiss)

interaction_model_hbO_c <- lmer(HRF ~ KSS * SteeringErrors * InstructionMiss + (1 |

Participant/Channel), data = clean_hbO_data)

summary(interaction_model_hbO_c)
```

```
interaction_model_hbR_c <- lmer(HRF ~ KSS * SteeringErrors * InstructionMiss + (1 |

Participant/Channel), data = clean_hbR_data)

summary(interaction_model_hbR_c)
```