EEG Correlates of Driving Performance

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***Abstract*—Techniques for monitoring human performance traditionally rely on subjective responses and task-specific scoring, yet research suggests EEG could offer multiple performance metrics with high temporal resolution and accuracy that could be leveraged for human-computer interaction purposes. The objective of the presented work is to investigate which EEG responses correlate with task performance and evaluate whether combinations of these produce effective predictive models, facilitating further understanding of the psychological link to performance. A user study was conducted with 32 participants required to negotiate a driving course with the ambition of learning and improving ability on the course during an EEG recording session. EEG was filtered and post-processed to find Power Spectral Density (PSD) in alpha (α), beta (β), delta (δ), and theta (θ) frequency bands, as well as frontal alpha asymmetry (FAA). The initial laps were considered a baseline and an average performance improvement was calculated over the remaining laps in terms of percentage improvement in duration of track traversal. Results demonstrate Event Related Desynchronisation (ERD) with increased task performance in the alpha (*p* = .000), delta (*p* = .000), and theta (*p* = .000) bands, as well as evidence of a relationship between overall change in FAA and task efficiency. A full electrode analysis identifies δ_{F_4} as the optimal for predicting collisions, with efficiency best predicted by a combination of β_{O_z} and δ_{F_4}.**

***Index Terms*—electroencephalography, regression modelling, human performance monitoring**

I. Introduction

MEASUREMENTS of cognitive function have been integrated into task performance monitoring protocols in a variety of environments, including medical [1], [2], military [3], [4], aviation [5], [6], and industrial training platforms [7], [8]. The demand for enhanced examination of task performance can be extended generally to training platforms [9], [10], performance critical industries [11], [12], and rehabilitation [13], [14]. Analysis of human performance is important in these domains as it is beneficial to effectively model improvement in order to enhance pedagogical practices, guidance, or treatments. Furthermore, adaptive systems could alter training to accommodate individual requirements during a task, with the potential for intelligent enhancements based on user-specific data. EEG metrics reveal key components of cognitive function such as workload and approach motivation, yet further research is required to better exploit these measurements for refined implementation into training protocols for optimised user experiences.

Previous research conducted focuses on driver workloads [15] and vigilance [16], but little work has been done to assess the relationship with human task performance. The focus of this work is hence on monitoring user performance using EEG, adopting driver training as an instance of an elaborate task requiring synthesis of complex neural systems for effective cognitive and motor function. Such insight would allow EEG signals to be interpreted as an additional performance metric, improving the understanding of an individuals training profile and facilitating optimisation protocols. The objective of this paper is to observe how different EEG features correlate with performance in a driver training context, and to combine features for improved predictions while retaining explainable results. The innovation of the work is the study design which allows EEG metrics to be related to driving performance using mathematical models, improving understanding of cognitive processes for future adoption in pragmatic monitoring implementations. The contributions are the observed relationships between EEG features and driving performance, the final model's predictions as a benchmark, and psychological interpretations of the final models pertinent to driving tasks.

In this study participant performance scores are extracted from a driver based virtual training environment, along with EEG recordings where PSD features alpha, beta, delta, theta, and FAA are extracted in a post-processing phase. The relationship between these features and their combinations are evaluated against driving performance leveraging regression modelling for interpretation.

This paper describes the system, experiment design, and data acquisition, including insight from the literature and contextual relevance of the work. The results are then analysed and discussed with relation to the wider theoretical implications.

II. Literature Review

There are a variety of techniques for measuring transitions in cognitive state, including heart rate variability [17], oculomotor activity (EOG) [18], pupilometry [19], functional near infrared imaging (fNIR) [20], and galvanic skin response (GSR) [21]. Each technique has merits, yet none compete with the temporal resolution of the EEG, which is able to reflect subtle shifts in cognitive processes [22]. There is a rich corpus of literature dedicated to analysing and interpreting EEG signals both mathematically and in psychological contexts. Typical applications include measuring cognitive workload [23], emotion [24], or approach motivation [25], which can be beneficial for a variety of purposes, including affective computing, medical understanding, and adapting to a humans capability.

Within the field of EEG research there are many techniques for monitoring cognitive states, including Event Related Potentials (ERPs), frequency band PSD, and FAA. Each technique reveals a different insight into cognitive function and is involved in various systems throughout the literature.

The PSD of the frequency bands are related to different psychological responses contingent on the observed band, it is hence a popular choice for monitoring aspects of neurological processing. The main features are the frequency bands alpha, beta, delta, theta, and the left to right ratio FAA, all of which are linked to different characteristics of cognitive activity. These relationships are discussed in further detail in *Section III. D*.

There have been various human monitoring system implementations using these signals. One common criteria monitored is alertness or drowsiness in an individual, which is useful in a variety of applications to observe human operators, such as in driving, industrial operation, and other safety critical environments. This has been accomplished using both support vector machines (SVM) [26] and artificial neural network (ANN) [27] classifiers, with some implementations based on single channel EEG alone [28]. Other techniques include the Hilbert-Huang transform (HHT), fast fourier transform (FFT), and continuous wavelet transform (CWT), which have also been adopted for obtaining frequency information from EEG signals to assess drowsiness [29]. Furthermore, hybrid based input systems comprised of both EEG and body movement data have been shown to increase efficacy, demonstrating promising results for detection in driver scenarios [30]. Fusion techniques have been successful for predicting driving characteristics, such as aggressiveness and stability using multiple EEG feature extraction algorithms combined with driving features [31].

This technology has also been used in training, adopting EEG based cognitive recognition to produce pass, fail, and retrain recommendations in a maritime virtual simulator using SVMs [32]. Other techniques exist in the literature centred around recognition of external stimuli, such as utilising ERPs to identify red, yellow, or green traffic lights with self-constructing neural fuzzy inference networks (SONFIN) [33].

Another common research approach is to observe driver distraction levels during activity. It has been shown that a second interference task significantly affects driving performance as well as judgment capability, finding different features of the additional task had different effects on the EEG responses [34]. Furthermore, online prediction of driver distraction has been successfully achieved using adaptive-threshold-based prediction (ATP), which utilises raw continuous EEG signals monitored by a sliding window and converted to pattern clusters consecutively through a two level feature extraction process [35]. Self organising maps have also been demonstrated as effective, achieving a 90% accuracy for recognition of EEG epochs of distracted and concentrated driving [36].

Other work observes the relationship between EEG and ordinary driving behaviours such as acceleration, space headway, speed, and lane deviations [37]. This has been compared with amplitude, log-transformed power (LTP), and PSD, observing that ordinary driving behaviours relate to all four brain regions, especially temporal, occipital, and frontal regions. It was further determined that acceleration, speed, and space headway may have potential correlation with neurological processes.

EEG features have been shown to modulate with increasing working memory load and during problem solving, integration of information, and analytical reasoning, leading to interpretations suggesting they are reflective of executive function [22]; this has led to many efforts towards the monitoring of cognitive workload using EEG data. These implementations come in many forms, with both traditional analyses and more modern deep learning based approaches reported across the literature. Traditional techniques preserve strength in explainability and are hence often favoured by the neuroscience community where understanding is considered paramount. Many modern engineering based approaches involve SVC or neural networks, which have been demonstrated as viable, efficient, and effective solutions. For example, SVC's have been used to classify different memory workloads, using the *n*-back task [38], with excellent results. In addition CNN's have been shown to have high classification accuracies for neuroscience applications, where a typical processing chain will convert 1-D EEG signals to 3D EEG images and enable a 3D CNN to learn the spectral and spatial information over the scalp [39]. However, these techniques are considered to be black-box techniques, which generally lack transparency and explainability, limiting psychological interpretations and often failing to progress the knowledge space, which is a fundamental requisite of neuroscience.

Human performance monitoring is another significant field pertinent to EEG research. Advances in this domain would augment training system implementations with adaptation functionality capable of accommodating individual ability, allowing pedagogical protocols to be optimised in myriad industries. Such skill catalysts contribute to societal practices in both professional and recreational capacities.

EEG driving studies focus on cognitive workload and engagement, despite suggestions in the theory that a relationship exists between neurological processes and task performance. This paradigm is less explored in the literature, yet shows promise [7], [40] with high classification rates being achieved from behavioural data and multi-modal approaches.

The objective of this paper is to explore the concept that task performance is correlated with EEG information in a driver training scenario, while maintaining the importance of psychological interpretations in order to contribute further understanding to the literature. Furthermore, implementations could be used to monitor performance in real time which has direct application to modern training, rehabilitation, and safety critical systems.

III. Methods

A. System Design

The virtual driver experience was comprised of a software implementation with integrated hardware to facilitate interaction with the participant. The software component was developed in the Unity Game Engine version *2018.3.1* using C# scripting, incorporating virtual assets from the Unity Asset Store, including functional game objects such as the vehicle that the user would engage with and visual components to give the illusion of an authentic driving experience such as trees, barriers, and grass.

The simulation utilised mid-level graphical quality as the main objective was for research, yet some level of realism was appropriate. This was displayed on a 46 inch monitor, setup in front of a Logitech Racing Chair with G920 steering wheel and pedals, isolated using a curtain to reduce distraction throughout the study.

Fig. 1: Driving Simulator

The performance of the virtual vehicle was tuned to meet the characteristic response expected in a standard road car, by tuning parameters such as steering control, speed, torque, and acceleration. Reverse was enabled on the vehicle so that candidates could continue in the instance of a collision. This was accomplished with the assistance of a member of the Queen's University Belfast Racing Team who had significant expertise in driving and racing with numerous vehicles. The course was developed to meet time constraints of the user study, so that candidates would be able to maintain maximum attention for as long as possible.

A system was incorporated to give haptic feedback during the user study, half of the participants were assigned to the visual-haptic group and hence received this feedback. The system integrated an Arduino Uno to output vibrations via four motors with attached inertial masses, using one motor on each wrist to give steering guidance during training phases, and one on each ankle to give pedal guidance.

An 8 Electrode Dry EEG cap by Neuroelectrics was used for EEG recordings throughout the experiment, which facilitates Bluetooth operation with a sampling frequency of 500Hz. The electrodes chosen were F_3, F_4, F_7, F_8, F_z, C_z, P_z, O_z, referenced to the right mastoid, as these allow analysis of frontal, parietal, and occipital lobes which are linked with activity from the different frequency bands, and allow for FAA measurements.

For the initial analysis, O_z is excluded to focus on the frontal and parietal lobes. However, in later full electrode analyses it is included.

B. Objectives

- To observe relationships between task performance and EEG features in order to determine the psychological processes pertinent to performance in this context.
- To exploit EEG relationships with performance to produce regression models, with an emphasis on model explainability, feature importance, and predictive quality.

C. Hypotheses

H1: Haptic feedback will modulate with aspects of cognitive workload, most likely beta PSD as it will likely place more demand and stress on the user [41], [42].

H2: Alpha band PSD (8-12Hz) will decrease with performance increase due to its active role in information processing, particularly attention [43], [44].

H3: Beta band PSD (12-30Hz) will decrease with performance increase due to the link with alertness and stress [41], [42], [45]–[47].

H4: Delta band PSD (0-4Hz) will decrease with performance increase due to links with proficiency in task performance [48], [49].

H5: Theta band PSD (4-8Hz) will decrease with performance increase due to links with cognitive resource demand [50], [51].

H6: FAA will decrease with performance increase because reduced FAA is linked with increases in engagement and motivation [52].

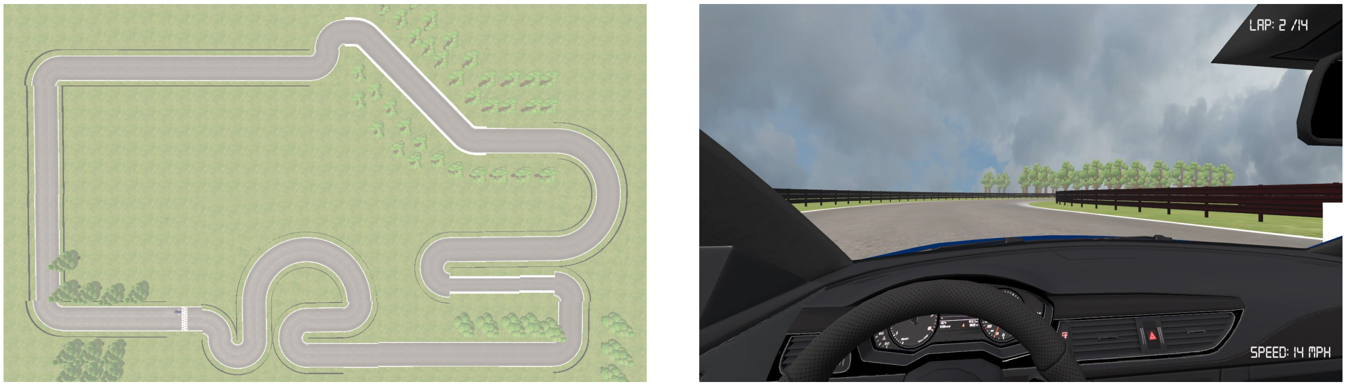
H7: A multivariate regression model based on the strongest features from these metrics will be able to make more insightful predictions than univariate models due to the explanation of different variances, allowing for a greater understanding of the psychological processes active.

D. Predictor Variables

The predictor variables are the different frequency bands in the brain. These have all been linked to a variety of locations [53] particularly the frontal and parietal cortices, hence this study observes an average of the results across the brain, with the frontal cortex being observed by 4 electrodes, and the parietal cortex being observed by 3, with the occipital lobe measurement excluded from the initial analysis.

1) Alpha Band Power: Alpha band power traditionally describes spectral power in the 8-12Hz range [54]. It is believed to play an active role in information processing and thought to be closely linked to the suppression and selection of information, which enable controlled knowledge access and semantic orientation [55]. Empirically, the alpha band has been shown to modulate with working memory [43], spatial attention [44], and to decrease with increased task difficulty [56], [57].

2) Beta Band Power: Beta band power typically describes spectral power in the 12-30Hz range [58], [59]. High workloads are thought to increase beta activity, and it is also linked to changes in alertness and stress [45]. Beta activity has been shown to reflect attention, perception, and more generally, cognitive function in humans [60].



(a) Driving Simulator Course Aerial View

(b) Driving Simulator Interface

Fig. 2: Driving Simulator

3) Delta Band Power: Delta band power describes spectral power in the 0-4Hz range [61]. High correlations between the amount of slow waves present during a task and execution proficiency have been reported [48], as well as links to working memory load [62]. It has been suggested that these waves are representative of 'Class II Inhibition', where non-relevant or inappropriate neural activity are selectively suppressed during the performance of a mental task [49], enabling concentration on the salient objectives present in the task.

4) Theta Band Power: Theta band power typically describes spectral power in the 4-8Hz range [62]. Increases in theta band power are generally associated with increased cognitive workload, and has been shown to modulate with increases in cognitive resource demand [50], time pressure [63], and the number of concurrent tasks to be processed [51].

5) FAA: FAA is a description of the power ratio between the left and right frontal cortex. This ratio is believed to signify an organisms motivational direction, such that greater left side activity is associated with approach motivation, where as greater right side activity is linked with avoidance motivation [52].

E. Dependent Variables

For the first experiment which looks at overall change, the baseline is defined as the average time taken to complete the first 2 laps, where the remaining 12 laps are averaged to produce a final overall score. Laps are sometimes referred to as phases in this study. The percentage difference is found for the average improvement over baseline performance by taking the difference between the two and dividing it by the baseline score, revealing the average percentage change in performance.

In the second experiment the raw lap time scores are utilised in the model, as linear mixed models (LMM) support the violation of independence.

1) Efficiency: This continuous variable measures the efficiency of the participants, using the number of seconds taken to complete one full circuit of the course. This is interchangeably referred to as the course traversal time throughout the document, as they are effectively the same.

2) Collisions: This variable is a positive integer value that measures the amount of collisions that occur between the vehicle and the railing (which can be identified in Fig. 2. (b)) for each phase of the course.

3) Definition of Performance Improvement: Human performance improvement is defined in this study as the overall improvement of a participant from baseline in the two metrics of course traversal efficiency, and quantity of collisions. Course traversal efficiency is measured using the time taken to complete one circuit, and the quantity of collisions is measured by counting the amount of physical interactions between the vehicle and the course railing.

4) Applications: Human performance can be applied to a variety of different applications, such as sports, education, military, and operating performance. Each of these applications would have a different ground truth, but in this study the course traversal time is a reasonable metric. If it can be demonstrated that performance modulates EEG bands, it is possible this will translate to other areas, if the mechanisms are understood and if the application domain is similar enough.

F. Participants

32 healthy adults were selected from a department wide study invitation, where 30 were male and 2 were female. Ages of participants ranged from 18 to 63, with a mean age of 26.77 years and a standard deviation of 10.81 years. All had normal or normal-corrected vision.

G. Task

The participant's objective was to efficiently negotiate the supplied driving course. There were two different types of lap in the study. The first was a performance assessment (non-guided) lap, which is characterised by an absence of guidance. In this lap participants simply drive around the course as efficiently as possible, ideally emulating the learned behaviours from the training phase. The second type of lap in the study was a training lap, in which the system would guide participants towards a pre-determined efficient trajectory. The guidance was designed to improve the understanding and driver negotiation skills of the participant, by demonstrating visual manifestations of the suggested optimal route as well as suggested braking and acceleration timings. In this lap, participants were required to drive around the course and follow the guidance as effectively as possible, which results in efficient traversal duration when performed correctly.

For the user study, subjects were required to drive 14 laps in total. This began with subjects driving two non-guided laps. Upon completion, the vehicle would be reset to the start line and participants would be required to complete four guided training laps. Following this, the vehicle would be reset and two non-guided training laps would be required followed by four guided training laps. This would then conclude with a further two non-guided laps, for a total of 14 laps. This quantity is selected as it allowed substantial data collection while keeping the total session to an acceptable duration. It also allowed for a significant guided training component while retaining a non-guided learning and evaluation phase. Guided laps were split up with non-guided laps so that individuals did not become reliant on the guidance and continued to learn effectively. All laps were completed successfully, with varying quantities of collisions and traversal times.

H. Protocol

Ethical approval was received from the Engineering and Physical Sciences (EPS) Faculty Research Ethics Committee at Queen's University Belfast, in accordance with the proportionate review process.

Prior to arrival candidates were issued an information sheet detailing the important information required to make an informed decision on whether to participate. On arrival they were required to acknowledge the procedure and to give consent for data usage. A written handout with an explanation of the user interface was then presented, outlining the responses required of the users. Understanding of the requirements were then tested verbally.

The right mastoid was disinfected with solution using tissue and the EEG headset was fitted to the participant, at which point impedance values were measured and kept below 40KΩ as an absolute maximum, but below 25KΩ in most cases. This was followed by visual inspection for abnormalities in the datastream using the Neuroelectrics software (NIC) GUI. Participants were then seated in the racing chair and the pedal and steering wheel height was adjusted to fit the candidate. The feedback system was attached to the ankles and wrists of the visual-haptic group and in-ear headphones were provided to enable system audio.

I. EEG Analysis

In order to analyse the EEG data, the data was loaded into EEGLAB [64] for post-processing. The initial data processing phase required filtering the data with a 0.5Hz high pass filter and a 30Hz low pass filter to remove DC offset and 50Hz line noise. The EEG files were divided into epochs at each lap commencement, giving one epoch per lap for a period of 60s, to eliminate possible time warping, yielding 14x60s epochs for each participant. Artefact rejection techniques were applied to reject low quality data using a moving peak to peak voltage threshold window with 100µV threshold, 500ms full width moving window, and 250ms step size. The window was rejected if an artefact was discovered. PSD was then found using Welch's estimation [65] in EEGLAB, on the alpha, beta, delta, and theta bands. A Blackman-Harris window was applied with no overlap, because the large amount of averaging over extensive periods reduces noise, hence the overlap is unnecessary for this purpose as it is typically used to help observe signal data with better temporal resolution, which is not required here. A window length equal to the sampling frequency of 500 samples per second was applied.

FAA was calculated using the following formula:

$$FAA = ln(\frac{F_4 + F_8}{F_3 + F_7}) \tag{1}$$

Where F_3, F_4, F_7, and F_8 denote the alpha power present in those electrode locations. In this work Event Related Desynchronisation (ERD) is defined as a decrease of oscillatory activity related to the ongoing event [66], [67] reflected by decreases in band power.

J. Regression Modelling

1) Between Subjects: Various techniques were employed to develop a model for predicting the efficiency and collisions of individuals from EEG features. Ordinary Least Squares (OLS) linear regression modelling established the relationships between performance and the dependent variables described. Variables were selected for the model with a threshold of $p <$ .05, as these metrics were considered adequate predictors of performance. Initially all dependent variables were analysed independently for hypothesis testing, yielding $R^2_{Adjusted}$ values and *p*-values for evaluation of relationship to task performance. An OLS multilinear regression model was then generated by combining the most appropriate individual variables to find the optimal predictive model, while retaining feature importance information to explain relationships in the psychological domain.

2) Within Subjects: For within subjects regression analysis different LMMs were developed allowing different effects within subjects to be considered. This model structure adopts both random or fixed slopes, and random or fixed intercepts, meaning that natural levels of corresponding performance for frequency band are taken into account as well as the gradient that relates the two factors. This means intersubject variability can be tested statistically, as well as testing for fixed effects with a random intercept to account for individual offset. In this study two standard LMMs are used: fixed slope with a random intercept, and random slope with a random intercept. This is because it is highly likely that each individual will require a different intercept due to variance in ability among the demographic; it is not known whether the neurological processing will vary with the response, which is defined by the slope. Each model was built with only one predictor variable as the focus is on the individual relationships which could have been otherwise masked by multivariate analysis. For all regression models an auto regressive correlation matrix is used for the repeated measures, which attempts to model the natural learning effects throughout the process.

Two different mixed model regression techniques were adopted in this study, as the dependent variable collisions is an integer value it is best modelled using Negative Binomial Regression (NBR), where as course traversal time is a continuous variable so a standard LMM is adopted.

K. Multivariate Linear Mixed Modelling

A multivariate LMM was then developed for the full electrode spectrum. This aimed to produce an overall model that only retains the most powerful predictive features. It does not aim to analyse all of the available electrode relationships, but instead to combine the optimal set of predictors into one model, offering insight into which are the most powerful. Six models were attempted, one fixed model, one random, and one mixed (collisions and course time). This was produced with the following methodology: all electrodes from one frequency band were analysed with the given model type in relation to the response variable. If the variable had a *p*-Value of > 0.2, it was eliminated from the round, with the remaining variables passing through to keep the model simple. A model was then built based on the winners of each frequency band, where the same technique was used to eliminate variables, except the variable was removed if AIC and BIC increased. This process was iterated until a fixed and random model had been produced. The mixed model was created by taking only the winners of the fixed and random pools, with a subsequent process of elimination as before.

L. Mathematical Models and Evaluation Metrics

This section outlines the models developed mathematically, as well as the metrics used to evaluate them.

1) Akaike Information Criterion (AIC): AIC is described as the following, where k is the number of parameters in the model, and $\hat{L}$ is the maximised value of the likelihood function.

$$AIC = 2k - 2log(\hat{L}) \tag{2}$$

2) Schwarz's Bayesian Criterion (BIC): BIC is described as the following with the same notation as above, where n is defined as the number of observations.

$$BIC = klog(n) - 2log(\hat{L}) \tag{3}$$

3) Fixed Effects Model: The model accounts for random intercepts with μ_{i}, where $\varepsilon_{\mathrm{ij}}$ is the unexplained individual error. This model is defined as the following, where β is the estimated coefficient and x_{ij} is the feature value for this participant.

$$y_{\mathrm{ij}} = \beta_0 x_{\mathrm{1ij}} + \beta_1 x_{\mathrm{2ij}} + ... + \mu_{\mathrm{0i}} + \varepsilon_{\mathrm{0ij}} \tag{4}$$

4) Random Effects Model: The random effects model allows for random variation in both the intercept and the slopes. This allows tests for the variability in relationships of frequency band and performance response, as some individuals may undergo different neurological processes. Variable definitions are the same as in the previous section, except each individual has their own coefficient μ_{i} for each variable x_{ij}. This also accounts for random intercepts with μ_{xi}.

$$y_{\mathrm{ij}} = \mu_{\mathrm{0i}} x_{\mathrm{1ij}} + \mu_{\mathrm{1i}} x_{\mathrm{2ij}} + ... + \mu_{\mathrm{xi}} + \varepsilon_{\mathrm{0ij}} \tag{5}$$

5) Mixed Effects Model: The mixed effects model allows modelling of both fixed effects and random effects. The parameters are described in the previous two sections.

$$y_{\mathrm{ij}} = \beta_0 x_{\mathrm{f1ij}} + \beta_1 x_{\mathrm{f2ij}} + ... + \mu_{\mathrm{0i}} x_{\mathrm{r1ij}} + \mu_{\mathrm{0i}} x_{\mathrm{r2ij}} + ... + \mu_{\mathrm{xi}} + \varepsilon_{\mathrm{0ij}} \tag{6}$$

6) Negative Binomial Regression: Here the same formulas are used except y_{ij} is replaced with $log(E(\mathrm{y_{ij}}|x))$ to account for positive integer data with natural characteristics of right skew and overdispersion.

IV. RESULTS

The linear regression models presented satisfied the necessary assumptions unless otherwise specified: independence, heteroscedasticity, normality, and linearity. Independence is naturally achieved by the experiment paradigm, in which all observations are obtained from different participants. Heteroscedasticity was examined using a scatter plot of residuals, and normality was confirmed with a normal predicted-probability plot and histogram of standardised residuals. Linearity was observed from graphical depiction of the relationships and correlation tests.

The Benjamini-Hochberg adjustment was applied to regulate the *p*-values. Each hypothesis was declared prior to the experiment, decreasing likelihood of a Type I error. All statistical tests applied are documented here for further interpretation. The *p*-values are calculated from the *Z* or *F*-statistic unless otherwise stated. The Pearson correlation is applied to evaluate the linear relationship between the two variables. It is chosen because it is a popular and powerful parametric test for correlation and both variables are continuous.

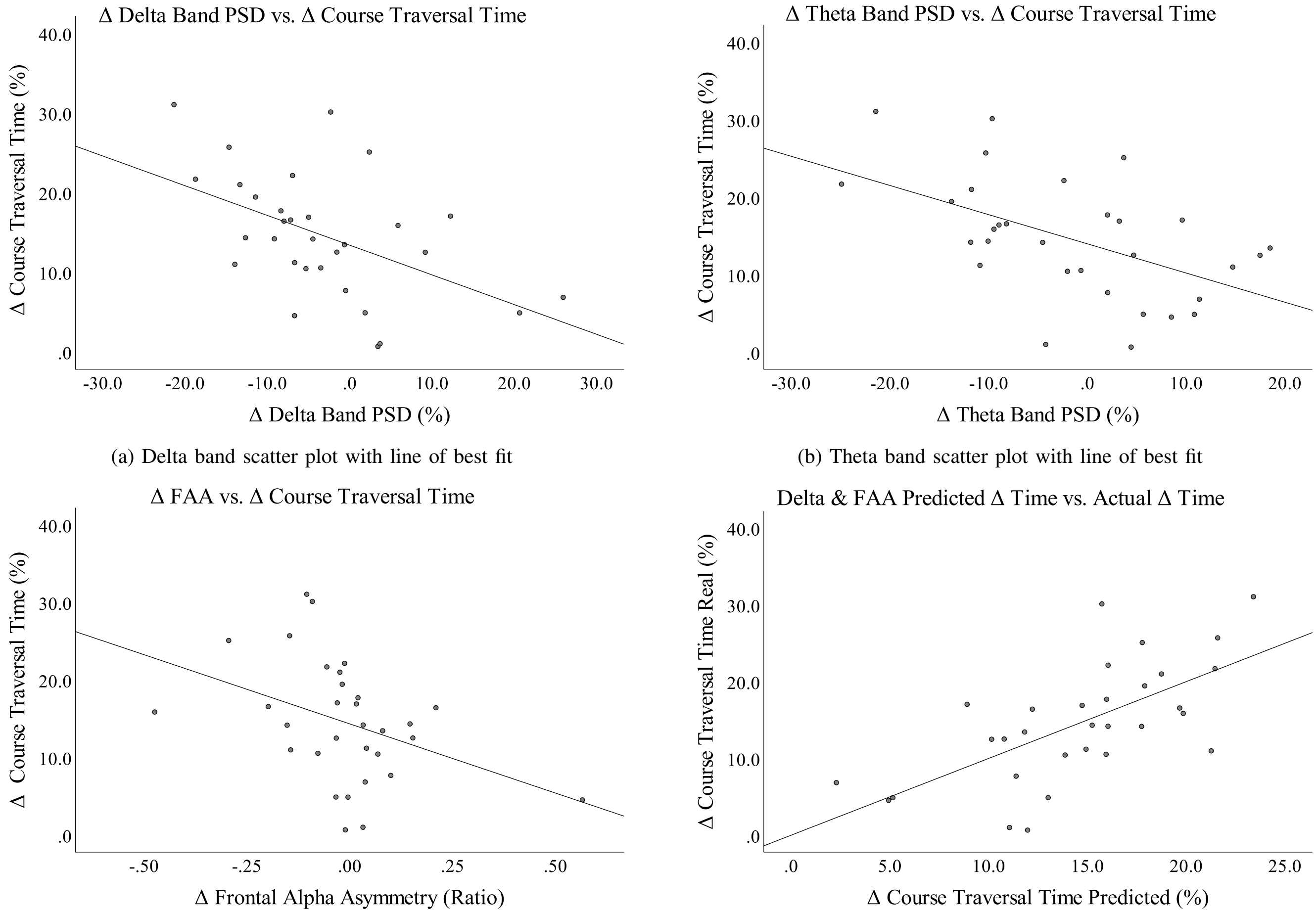
The graphics presented describe the percentage change in PSD (*dB*) in the frequency band against the percentage change in driving performance in terms of course traversal time (*s*). These values are relative to observations in the baseline, which were observed over the first two laps.

Generated models are presented in tables along with the *p*-value, AIC, BIC, and other relevant statistics.

Results for between-subjects regression models can be observed in Tables I and II, with a comparison of the multivariate models in Table IX, and correlations in Table X. Within-subject regression model results can be observed from Tables III-VI for both random and fixed effects, and the ANOVA statistics for PSD and phase are found in Table VII.

A. Haptics

A five-way ANOVA found no statistically significant effects from the haptic group on any of the variables, including average course traversal time. The ANOVA model for haptics with alpha, delta, theta, and FAA, each produced an *F*-statistic less than 0.30 and a *p*-value greater than 0.60 for each variable. Both beta and traversal times had an *F*-statistic of less than 1.80 and a *p*-value greater than 0.20. To include all observations and increase statistical power a repeated measures ANOVA was utilised, finding no statistically significant differences where all *p*-values were greater than 0.15 and all *F*-statistics are greater than 2.12. There is hence no evidence to reject the null hypothesis for H1: haptics have had no statistically significant overall effect on the studied variables.



(a) Delta band scatter plot with line of best fit

(b) Theta band scatter plot with line of best fit

(c) FAA scatter plot with line of best fit

(d) Delta x FAA scatter plot with reference line y = x, where proximity to reference line indicates quality of prediction

Fig. 3: EEG Correlates of Driving Performance

TABLE I: Overall ΔPower $\propto$ ΔEfficiency

Var.	$R^2_{Adjusted}$	*Sig.*	*Adj. Sig.*	dF	*F*-Stat	Freq. (Hz)
α	-0.012	0.428	0.555	29	0.650	8-12
β	0.006	0.288	0.438	28	1.170	12-30
δ	0.230	0.004	**0.013**	29	9.950	0-4
θ	0.256	0.002	**0.008**	29	11.300	4-8
FAA	0.149	0.019	**0.044**	29	6.152	-

B. Alpha Band

1) Between Subjects: The percentage change in performance demonstrated no correlation with the PSD in the alpha frequency band ($F_{2,29}$ = 0.650, p = .555), and produced a model worse than the mean in the regression analysis ($R^2_{Adjusted}$ = -0.012, *RMSE* = 7.78). Furthermore a Pearson test finds minimal correlation (r_{31} = -0.148). Visual evaluation demonstrates that the results are not linear, and hence this assumption is violated. There is no statistically significant relationship with the percentage change in quantity of collisions and alpha band PSD ($F_{2,29}$ = 0.356, p = .670), again producing an insufficient predictive model ($R^2_{Adjusted}$ = -0.022, *RMSE* = 34.026). Furthermore a Pearson test finds minimal correlation (r_{31} = 0.110). No statistically significant relationship between the change in alpha band PSD and change in course traversal duration or collision quantity is observed and there is hence no evidence to support H2 from this experiment.

2) Within Subjects: There is a statistically significant relationship observed between alpha band PSD and course traversal time (F = 14.344, p = 0.000), as well as with collisions (F = 68.261, p = 0.000), with a fixed effect and random intercept specified. The null hypothesis can be rejected and there is a fixed effect relationship between alpha band PSD and course traversal time, as well as with collisions.

TABLE II: Overall ΔPower $\propto$ ΔCollision

Var.	$R^2{}_{Adjusted}$	*Sig.*	*Adj. Sig.*	dF	F-Stat	Freq. (Hz)
α	-0.022	0.555	0.670	29	0.356	8-12
β	-0.035	0.859	0.859	28	0.032	12-30
δ	0.241	0.003	**0.011**	29	10.522	0-4
θ	0.094	0.052	0.096	29	4.106	4-8
FAA	-0.028	0.674	0.737	29	0.181	-

TABLE III: LMM: Random Effect with Random Intercept $\propto$ Efficiency

Var.	*AIC*	*BIC*	*Var. Est.*	*Z*	*Sig.*	*Adj. Sig.*
α	3980.088	3996.380	3.892	0.338	0.735	0.757
β	3978.899	3995.191	6.400	0.936	0.349	0.489
δ	3978.598	3994.890	7.081	1.067	0.286	0.455
θ	3977.756	3994.048	20.749	1.228	0.219	0.383
FAA	3979.178	3995.470	572.828	0.819	0.413	0.556

TABLE IV: LMM: Random Effect with Random Intercept $\propto$ Collision

Var.	*AIC*	*BIC*	*Var. Est.*	*Z*	*Sig.*	*Adj. Sig.*
α	1209.763	1225.962	0.075	2.200	0.028	0.061
β	1252.134	1268.333	0.020	1.088	0.277	0.462
δ	1236.594	1252.594	0.009	3.678	0.000	**0.000**
θ	1239.273	1255.472	0.031	2.537	0.011	**0.030**
FAA	1252.526	1268.725	0.327	0.456	0.649	0.757

TABLE V: LMM: Fixed Effect with Random Intercept $\propto$ Efficiency

Var.	*AIC*	*BIC*	*Est.*	*F*	*Sig.*	*Adj. Sig.*
α	3964.277	3976.489	4.139	14.344	0.000	**0.000**
β	3972.434	3984.646	1.685	4.892	0.028	0.061
δ	3912.027	3924.239	5.444	368.435	0.000	**0.000**
θ	3937.829	3950.041	9.468	190.608	0.000	**0.000**
FAA	3972.272	3984.484	-3.922	0.357	0.551	0.689

This indicates the alpha band response is related to candidate performance when accounting for variable subject intercepts.

The random effects model finds no statistical significance when testing the variation of the slopes with efficiency (Z = 0.338, p = 0.735), meaning that there is not significant random variability among participants. In contrast, the relationship between collisions and alpha as a random effect finds a borderline significant result (Z = 2.200, p = 0.061), indicating that more evidence is needed, but there is some weak evidence to consider that that there is random variability among participants in the relationship between alpha band power and collisions, especially considering the significant result prior to adjustment, yet this is inconclusive. The fixed effects model produces the optimal AIC and BIC, suggesting that this model is a superior fit. Furthermore, a repeated measures ANOVA uses the course phase as a group to predict the alpha band PSD as the response variable, finding significance in the alpha band. This means there is a difference between some of the alpha frequencies between the laps. Post-hoc testing demonstrates a difference between phase 4 and phase 10 only. It is not clear why this is and hence should be interpreted with caution, though it is possible there is some effect here.

C. Beta Band

1) Between Subjects: The percentage change in performance also demonstrated no statistical significance with the

TABLE VI: LMM: Fixed Effect with Random Intercept $\propto$ Collision

Var.	*AIC*	*BIC*	*Est.*	*F*	*Sig.*	*Adj. Sig.*
α	1188.329	1200.489	0.261	68.261	0.000	**0.000**
β	1244.231	1256.387	0.079	5.380	0.021	**0.049**
δ	1079.041	1091.197	0.090	174.858	0.000	**0.000**
θ	1098.160	1110.316	0.184	185.260	0.000	**0.000**
FAA	1250.975	1263.131	0.102	0.125	0.724	0.768

TABLE VII: Repeated Measures ANOVA: Grouped by Phase $\propto$ Freq. PSD

Dep. Var.	*F*	*Sig.*	*Adj. G-Geisser Sig.*
α	3.091	0.004	**0.013**
β	5.950	0.000	**0.000**
δ	2.361	0.038	0.074
θ	1.130	0.345	0.503
FAA	0.700	0.659	0.744

TABLE VIII: Individual Electrode Multivariate LMM Comparison

Model	Var.	*AIC*	*BIC*
Collisions			
Fixed	δ_{F_4}	**1076.122**	**1088.278**
Random	α_{F_z} β_{F_8}	1199.392	1219.617
Mixed	F: δ_{F_4} R: α_{F_z} β_{F_8}	1081.798	1102.011
Course Time			
Fixed	β_{O_z} δ_{F_4}	**3868.785**	**3880.990**
Random	δ_{F_3}	3967.003	3983.296
Mixed	F: β_{O_z} δ_{F_4} R: δ_{F_3}	3870.292	3886.565

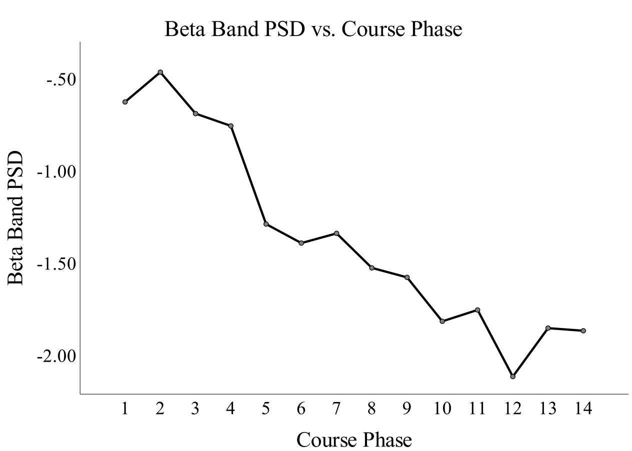


Fig. 4: Beta Band PSD vs. Course Phase

beta band PSD ($F_{2,29}$ = 0.011, p = .918). The regression analysis yields (R^2_{Adjusted} = -0.034, *RMSE* = 7.86), however this result has an extreme outlier which is an impossible measurement. When this outlier is removed there is still no statistical significance ($F_{2,28}$ = 1.170, p = .438) and no explanation of the variance ($R^2_{Adjusted}$ = 0.006, *RMSE* = 7.83). The Pearson test demonstrates minimal correlation (r_{30} = -0.200). There is no significant evidence for a relationship between change in beta band PSD and change in collision quantity ($F_{2,29}$ = 0.032, p = .859), producing an inadequate predictive model ($R^2_{Adjusted}$ = -0.035, *RMSE* = 34.231). Furthermore a Pearson test finds almost no correlation (r_{31} = 0.015). There is no statistically significant relationship observed here between the change in beta band PSD and change in course traversal duration or collision quantity, and hence no evidence to support H3.

2) Within Subjects: There is limited statistical evidence to suggest a relationship between beta band PSD and course traversal time (F = 4.892, p = 0.065), as well as with collisions (F = 5.380, p = 0.049) in the fixed effects model, resulting in the conclusion that there is possibly a fixed relationship between beta band PSD and performance within subjects.

There is no significant random variability found in the relationship between beta power and efficiency (Z = 0.936, p = 0.489), or collisions (Z = 1.088, p = 0.462).

The repeated measures ANOVA demonstrates that there are statistically significant differences in some of the groups (F = 5.950, p = 0.000). Post-hoc tests then demonstrate that there is statistical significance between: phase 1 and phases 10, 12, and 14; phase 2 and phases 10, 11, 12, 13, and 14; phase 3 and phases 12 and 14; phase 4 and phase 14. Some of the earlier phases are significantly different to some of the latter phases, and on average beta frequency PSD declines as the phases progress which is depicted in Fig. 4. The fixed effect relationship between performance and beta power is attributed largely to the strong relationship between beta and course phase, which in itself is a powerful predictor of performance.

D. Delta Band

1) Between Subjects: The percentage change in performance is demonstrated as having a negative linear correlation with the PSD of the delta frequency band, which is found to be statistically significant ($F_{2,29}$ = 9.950, p = .013). A linear regression model based on OLS yields ($R^2_{Adjusted}$ = 0.230, $RMSE$ = 6.78) meaning that this relationship explains 23% of the variance. The standard deviation of the residuals is described by the $RMSE$, which is higher than observed in the theta band but considerably less than observed in the beta and alpha models, meaning that the data fits this model better and is more concentrated around this models predictions. The Pearson test for correlation demonstrates a medium strength correlation (r_{31} = -0.506). There is evidence that the change in delta band is linked with the change in collision quantity ($F_{2,29}$ = 10.522, p = .011), producing an effective predictive model ($R^2_{Adjusted}$ = 0.241, $RMSE$ = 29.325). Furthermore a Pearson test finds a relatively strong correlation (r_{31} = 0.516). Change in delta band PSD modulates with the change in task temporal performance exhibited by the subject, providing substantial evidence of H4.

2) Within Subjects: There is a statistically significant relationship found between delta band PSD and course traversal time (F = 368.435, p = 0.000), as well as with collisions (F = 174.858, p = 0.000) for fixed effects. There is strong statistical evidence for a relationship between the delta band PSD and task performance generally, as in H4.

There is no statistically significant variability between subjects for the relationship with efficiency (Z = 1.067, p = 0.455), however there is for collisions (Z = 3.678, p = 0.000), meaning that there is appreciable random variation in the gradients.

A repeated measures ANOVA finds no statistical evidence for a relationship between the phase and the delta band PSD (F = 2.361, p = 0.074).

E. Theta Band

1) Between Subjects: The percentage change in performance also has a negative linear correlation with the PSD of the theta frequency band, which is found to be statistically significant ($F_{2,29}$ = 11.300, p = .008). A linear regression model based on OLS yields ($R^2_{Adjusted}$ = 0.256, $RMSE$ = 6.67) which explains 25.6% of the variance in this relationship. Pearsons test for correlation yields (r_{31} = -0.530). There is no statistically significant relationship between the change in theta band and change in quantity of collisions ($F_{2,29}$ = 4.106, p = .096) although it is quite possible that there is a small effect size here as the p-value is quite low even after adjustment, however more results would be required to further interpret this result. The produced predictive model explains 9.4% of the variance in the relationship and marginally improves RMSE ($R^2_{Adjusted}$ = 0.094, $RMSE$ = 32.041). Furthermore, a Pearson test finds a medium strength correlation (r_{31} = 0.352). The $RMSE$ and $R^2_{Adjusted}$ are improvements on the delta band model for predicting efficiency, but deficit predictions of collision quantity. These results provide significant evidence for H5.

2) Within Subjects: There is a statistically significant relationship found between theta band PSD and course traversal time (F = 190.608, p = 0.000) as well as with collisions (F = 185.260, p = 0.000), for a fixed effect relationship, as in H5.

There is no statistical evidence to suggest that there is within subject random variability in gradients for efficiency (Z = 1.228, p = 0.383), however there is some evidence of this for collisions (Z = 2.537, p = 0.030), suggesting the gradients randomly vary between participants.

A repeated measures ANOVA finds no statistical evidence for a relationship between the phase and theta band PSD (F = 1.130, p = 0.503).

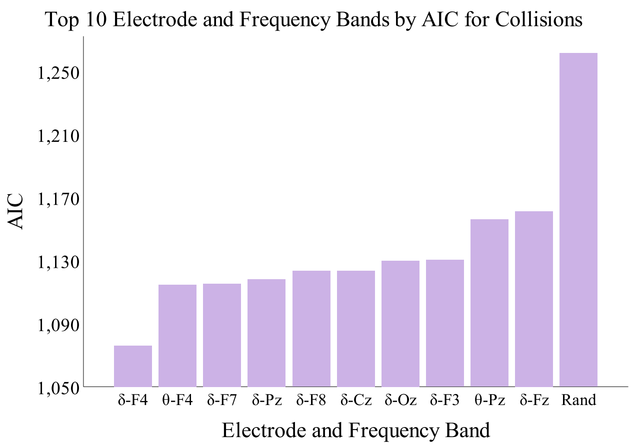
F. Frontal Alpha Asymmetry

1) Between Subjects: The percentage change in performance has a negative linear correlation with FAA, which is found to be statistically significant ($F_{2,29}$ = 6.152, p = .044). A linear regression model based on OLS yields (R^2_{Adjusted} = 0.149, $RMSE$ = 7.141), explaining 14.9% of the variance in this relationship. This model has two outliers more than 3 standard deviations away from the mean, however they are realistic values and should be considered in the analysis. In the interest of avoiding a Type I error, with these outliers removed the statistical significance remains ($F_{2,27}$=6.077, p = .047), and the linear regression yields (R^2_{Adjusted} = 0.153, $RMSE$ = 7.142). The outliers do not change the significance, and have only a minor impact on the model; they are also realistic values and are hence left in for the graphic. Pearsons test yields a medium negative correlation between the variables (r_{31} = -0.429). There is no statistically significant evidence for a relationship between FAA and collision quantity ($F_{2,29}$ = 0.181, p = .737). The produced predictive model is completely ineffective ($R^2_{Adjusted}$ = -0.028, $RMSE$ = 34.128). Furthermore, a Pearson test finds minimal correlation (r_{31} = 0.079). There is some evidence for H6 in a between subjects condition and considering the overall course.

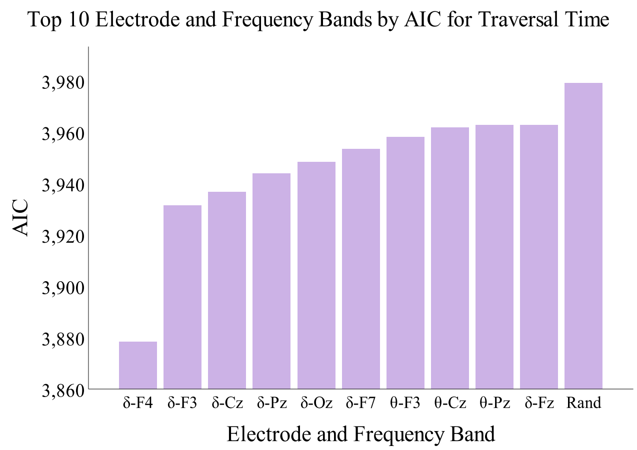
2) Within Subjects: FAA was not found to link with any of the within subject responses of efficiency (Table III and V), quantity of collisions (Table IV and VI), or phase (Table VII). There is no evidence that these changes relate to performance within a subject for either collisions or efficiency, and hence no evidence here for H6.

TABLE IX: Model Comparison

Var.	δ	θ	FAA	δ & FAA	θ & FAA	δ & θ	δ & θ & FAA
R^2_{Adjusted}	0.230	0.256	0.127	**0.393**	0.320	0.280	**0.393**
RMSE	6.58	6.55	7.00	**6.00**	6.31	6.38	6.24
MAE_{Mean}	5.42	5.64	5.96	**4.98**	5.53	5.40	5.33
$\text{MAE}_{\text{Median}}$	4.58	4.52	5.69	**4.26**	4.84	5.07	4.47
Max Error	12.51	12.37	13.02	11.69	**11.37**	11.81	12.17
$\delta_{\text{Coefficient}}$	-0.502	-	-	-0.525	-	-0.279	-0.404
$\theta_{\text{Coefficient}}$	-	-0.529	-	-	-0.469	-0.349	-0.189
$\text{FAA}_{\text{Coefficient}}$	-	-	-0.397	-0.422	-0.299	-	0.379



(a) Collisions



(b) Course Traversal Time

Fig. 5: Top 10 electrodes and frequency bands by AIC, lower is better

G. Model Comparison

1) Between Subject Regression Model: Regarding the single variable models it can be seen that the predictive quality of theta PSD is superior to delta PSD and FAA, on all metrics except for MAE_{Mean}.

In order to create a multiple regression model to make predictions about task performance based on EEG components, the optimal predictors were selected. This was accomplished by eliminating the alpha and beta frequency band models as they demonstrated no significant relationship with performance.

All of the possible combinations of the remaining models were tested to find the optimal combination as a correlate of human task performance, the results can be observed in Table III. The optimal model combines the delta band PSD with FAA yielding significant improvements over the univariate models ($R^2_{Adjusted}$ = 0.393, *RMSE* = 6.00) and other multivariate models.

k-Fold Cross Validation (CV) was used to ensure that the models were not subjected to overfitting, splitting the data with a metric specific k-Fold and training the model on the remainder. These results were averaged to give a better indication of the predictive power of the model and hence the strength of the relationship. A k-Fold of 10 was used for all metrics except the maximum error (k-Fold=4) and the $R^2_{Adjusted}$ (k-Fold=none), because these are not designed to accommodate larger amounts of folds.

The feature importance was calculated by observing the coefficients produced when the inputs had been scaled. For the model that combines all three variables the delta coefficient ($\delta_{\text{Coefficient}}$ = -0.404, $\delta_{\text{Contribution}}$ = 41.55%) was found to be the most important, with the FAA coefficient ($\text{FAA}_{\text{Coefficient}}$ = -0.379, $\text{FAA}_{\text{Contribution}}$ = 38.99%) second and the theta coefficient ($\theta_{\text{Coefficient}}$ = -0.189, $\theta_{\text{Contribution}}$ = 19.46%) with the least impact on the result. Observing the most successful model (FAA & delta) finds the delta coefficient ($\delta_{\text{Coefficient}}$ = -0.525, $\delta_{\text{Contribution}}$ = 55.44%) to be the most important, with the FAA coefficient ($\text{FAA}_{\text{Coefficient}}$ = -0.422, $\text{FAA}_{\text{Contribution}}$ = 44.56%) also having a significant impact on the results. It follows logically that the delta band power is having the largest impact on the results in the more successful models, where asymmetry is also contributing; in their presence the theta bands coefficient is substantially reduced.

Collinearity is observed between the delta band and theta band, where the correlation between them is 0.642. In the model where they are paired, they produce a Variance Inflation Factor (VIF) of 1.70 and a tolerance of 0.588, which are both high and low values respectively, given the model size, suggesting they are explaining some of the same variance in the relationship. This is also true for the model with all three variables, producing a high VIF for the model size (δ_{VIF} = 1.811, θ_{VIF} = 1.889), and a relatively low tolerance ($\delta_{\text{Tolerance}}$ = 0.552, $\theta_{\text{Tolerance}}$ = 0.529). The most successful model yields a low VIF ($\text{FAA}_{\text{VIF}} = \delta_{\text{VIF}} = 1.003$), and a high tolerance ($\text{FAA}_{\text{Tolerance}} = \delta_{\text{Tolerance}} = 0.997$). The correlation between these two was also low (r_{31} = -0.051, p = .786), meaning that they are explaining different variances in the relationship, which could explain the improvement yielded from the combination.

There is hence substantial evidence for H7, that integrating multiple variables can improve model predictive power.

2) Within Subjects Regression Model: This approach observed relationships with the individual electrodes and attempted determine the optimal combination to produce the most effective model, with both fixed and random effects considered. The results for this experiment are observed in Table VIII, with a graphic comparison of variable by AIC available in Fig. 5a and 5b. For collisions as a response variable it was found that the optimal model consists of δ_{F_4} on its own. Any addition to this appears to reduce the quality of the model in terms of AIC and *BIC*. This could be a result of AIC and *BIC* favouring a simple model, it suggests that δ_{F_4} has sufficient predictive power on its own, and perhaps explains a lot of the same variance that the other electrodes explain.

For the relationship with course time a fixed effects model containing δ_{F_4} and β_{O_z} is found to be the optimal. β_{O_z} is found to have limited predictive quality, but it appears to explain a different variance to δ_{F_4} and compliment it. Additional random effects reduce the model fit as do the extra electrodes observed. It should be noted that there are possibly better combinations of electrodes for both models; these are the results determined using this particular technique, as there are too many possible electrode combinations to attempt.

TABLE X: Correlation Matrix

Var.	δ	θ	FAA
δ	1	0.642	-0.051
θ	0.642	1	-
FAA	-0.051	0.21	1

V. Discussion

A. Haptics

There is no observed overall effect produced by the haptics which was not anticipated. It is possible there are more influential variables involved, such as other psychological processes that modulate the studied variables.

B. Alpha

The observations from this study suggest that there is some relationship between alpha band power and driving performance. While there is no relationship observed between subjects, there is a significant fixed effect relationship between alpha band power and course traversal time, as well as quantity of collisions in the within subjects model. The relationship between course traversal time and alpha band power is weaker than with delta and theta.

There is no significant random variability in participant alpha band power in relation to collisions or efficiency, psychologically this implies that the neurological processing, described by the relationship between alpha band power and performance, does not randomly vary among the participants, although more research efforts would be required to confirm this.

Alpha band power has been linked with a variety of different psychological processes, such as attentional operations [68], [69], working memory and short-term memory retention [70]. This relationship could hence be explained by more efficient allocation of attentional resources, or by improvements in working memory, resulting in performance increase, although these neurological mechanisms are closely linked.

It's possible that increases in collisions result in heightened attention levels to help avoid future collisions. Other studies have linked alpha frequencies with increased task difficulty [56], [57], which is likely reflected by collision quantity and could explain why there is a significantly closer relationship between alpha power and collisions than with efficiency. Based on the literature, and the evidence supplied here, the relationship between alpha power and performance could correspond to either task demands or attentional processes, but conclusively correlate with task performance in this context. The relationship with efficiency is not as strong, possibly because collision quantity has a closer relationship with both attention and task demands.

C. Beta

There is no evidence of beta band power modulation in the between subject responses with either collisions or efficiency. There is some evidence of a fixed effect relationship with efficiency and collisions within subjects, where both are borderline significant relationships, this is likely explained by the strong relationship between beta band power and course phase, which is strongly related to performance. Furthermore, there is no evidence to suggest that there is significant random variation in relation to collisions or efficiency meaning individual neurological processing does not appear to randomly vary among participants. Beta band power has been linked with multiple neurological responses such as feelings of anxiety [71] or stress [41], [42] and vigilance [72], [73] or alertness [46], [47]. The results from this study demonstrate declines in beta power as the course progresses, indicating that either the subjects alertness or stress levels decline throughout the course of the study. It could be both, and they are related behavioural mechanisms and likely to be correlated. It is unclear whether alertness and stress are closely related with performance in this context, as beta power is strongly related to the duration of the task, which is correlated with performance.

D. Delta

There is strong evidence of a link between change in delta band PSD and change in driving performance for both efficiency and collision quantity for both between subjects and within subjects. This could be due to the link between delta activity and inhibition of certain neural procedures in the brain. Other studies reflect this result through an association with learning, motivational processes, and the brain reward system [74]–[76]. In this experiment, evidence of delta ERD suggests that selective suppression of neural activity is related to an improvement in driving performance, echoed by other work observing mental tasks and task related performance [49], [77].

There is no significant random variability observed in relation to efficiency but there is for collisions, suggesting that the neurological processes in response to these events randomly varies among subjects.

Delta band power is the only band to relate to driving performance across all of the experiments. For within subjects delta power shares the strongest relationship with task efficiency over frontal and parietal regions. Further breakdown reveals delta at O_z, F_4, F_8, P_z, F_3, F_7, F_z, and C_z are all ranked in the top 10 by AIC for collisions and F_4, F_3, C_z, P_z, O_z, F_7, and F_z are in the top 10 by AIC for traversal time. δ_{F_4} is especially noteworthy as it appears top on each metric, suggesting that power at F_4 is the strongest in relation to driving task performance.

Electrode F_4 monitors the premotor cortex which is involved in the preparation and guidance of movement in primates [78], the relationship between δ_{F_4} and task proficiency in this experiment could hence be thought of as selective suppression of neural activity related to guidance of movement throughout a task, which would make it a useful metric for movement related task performance. O_z is also highly ranked on both metrics and is located on the occipital lobe which is responsible for visual processing, which is understandably related to driving performance in this context as visual information is an important component of the task.

E. Theta

Increases in theta band activity are typically linked with increases in cognitive resources [50], time pressure [63], and the number of concurrent tasks to be processed [51]. In this experiment, evidence of theta ERD suggests a link between cognitive resource allocation and driving performance. This is observed between subjects for efficiency but not for collisions, although that is marginally significant and shouldn't be discounted hastily. Furthermore, the relationship is evident for the within subjects experiment, demonstrating a strong relationship between theta power and both task performance metrics.

There is no random variability observed among participants for efficiency, but there is for collisions, finding that there is some random variation in how subjects process collisions neurologically in terms of theta activity.

In further detail it can be observed that theta at F_4, and P_z are well ranked for collisions, as well as F_3, C_z, and P_z for traversal time. Electrode location P_z monitors the parietal lobe, the only location to appear in the top 10 for both metrics for theta band. This lobe is thought to be specialised for particular visuomotor actions such as grasping and eye movements [79], which could be linked to the steering aspect of driving performance.

F. FAA

The between subjects results demonstrate that candidates with increase efficiency had a greater increase in left frontal activity, which is strongly linked to approach motivation and positive feelings. Equally, right frontal activity is linked with negative feelings and withdrawal motivation, which the lower improver's exhibited.

This relationship explains a different variance to that explained by the delta and theta power. This would be expected as FAA is a motivational response unrelated to cognitive resources reflected by theta band and selective suppression demonstrated by delta band activity.

FAA does not modulate with any of the within subject responses. This result is unexpected as it seems as though the approach motivation and withdrawal motivation would be linked to aspects of performance, particularly collisions which would be frustrating and likely induce withdrawal motivation in candidates. It could be that in this context motivation does not have a high temporal resolution and only shifts over time, over prolonged periods of poorer performance, yet research would be required to confirm this theory.

G. Between Subjects Multivariate Regression

Combining variables enables modelling of different psychological processes. Theta and FAA can be considered as a combination linking to change in cognitive resources and approach motivation. While this relationship is an improvement on the univariate models, as both variables explain different variances, it is significantly inferior to the delta and FAA model, which can be thought of as a combination relating to change in neural inhibition and approach motivation. The theta and delta model is also slightly superior to the univariate models, with its representation of change in cognitive resources and neural inhibition, which explain a lot of the same variance and hence do not improve one another considerably. The model utilising theta, delta, and FAA combines the relationships to change in cognitive resources, neural inhibition, and approach motivation. This model explains the joint largest amount of variance, but the k-Fold cross validation confirms that this relationship is weaker than the delta and FAA model, possibly because of variance inflation resultant of including correlated variables in the same model, as there is a moderate correlation between theta and delta power.

Hence, the strongest relationship observed is the delta and FAA model, representing neural inhibition and approach motivation as predictors in the psychological domain. This particular result is specific to driving performance and should not necessarily be applied generally, yet the concept of combining multiple metrics to measure performance in a task with EEG correlates is here shown to have merit. In real world applications the optimal combinations are likely to depend on the requirements of the particular task. It is likely that approach motivation will normally improve task performance, simply because there is greater engagement and investment in the task, but the magnitude of cognitive workload and neural inhibition will not always modulate with performance. These results suggest that for complex tasks with large amounts of information to be processed, suppression of delta band power is likely to be equated with higher performance. Furthermore, for certain tasks it is likely that decreases in cognitive workload can signify improvements in ability, as less cognitive resources are required to accomplish the task.

H. Within Subjects Multivariate Regression

The within subjects model observes that δ_{F_4} and β_{O_z} is the optimal combination for predicting course time, and the δ_{F_4} is the optimal for predicting collisions. It should be noted that the objective of this work is explanation, which is why simple models are preferred. It is highly likely that this model can be improved with machine learning techniques leveraging all inputs as well as interaction effects to optimise predictive power, especially with more data. Yet this could mask feature importance and reduce contribution to the neuroscience knowledge base. Overall, in this case it is a simple model that fits best with δ_{F_4} having the strongest relationship to performance throughout. Evidence for H7 is hence minor, with just one extra electrode improving the model, and only by a minimal amount.

VI. Conclusion

There are numerous significant findings in this study. The strong relationship between δ_{F_4} PSD and driving performance has important implications in neurological performance monitoring. Other findings include: the relationship between performance, delta power, and theta power; an overall relationship with FAA and performance; and a relationship between beta band power and course phase. In conclusion, various aspects of EEG signals modulate with performance. Increased performance in certain tasks is associated with decreased cognitive workload, as well as increased motivation readings. These can be combined to produce a model capable of estimating a subjects final performance based on EEG readings, achieving reasonable levels of accuracy.

This study suggests that delta and theta band activity are best suited for monitoring performance in training systems of this nature, where FAA is also useful for interpreting motivational direction. The between subjects results suggest that performance can be mathematically modelled as a combination of neurological processes interpretable from the EEG readings. Modelling this mathematically significantly increases the variance explained by the model and reduces *RMSE*, meaning that combining EEG features has resulted in improved predictive performance and allowed for a more general interpretation of psychological experience undertaken throughout the training procedure.

Further analysis within subjects finds that there is a relationship between alpha, delta, and theta band power with the driving performance metrics of efficiency and collision quantity. Subsequent extensive analysis observed that δ_{F_4} has the strongest relationship with driving task performance of the electrodes and frequencies available, which could be related to selective suppression of neural activity related to guidance of movement. This could potentially translate over to domains that require skill in movement such as other driving scenarios, sports, and military applications. Delta and theta frequencies would be particularly recommended for analysing driving performance from a neurological perspective, but δ_{F_4} is the salient metric for analysis of this nature according to this experiment.

VII. Limitations

The study only analyses 32 individuals, which is a reasonable sample size but it could be much larger; how well the interpretations translate over to other samples is unknown. There are very few females in the study, and most of the individuals are 18-30, not necessarily reflecting the whole population. The study is making interpretations based on assumptions and attributes of the existing literature, hence the efficacy of these metrics in non-driving environments is unclear.

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