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# The Impact of Sleep Deprivation on Drivers' Emotional Responses: An Event-Related Potentials Study

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**ABSTRACT**

Driver fatigue poses a significant threat to road safety. This study investigates the potential of emotion-related Event-Related Potentials (ERPs) as a novel biomarker for differentiating between sleep-deprived and non-sleep-deprived drivers. A comprehensive research protocol comprising four stages was employed: initial brainwave recording, emotional stimulation experiments (happiness, fear, sadness, calm), driving tests, and final brainwave recording. EEG data underwent pre-processing and subsequent classification using Binary Linear Regression (BLR) to distinguish sleep-deprived from non-sleep-deprived states based on emotion-related ERPs. The BLR model achieved an accuracy of 86.1%, suggesting promising potential for emotion-based ERPs as a means to objectively assess driver fatigue. These findings lay the groundwork for further research to refine the classification model and explore its real-world application, ultimately contributing to enhanced road safety through the development of non-intrusive fatigue detection methods.

***Keywords:***
Event-related potential (ERP); mental workload; emotion recognition; binary linear regression (BLR)

## 1. Introduction

This paper delves into the intricate relationship between sleep deprivation, drowsiness, and their influence on emotional processing. Sleep deprivation is a well-established factor linked to a cascade of detrimental effects, including mental exhaustion, diminished physical efficiency, and a heightened risk of errors [1, 2].

While the concept of "tiredness" often occupies a middle ground between alertness and sleepiness, it too can manifest as a decrease in both mental and physical productivity, decision-making abilities, and overall performance [1]. Furthermore, a strong body of research underscores the cyclical nature of drowsiness and fatigue, where drowsiness amplifies feelings of weariness, and fatigue itself contributes to increased drowsiness [3]. Therefore, for the purposes of this study, we will encompass both sleep deprivation and drowsiness under the umbrella term "fatigue."

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Despite significant advancements in understanding the impact of sleep deprivation on cognitive performance, scientific exploration remains in its early stages [4]. While a consensus exists regarding the detrimental effects of insufficient sleep on response speed and performance variability, the relationship between sleep deprivation and emotional processing remains less clear. However, emotions undeniably represent a cornerstone of human experience, and their functions are demonstrably intertwined with sleep deprivation [5].

From a biological standpoint, emotions can be viewed as potential biomarkers, akin to other physiological signals. External stimuli act as inputs, triggering a cascade of responses within the human brain that culminate in the experience of a broad range of emotions, including happiness, calmness, fear, and sadness [6]. Researchers have employed various techniques for emotion recognition, including analysis of facial expressions, speech patterns, and electroencephalogram (EEG) activity. Among these methods, EEG-based approaches hold particular promise as they offer a unique window into the brain's internal neural processes, which are less susceptible to conscious manipulation or masking [7].

Event-Related Potentials (ERPs) provide a powerful tool for investigating the human brain by measuring its electrical activity during cognitive processing [8]. By analyzing averaged raw EEG signals, ERPs enable researchers to glean valuable insights into cognitive processes related to perception, attention, and emotion [9, 10]. Given the rich information about cognitive processes that ERPs can reveal, this study aims to leverage EEG-monitored ERPs to assess the state of mental fatigue.

However, previous research has primarily focused on a limited set of ERP features, leaving a gap in our understanding of the specific emotions associated with sleep deprivation and non-sleep deprivation. This study proposes a comprehensive and systematic exploration of a wider range of emotional characteristics using ERPs. This approach will allow us to gain a deeper understanding of the complex relationship between EEG signals and the emotional state in the context of sleep deprivation and non-sleep deprivation.

## 2. Methodology

### *2.1 Participants*

For this initial investigation, data was collected from six subjects (N=6) aged between 18 and 40 years. The subjects were divided into two distinct groups: three sleep-deprived participants and three non-sleep-deprived participants. The non-sleep-deprived participants were required to have a sufficient amount of sleep prior to the experiment, defined as approximately seven hours or more. Conversely, the sleep-deprived participants were restricted from sleeping more than six hours before the experiment.

This experimental design is grounded in the finding that sleeping for seven hours or more maintains healthy mental alertness [11]. In contrast, sleeping less than six hours per night is classified as sleep deprivation [12]. To ensure the validity of the study, all participants were required to possess a valid driving license and have a minimum of two years of driving experience. Furthermore, participants must have no history of events leading to brain damage. Each subject was required to complete a consent form and a questionnaire regarding their sleep/wake patterns prior to the experiment. Additionally, they were instructed to abstain from consuming caffeine, medications, or any substances that could influence brain activity before the experiment.

This rigorous methodology was designed to ensure the reliability and accuracy of the data collected, providing a robust foundation for understanding the impact of sleep deprivation on mental alertness.

### *2.2 Experimental Procedure*

This study complies with the Declaration of Helsinki and was performed according to ethics committee approval. The experiment was conducted at the Pervasive Computing and Brain Development Research Group Lab (PCBDG) at the International Islamic University Malaysia (IIUM). Prior to their participation, all potential subjects were required to complete a standardized informed consent form. Additionally, a comprehensive questionnaire was administered to gather detailed information regarding their sleep and wake patterns. This data collection process ensured informed consent and facilitated accurate participant categorization for subsequent analysis.

EEG data was recorded using a 19-channel EEG DABO Machine. The bandpass filter for the EEG recordings was set from 0 to 40 Hz, encompassing Delta, Theta, Alpha, Sigma, and Beta wave frequencies, with a sampling frequency of 250 Hz. This configuration was chosen to capture a comprehensive range of brainwave activity, ensuring the collection of high-quality data.

The setup of the EEG equipment was completed in under 10 minutes. The simulations performed by the students were recorded using an unaltered EEG device configuration to measure ambient noise and obtain relevant data. The experimental protocol, or task sequence for the participants, was divided into three main tasks. Throughout the execution of these tasks, continuous EEG data was recorded using the EEG DABO machine.

The detailed design of this experimental setup aimed to ensure the collection of high-quality, reliable data. By controlling the environment, precisely configuring the EEG equipment, and systematically organizing the task sequence, external variables were minimized, and accurate representations of brain activity were captured. The thorough methodology employed in this experiment enhanced the validity of the findings and demonstrated the feasibility of using ERPs to investigate the effects of sleep deprivation on cognitive and emotional functions.

### *2.3 Research Protocol*

This study employed a comprehensive data acquisition protocol designed to investigate the interplay between sleep deprivation, emotional processing, and driving performance. The protocol comprised four distinct stages, each tailored to elicit specific neural responses and behavioral data (Figure 1).

| Base Line | | Emotional State | | | | Task 1 | Task 2 | Task 3 | Base Line Extension | |
|---|---|---|---|---|---|---|---|---|---|---|
| Eyes Closed (1 minutes) | Eyes Open (1 minutes) | Happy (1 minutes) | Calm (1 minutes) | Sad (1 minutes) | Fear (1 minutes) | Driving Simulation (Easy) | Medium | Hard | Eyes Closed (1 minute) | Eyes Open (1 minute) |
| 2 minutes | | 4 minutes | | | | 5 minutes | 5 minutes | 5 minutes | 2 minutes | |

**Fig. 1.** Structure for the data acquisition research protocol

#### *2.3.1 Baseline recordings: Establish a reference point*

The first stage involved a two-minute baseline EEG recording to establish a reference point for subsequent analyses. This recording was further divided into two sub-stages:

i. Eyes Open: Participants were instructed to sit still and fixate on a blank white computer screen for one minute. This minimized motion artifacts in the EEG signals and provided a baseline for brain activity during visual processing.
ii. Eyes Closed: Following the eyes-open recording, participants closed their eyes and remained still for another minute. This standardized procedure assesses the brain's default state, with minimal information processing due to the lack of visual input. The data acquired during this sub-stage serves as a reference for evaluating emotional and cognitive processing in subsequent stages.

#### *2.3.2 Emotional state stimulation: Eliciting affective responses*

The second stage aimed to elicit specific emotional responses in participants. This was achieved by presenting a series of four one-minute video clips designed to induce happiness, calmness, fear, and sadness. The specific content and presentation order of the video clips would be elaborated upon in a separate section of the manuscript. By carefully selecting these stimuli, the researchers sought to activate distinct emotional states within the participants' brains, enabling subsequent analysis of how these emotions relate to brain activity and driving performance, particularly in the context of sleep deprivation.

#### *2.3.3 Driving simulation: Assessing performance under varying conditions*

The third stage involved a 15-minute driving simulation task designed to assess participants' performance under different driving conditions and levels of cognitive demand. Participants wore the EEG equipment throughout this stage to capture brain activity during the simulation. The driving scenario unfolded in three distinct phases:

i. Easy (5 minutes): During the initial five minutes, participants were required to navigate a straightforward, obstacle-free road while maintaining a steady speed of 100 km/h. This initial phase aimed to minimize motion artifacts in the EEG data and allow participants to acclimate to the driving simulator.
ii. Medium (5 minutes): The following five-minute phase introduced simple obstacles, such as slippery road surfaces and minor distractions, into the driving simulation. This phase aimed to elevate the cognitive demands on participants and gauge their ability to respond to unexpected situations.
iii. Hard (5 minutes): The final five minutes presented the most challenging driving scenario. The road surface became more complex, and participants encountered more frequent and demanding distractions, requiring them to utilize higher-order cognitive skills and potentially engage in distracted driving behaviors. This phase aligns with previous research suggesting that decision-making plays a vital role in distracted driving, with individuals experiencing greater difficulty in maintaining control exhibiting higher levels of such behaviors [13].

### 2.3.4 Closing baseline recording: Evaluating post-driving state

The final stage mirrored the initial baseline recording (Stage I). Participants completed a two-minute EEG recording with both eyes open and closed to assess their brain's default state following the driving tasks. This closing baseline serves as a crucial reference point for analyzing the potential impact of sleep deprivation, emotional responses, and driving performance on brain activity. By comparing the opening and closing baseline recordings, researchers can gain valuable insights into the participants' overall cognitive state and potential changes induced by the experiment.

The comprehensive nature of this data acquisition protocol allows for a multifaceted investigation into the complex interplay between sleep deprivation, emotional processing, and driving performance. By analyzing EEG data alongside driving simulation data, researchers can gain a deeper understanding of how these factors influence each other and potentially develop strategies to mitigate the risks associated with sleep-deprived driving.

### 2.4 EEG Signal Acquisition

The human brain represents a complex nexus that orchestrates and interlinks various physiological, mental, emotional, and even spiritual functions. Among these multifaceted activities, the process of evaluation and coordination stands out as paramount [14]. In delving into the intricate workings of the brain, particularly in deciphering the interplay between cognitive states and corresponding brain dynamics, the Electroencephalogram (EEG) signal emerges as a pivotal source of invaluable information [14].

Electroencephalogram (EEG) stands as a well-established modality for discerning brain activities. It captures the electrical impulses produced by the brain's neuronal activity, revealing the neural firings during cognitive processes. These brain signals emanate through the scalp and are intercepted by EEG electrodes strategically placed on the head. Similar to other instruments gauging physiological signals, EEG employs electrode patches, albeit focused specifically on the scalp region [2, 15].

In this study, the EEG signals were captured using the 19-channel DABO machine. The signal-to-noise ratio exhibited by this apparatus is notably high when connected to a power source, transitioning to normal noise levels upon disconnection, rendering it particularly pertinent for scientific investigations and routine applications alike. Complementing the DABO machine is an electrode cap, facilitating the placement of EEG silver-silver chloride electrodes on the scalp surface of participants adhering to the standardized 10-20 EEG electrode placement system, as illustrated in Figure 2 below. The widely adopted 10-20 method for EEG sensor positioning derives its nomenclature from the fact that the actual distances between adjacent electrodes correspond to 10% or 20% of the skull's total front-back or right-left dimensions [16].

The EEG signals recorded are subsequently subjected to an analysis using EEGLAB, a MATLAB toolbox designed for processing electrophysiological data. This methodology, coupled with advanced technological tools, ensures the precision and reliability of the findings garnered from EEG data analysis, fostering deeper insights into the intricate neural mechanisms underlying cognitive processes.

**Fig. 2.** A participant is wearing a 19-channels DABO EEG electrode cap

*2.5 Feature Extraction*

The first step of EEG analysis is featuring extraction, specifically using the ERPs. In this study, the ERPs are extracted based on alpha, delta, and theta bands as these frequency bands are related to human emotions and the state of drowsiness. At this stage, the ERP feature patterns were evaluated based on alpha, delta, and theta bands. The 19 channels recorded signals were grouped into four separate regions: frontal, temporal, central, occipital, and parietal. The foundation of this step to extract the ERPs is established in previous works that utilize the separation of EEG signals into different frequency bands to classify emotions. The EEG frequency bands-mainly the alpha, beta, delta, and theta are the most consistent in terms of emotional occurrence and thus reliable for analysis. However, for this work, the beta band is excluded from the analysis as the band is unrelated to the state of sleep deprivation and drowsiness formed from emotional analysis and did not differ significantly between normal sleep and sleep deprivation conditions [17-21].

*2.6 Data Visualization and Classification*

Prior to classification, the ERP data was visualized to identify and select the potential ERPs and EEG channels [22]. Next, the data from selected ERPs and channels is preprocessed for further classification. First, the ERP data is extracted by averaging multiple temporal segments from the EEG signals, and then grouped into differing channels and temporal segments. Before the data is fed into the classifier, the data is normalized i.e., transformed into binary matrix, 0 to 1. Value "1" indicates a sleep-deprived condition; and value "0", for non-sleep deprivation. Based on the obtained binary matrix, the connection network of the nodes of the channel was built. This work will use two classification techniques: binary logistic regression (BLR) and linear support vector machines (SVM). The performance of the classification based on the selected features is compared and analyzed per accuracy and area under the curve (AUC).

**3. Results**

The grand average of ERP in this study is the reference EEG signal for mental fatigue in non-sleep-deprived and sleep-deprived conditions. When discussing event-related potentials (ERPs), the average waveform that results from averaging the EEG data from several subjects or trials is referred to as the grand average. The brain's reaction to a particular event or stimulus is deduced from the grand average ERP. Attention, memory, and emotion are examples of cognitive processes that may be impacted by variations in the amplitude or latency of ERP components.

### *3.1 EEG Channels for ERP Emotion Analysis*

A greater magnitude of grand average ERPs of the delta, alpha, and theta frequencies are found in the prefrontal, frontal, and occipital areas compared to the other sub-regions. Figures 3 and 4 illustrate the 19- channels of EEG indicated by the regions: frontal (F), temporal (T), central (C), occipital (O), and parietal (P) for the alpha and theta band, respectively. Both figures show a higher amplitude of grand average ERPs of the delta and theta frequencies in the prefrontal, frontal, and occipital areas.

**Table 1**
Selected channels for ERP emotion analysis

| Region | Channels |
| --- | --- |
| Frontal area | Fp1, Fp2, F7, F8 |
| Occipital area | O1, O2 |

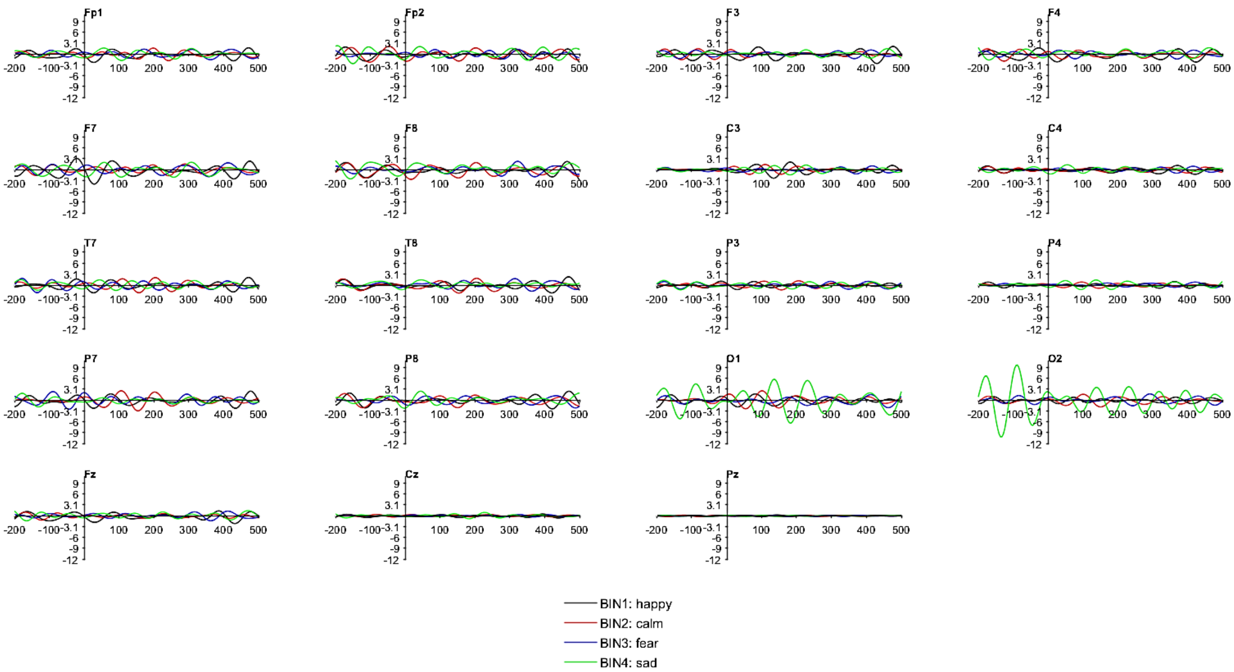



**Fig. 3.** ERP emotion features of the alpha band from the 19-channels DABO EEG

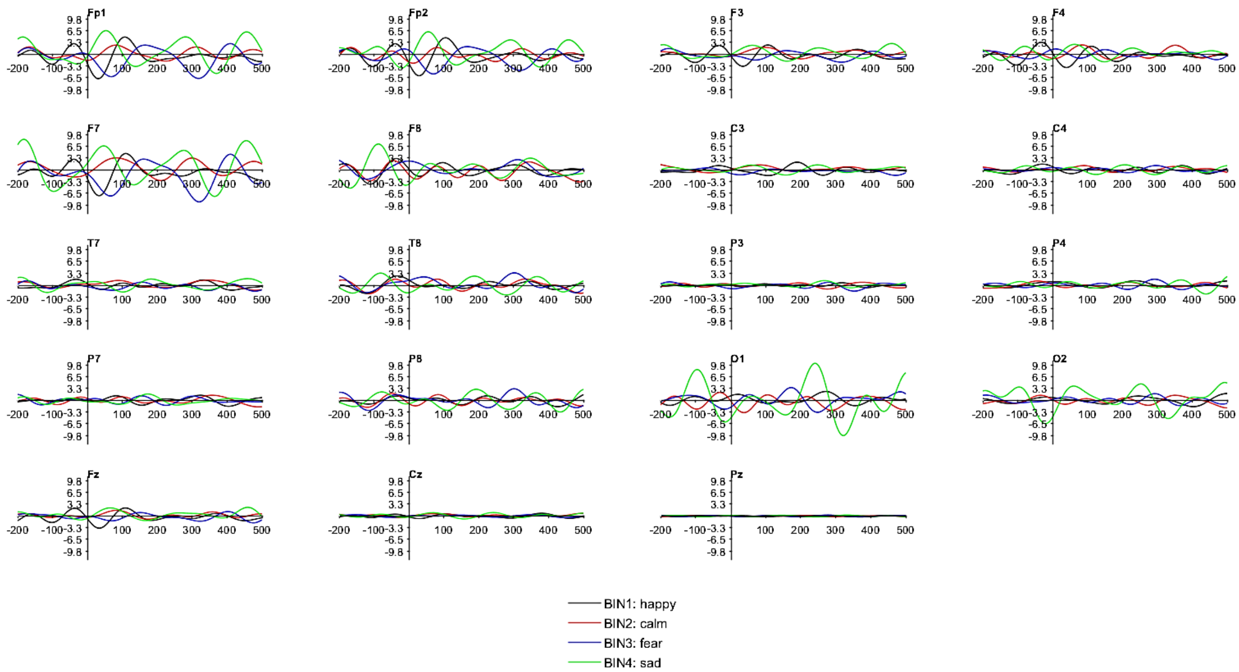
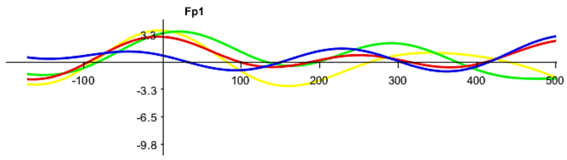



**Fig. 4.** ERP emotion features of the theta band from the 19-channels DABO EEG

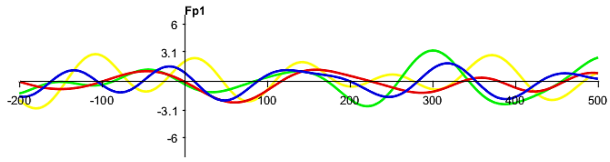
Figure 4 exhibits substantial amplitude changes in the frontal pole (Fp1, Fp2, F7, and F8) and the occipital lobe region (O1 and O2). This initial finding is consistent with a study of ERP coherences in both non-fatigued and fatigued states by Liu *et al.,* [22]. In their experimental studies, they found that the ERP alpha coherences at frontal regions (FP1-FP2 and F3-F4) were significantly higher than at central (C3-C4), parietal (P3-P4) and occipital (O1-O2) regions [22]. Additionally, in the other mental fatigue study, there is an increase in both theta and alpha power over time which suggests recovery of mental fatigue following cognitively demanding tasks. Considering the initial finding and the previous report, this explains the basis of utilizing ERP emotion features on Fp1, Fp2, F7, F8, O1, and O2 (Table 1) on the selected time frames for the further classification of this work.

### *3.2 Frequency Bands for ERP Emotion Analysis*

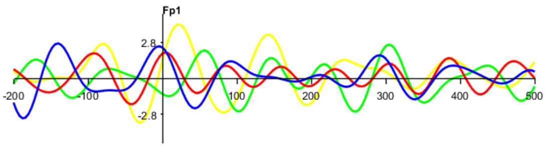
The first glance at the EEG-frequency bands visualizes a burst-like oscillation of the sigma band similar to the beta band in Fp1, as illustrated in Figure 5. Though the underlying mechanism cannot be confirmed at this point of the study, there are chances that the changed of amplitude in the other bands is more likely to be caused by sleep deprivation. It was reported by Wu et. al. that the change in alpha-band oscillations is closely associated with sleep deprivation [20]. For the beta (12.5-30Hz) and sigma band (12-15Hz), to the best of the authors' knowledge, there is limited research that can explain the changes affected by sleep deprivation. Additionally, a comparison of different frequency bands from a single channel (Fp1) also revealed a burst-like activity of the beta band (Figure 5). Such variations of the beta frequency are considered enigmatic by some researchers, and their contribution to emotion studies is largely unknown. Besides, the beta power spectrum did not differ significantly between normal sleep and sleep deprivation conditions [21]. Thus, further analysis will focus on the delta, theta, and alpha bands.



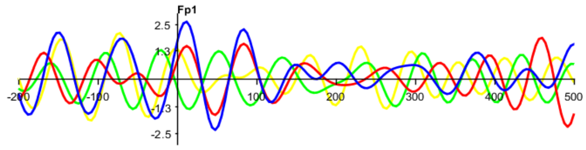

(a)




(b)




(c)

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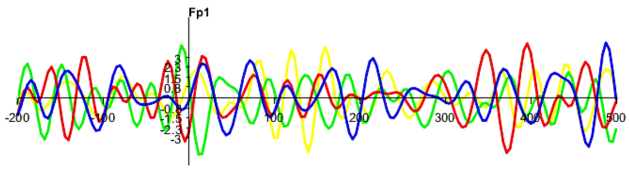



(e)

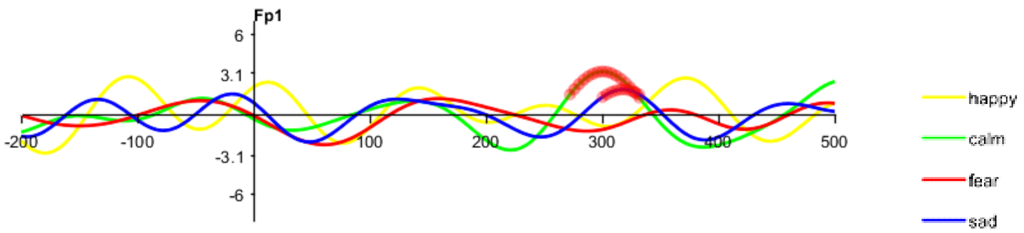
**Fig. 5.** ERP emotion features for each frequency band in single channel FP1 (a) Delta (b) Theta (c) Alpha (d) Sigma (e) Beta

### *3.3 ERP Emotion Features in Non-Sleep Deprived and Sleep Deprived Conditions*

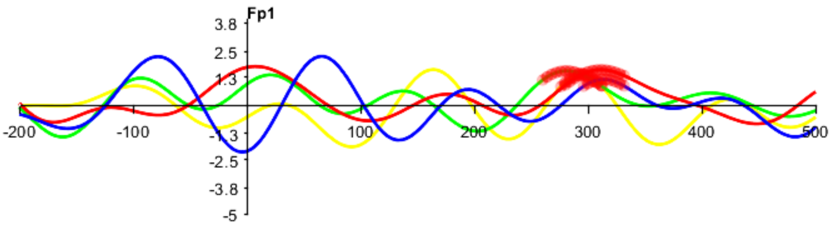
ERP components relevant to sleep-deprived and non-sleep-deprieved conditions: ERP waveforms for these conditions are detected at P3 (also known as the P300). P3, a positive deflection, usually happens 300ms or more after the stimulus starts. P3 amplitude changes might be a sign of changes in mental fatigue-related cognitive resources. Comparatively speaking, shorter latencies show better mental performance than longer latencies, greater attention appears to create larger P3 waves, as P3 amplitude appears to reflect sensory information [23].

ERP Components relevant to human emotions: P3a is a positive component linked to the emotional stimuli response, peaking 250–300 ms after stimulus initiation. The attentional capture by emotionally relevant items may be reflected in emotional processing and additionally, the components responded differently to the stimuli's emotional content [24].

As shown in (Figure 6), the non-sleep deprived condition in the red-shaded area of P300, peaked at the ERP emotion features of calm and sad. For the sleep-deprived condition, the P300 ERP components peaked at emotions calm, happy, fear, and sad. Thus, we can see that there are some emotional related between non-sleep deprived and sleep-deprived conditions.




(a)




(b)

**Fig. 6.** Non-sleep deprived and sleep deprived graph in FP1 channel (a) Non-sleep deprived graph (b) Sleep-deprived graph

### *3.4 Preferred Classification Method for Mental Fatigue*

The classification of ERP emotion features data into each frequency band revealed that the highest accuracy reached is on the alpha dataset using binary logistic regression with 86.1 (AUC = 0.89) and 83.1% (AUC = 0.88) accuracy using linear SVM. Linear SVM classification on delta is 69.4% (AUC = 0.78) and theta is 72.2% (AUC = 0.83) meanwhile for binary linear regression on delta is 80.6% (AUC = 0.85) and theta is 77.8% (AUC = 0.86). The performance of linear SVM was not as good as that of binary logistic regression on alpha, delta, and theta bands, thus leading us to use binary logistic regression as our main classification method as its consistency in the accuracy results.

The classification accuracy and AUC of the ERPs band are summarized in Table 2. For all bands, BLR indicates higher performance in terms of accuracy and AUC. Out of the three bands, alpha indicates the highest performance for both BLR and linear SVM. This preliminary analysis concluded that the ERP alpha from the selected channels has the potential to classify sleep-deprived and non-sleep-deprived.

**Table 2**
BLR and linear SVM classification for delta, theta, and alpha band

| Frequency band | Classification | Accuracy | Area under curve (AUC) |
|---|---|---|---|
| Delta | Binary logistic regression | 80.6 | 0.85 |
| | Linear SVM | 69.4 | 0.78 |
| Theta | Binary logistic regression | 77.8 | 0.86 |
| | Linear SVM | 72.2 | 0.83 |
| Alpha | Binary logistic regression | 86.1 | 0.89 |
| | Linear SVM | 83.3 | 0.88 |

### *3.5 Future Works: Unveiling the Potential of ERPs for Fatigue Classification*

The results indicate that Event-Related Potentials (ERPs) hold promise as features for classifying mental fatigue. For future advanced experiments, incorporating a Virtual Reality (VR) simulator into the methodology could be beneficial. Carefully designed animations in VR can enhance the sense of presence and realism, leading to increased user immersion [25]. Leveraging VR technology opens avenues for expanding this research towards achieving therapeutic objectives, such as fatigue management and rehabilitation.

## **4. Conclusions**

{This paper has discussed the results of a research study comprising signal acquisition based on a research protocol in differing emotional states and sleep conditions, ERP feature extraction, and classification. As a preliminary work, only six EEG datasets (sleep-deprived: 3; non-sleep-deprieved: 3) were considered for ERP analysis and classification.

Grand average ERP analysis revealed that only six out of 19 EEG channels were found to be most meaningful in explaining emotional activities in sleep-deprived and non-sleep-deprived conditions. These channels are located at the frontal and occipital regions, namely Fp1, Fp2, F3, F4, O1 and O2. Then, we detected burst-like oscillations of the sigma (12-15Hz) and beta band (12.5-30Hz) which are largely unexplained at this point of study particularly concerning human emotion studies. Thus, we ascertain relevant frequency bands of delta, theta, and alpha based on related works on sleep studies. Additionally, ERP plotting of P3 (300 ms) and P3a (250-300 ms) components showed consistent activation for low arousal emotions of calm and sad in both sleep-deprived and non-sleep-deprived groups, whereas the same ERP components were non-activated for emotions happy and sad in non-sleep-deprived conditions. The classification of the ERP alpha bands from the selected channels shows the highest accuracy of 86.1%.

In a conclusion, we believe there are more features from the EEG signals based on the emotional stimulation and driving activities that can be utilized to understand and differentiate emotional states in both sleep-deprived and non-sleep-deprived conditions. Potential future work may include the study on EEG phase coherence, for assessing the connectivity of different brain regions in emotional processing.

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