

## ORIGINAL ARTICLE

# The Influence of Driving Duration, Body Mass Index, Types of Roads and Gender on Decision-Making Skills through $\beta$ -Waves Analysis in Fatigue Driving

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## ABSTRACT

**Introduction:** The research on driving fatigue is gaining popularity as the frequency of fatigue-related accidents increases in many countries. However, there has been limited study on the importance of cognitive skills like decision-making skills (DMS) and the variables that influence them in indicating driving fatigue. The study aims to conduct a regression analysis to determine whether variables such as driving duration, body mass index (BMI), types of roads and gender are relevant in influencing DMS and how these variables interact to suggest driving fatigue. Previous research has not examined the combination of these four variables. **Materials and methods:** DMS was assessed using an electroencephalogram (EEG) through beta,  $\beta$  brain waves. The EEG frequency was recorded for five minutes before driving and completing the driving assignment. The regression analysis was performed using Design Expert software. **Results:** The Analysis of Variance (ANOVA) found that all variables have Prob > F values less than 0.05, indicating significant effect on  $\beta$ -waves (DMS). Overall, as the driver fatigues,  $\beta$ -waves decrease, indicating an impairment in DMS.  $\beta$ -waves decrease as driving duration and BMI increase due to the stress of dealing with hazardous driving conditions and obesity-related health concerns, respectively.  $\beta$ -waves drop as road geometry changes from winding to monotonous and gender changes from male to female because of physiological signs of boredom generated by road geometry and sex hormone variations, respectively. **Conclusion:** The findings could be a reference to road safety professionals to control the cause of driving fatigue and hence lower the number of road accidents. *Malaysian Journal of Medicine and Health Sciences* (2025) 21(4): 24-31. doi:10.47836/mjmhs.21.4.4

**Keywords:** Driving fatigue, Beta waves, Decision-making skills, Regression analysis, Design expert

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## INTRODUCTION

Driving fatigue is a major cause of traffic accidents in many nations, as it impairs attention and awareness, reduces vehicle control and weakens mental coordination. For example, driving fatigue is currently estimated to have played a role in 2.3% of the 824 fatalities on US highways in 2015 (1) and 80.6% of the 521,466 traffic crashes in Malaysia in 2016 (2). Sleep disorders have long been thought to be one of the biggest contributing factors to driving fatigue. Drivers with sleep disorders are either sleep-deprived, have excessive daytime somnolence, suffer with obstructive sleep apnea syndrome (OSAS) or have intermittent, broken, and sleep disruption, which causes them to become fatigued. Therefore, to prevent fatigue related vehicular crashes, the indicator of driving

fatigue and the variables that influence the indicator must be identified and investigated.

Studies demonstrate that cognitive skills like decision-making skills (DMS) are a good indicator of driving fatigue. DMS is a high-level cognitive activity that involves selecting a belief or action from a set of options according to particular criteria (3). Drivers are likely to encounter rare but life-threatening scenarios in which fatalities are inevitable and predictable. As a result, making the right judgements in a timely manner is crucial. For example, in order to spare a group of pedestrians crossing the street, drivers may have to choose between veering to the side and striking only one pedestrian. In this tight position, it is difficult for the drivers to make the best decision as the time remaining to do an action (swerve right or left) decreases. As a result, drivers with insufficient DMS are more likely to be involved in collisions.

Previous research found a link between DMS and beta,

$\beta$  brain waves.  $\beta$ -waves are dominantly produced in the left hemisphere of the brain and typically have a frequency range of 13 to 30 Hz.  $\beta$ -waves are produced when humans have their eyes open and are listening and thinking during analytical problem solving, judgement, decision-making and processing information about their surroundings (4).  $\beta$ -waves boost the body's energy level, allowing for better processing and integration of associated information. An enhanced  $\beta$ -waves suggests that an individual is cognitively busy, learning, and digesting information to discover answers to problems (5). As a result, the cognitive ability to make decisions was assessed using  $\beta$ -waves. In terms of fatigue,  $\beta$ -waves activity (examined in 19 studies) was found to increase significantly in six and decrease significantly in 13 studies (6). Thus, a decrease in  $\beta$ -waves signifies an impairment in DMS.

Recently, there has been an increase in the development of regression analysis to indicate driving fatigue. A study developed a linear regression model to assess the effect of four time-related variables on driving fatigue: circadian rhythms, hours of sleep before driving, driving duration and break time during driving (7). The study revealed that by planning the driving and break times optimally, fatigue-related driving behavior might be prevented. Ani, Kamat (8) conducted regression analysis to investigate the effect of gender and time exposure on whole-body vibrations (WBV) in indicating driving fatigue. According to the study, the WBV rose, indicating driving fatigue as the gender shifted from female to male subjects and the time exposure was raised from 15 to 30 minutes. A study conducted a quadratic regression analysis to assess the causes of driving fatigue in south-western Nigeria, and discovered that driving time, stress, sleep deficiency and alcohol all contributed significantly to the causes of driver fatigue at both the 5% and 10% significance levels (9). To the best of our knowledge, limited study has looked into the effect of some explanatory variable on the cognitive skills like DMS in indicating driving fatigue using the regression analysis.

As a result, the goal of this study is to perform a regression analysis to determine which variables, such as driving duration, body mass index (BMI), types of roads and gender, are significant in influencing DMS and how these variables interact to indicate driving fatigue using  $\beta$ -waves. The relationship between how driving duration, BMI, types of roads and gender influence DMS through  $\beta$ -waves in indicating driving fatigue could provide valuable insights for road safety researchers and decision-makers looking to reduce the number of traffic accidents caused by driver fatigue.

**MATERIALS AND METHODS**

**Experimental Design Layout**

This study used Design Expert software to conduct regression analysis to determine the relationship

between driving duration, BMI, types of roads and gender (independent variables) and DMS (dependent variable) in indicating driving fatigue. The experimental design layout was first created based on the minimum and maximum level of independent variables, as summarized in Table I.

**Table I: Minimum and maximum level of independent variables**

Independent Variable	Level		
Driving Duration, min	1-40		
Body Mass Index, kg/m	18.5-24.9 (Healthy)	25.0-29.9 (Overweight)	30.0-35.0 (Obese)
Types of Roads	Monotonous	Winding	
Gender	Female	Male	

Based on the four independent variables and their levels, the Design Expert software created 52 trial runs. A total of 52 volunteers, aged between 20 and 25 were needed to complete all 52 trial runs. The age range was chosen based on statistics indicating that the crash rates within this demographic are more than twice as high as those aged 30 to 34 (10). The volunteers were final-year students pursuing a bachelor's degree in manufacturing (Hons) at Universiti Teknikal Malaysia Melaka who are studying the Ergonomic Industry subject in session 1-2023/2024 and Supply Chain and Logistics Management in session 2-2022/2023.

**Real - World Driving Experiment**

Driving simulation has gained favor in EEG-based driving fatigue studies due to its ability to reduce noise contamination. However, there is a validity question, which is whether the competence or performance gained in the simulator is valid in real-world driving. Because of mechanical limits, the driving simulator, for example, cannot precisely recreate driving circumstances in an actual road context, and hence may be unable to measure the workload that a driver must handle. Meanwhile, EEG signals are easily corrupted by physiological artifacts such as eye movements and blinks, cardiac activity, head movements and muscle activity while driving in real road conditions. Drivers, for example, tend to move their heads when confronted with distractions such as road bumps, unevenly paved roads, brightness, and other vehicles. Head motions (rotation and translation of the head) frequently cause positional changes in several EEG electrodes on the head, adding artefacts to the EEG signals. Due of its recognizable frequency spectrum, there are several filtration techniques available today to reduce such artifacts (11). Therefore, the whole experiment in this study was conducted on a real road.

The monotonous road driving tests were conducted from Ayer Keroh Plaza Toll (2.301618847297943, 102.31063058662528) to Pedas Toll Plaza / Linggi Inbound (2.568581524084198, 102.04613312384214), which meet the monotonous road criteria like low traffic, few curves and constant noise levels. In most

circumstances, drivers must go along primary and minor roads before entering the highway. As a result, in this study, monotonous road driving tests were started from Universiti Teknikal Malaysia Melaka (2.314070905071167, 102.32063301420962) to Mydin MITC Ayer Keroh (2.272478690220136, 102.2910843316648), followed by the entry to Ayer Keroh Plaza Toll. The driving duration measurement began after the subjects arrived at the Ayer Keroh Plaza Toll. Meanwhile, the winding road driving tests were conducted out from Kolej Al-Jazari UTeM (2.3217602455414634, 102.32709907855994) to Selandar Police Station (2.3899148390907374, 102.37916260385438) via M8 and Jalan Simpang Gading / Ayer Pasir/M19 and continue to Agrofarmstay @Skill-Tech (2.3433093003399565, 102.33044718876545) via Jalan Selandar-jasin/M13 and Jalan Simpang Gading / Kesang Pajak/Jalan Tangkak - Durian Tunggal, which meet the winding road criteria where there are three or more curves in it that are separated by a tangent distance of less than 600 feet. In most cases, drivers must first go along primary and minor roads before beginning to drive on windy roads. Therefore, in this study, winding road driving test were conducted from Universiti Teknikal Malaysia Melaka (2.314070905071167, 102.32063301420962) to PETRONAS-Lebuh SPA Ayer Keroh (2.2868042643794158, 102.26586022104732), followed to Kolej Al-Jazari UTeM. According to Google Maps, the length of the road for monotonous (from Ayer Keroh Plaza Toll to Pedas Toll Plaza / Linggi Inbound) and winding roads (Kolej Al-Jazari UTeM to Selandar Police Station via M8 and Jalan Simpang Gading / Ayer Pasir/M19 and continue to Agrofarmstay @Skill-Tech via Jalan Selandar-jasin/M13 and Jalan Simpang Gading / Kesang Pajak/Jalan Tangkak - Durian Tunggal) are 50 km and 40 km, respectively. Figure 1 and Figure 2 illustrate the routes of monotonous and winding driving tests via Google maps, respectively. The experiments were repeated and rescheduled if the subjects were required to stop the vehicle due to abnormal driving scenarios like animal or pedestrian crossings, traffic accidents or road construction.

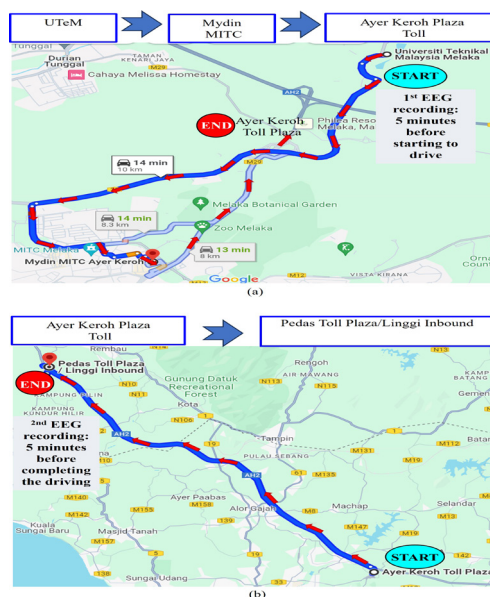


Fig. 1: Driving routes of monotonous driving test (a) primary and minor roads before entering the highway, (b) monotonous road

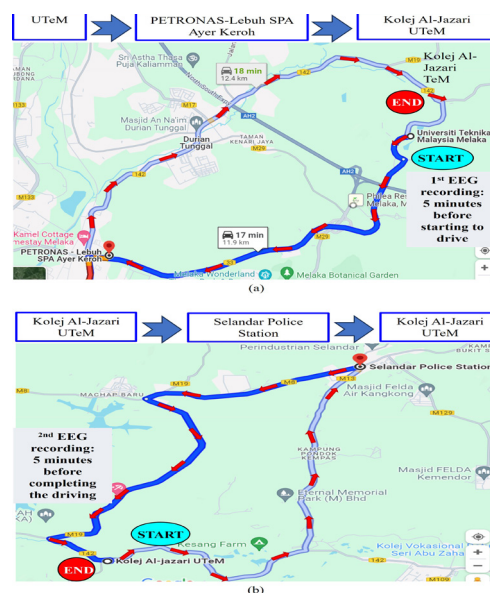


Fig. 2: Driving routes of winding driving test (a) primary and minor roads before entering the winding road, (b) winding road

### Experimental Procedures

Electroencephalography (EEG) is a technique for recording an electrogram of the brain's spontaneous electrical activity. EEG signals are thought to be intricately linked to human cognitive skills because the human brain is at the root of every response to specific stimuli, making them an ideal approach for identifying fatigue while driving (12). The subject's head was initially fitted with an EEG headset. A commercial 14 electrodes EMOTIV EPOC X headset by EMOTIV Inc, United States of America was used to measure the  $\beta$ -waves. The EEG frequency was first recorded for five minutes before driving. The second recording was taken in the final 5 minutes before completing the driving assignment.

The driving test was conducted with the Perodua Bezza 1.0 GA-T automatic gearbox between the hours of 8.30 a.m. and 10.30 a.m., when there have been minimal instances of fatigue-related accidents (13). The entire experiment was carried out on sunny or clear weather. The vehicle cabin temperature was monitored using a digital thermometer by Yueqing Xinyang Technology Co., Ltd, China and kept at  $22 \pm 2$  degrees as driver concentrates best under this conditions (14). It was illegal to use cell phones, listen to radios or talk while driving.

### Initial Fatigue Assessment

To guarantee that the subjects were fit and the baseline fatigue was comparable, the experiment was started by instructing the subjects to undergo three steps of initial fatigue assessments.

#### Step 1: Complete the Subject's Readiness Checklist

To ensure the subject's readiness, a question checklist was given before the experiment. Questions like "Did you receive at least seven to nine hours of adequate sleep last night?" "Did you consume alcohol or caffeine-containing beverages in the last seven hours?" "Do you suffer from both short- and long-term diseases?" "Do you need daily medication?" "Did you take any medication in the last 3 days?" and "Did you have breakfast this morning?" were included. If any of these conditions were not met, the subjects declined to participate.

#### Step 2: Conduct the Blood Pressure Measurements

A lack of sleep can lead to sleep deprivation, which increases the likelihood of falling asleep while driving. Drivers who do not get enough sleep for at least eight to nine hours every night may develop hypertension, which may cause cognitive impairment and consequently affect their driving performance. As a result, blood pressure was taken with an Omron Evolv by OMRON Corporation, Japan to identify hypertension symptoms. The measurement was recorded before the driving session. The subjects were not permitted to participate in the experiment if their readings of blood pressure before the experiment were out of normal ranges (systolic:  $<120$ , diastolic:  $<80$ ), indicating that they were already

fatigued and not fit to drive.

#### Step 3: Perform Karolinska Sleepiness Scale (KSS)

KSS (15) is a popular approach to determine the subjective level of sleepiness during the last 10 minutes. Therefore, KSS was employed in this study to assess the driver's fatigue state level before the driving task. The subjects were not permitted to participate in the experiment if their initial scales before starting to drive were 4 (rather alert), 5 (neither wake up nor sleepy), 6 (a little sleepy), 7 (sleepy, but easy to stay alert), 8 (sleepy, need to work hard to stay alert) or 9 (sleepy, struggle hard to stay alert), indicating that they were in a fatigued state and not fit to drive.

### EEG Electrode Selection and its Artifact Removal

The amplitudes of  $\beta$ -waves are largest in the frontal areas (16, 17, 18, 19). Therefore, by referring to the international 10-20 electrode placement system (20),  $\beta$ -waves were measured using AF3, AF4, F3, F4, F7 F8, FC5 and FC6 electrodes. The BrainVision Analyzer tool was employed to filter the raw EEG data. Using the Fast Fourier Transform (FFT), the waves were then divided into four frequency bands: delta (0- 4Hz), theta (4-8Hz), alpha (8-13Hz) and beta (13-30Hz), which contain the main distinctive waveforms of the EEG. In this study, only  $\beta$ -waves were investigated. The Hamming window was used to limit spectral leakage. The magnitude of beta brain wave frequencies was then transformed into Power Spectral Density (PSD), (dB).

### Ethical Clearance

This study was approved by the Research and Ethical Committee, Pejabat Pengurusan Penyelidikan dan Inovasi, Universiti Teknikal of Malaysia Melaka (UTEM.11.02/500-25/1/4 Jilid 3(14).

## RESULTS

### EEG Power Spectral Density (PSD) Experimental Data

Fig.3 depicts EEG PSD data of  $\beta$ -waves (DMS) during 5 minutes before driving and final 5 minutes before completing the driving for all 52 experimental runs.

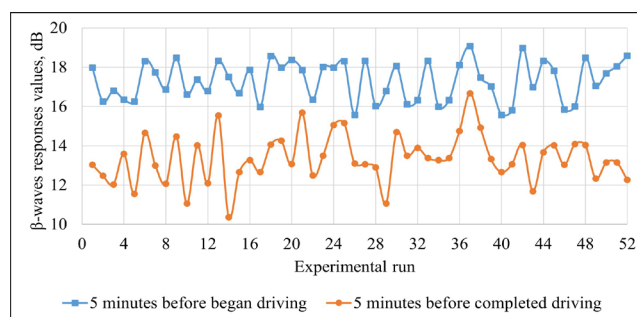


Fig. 3: EEG Power Spectral Density data of  $\beta$ -waves (DMS)

Across all 52 experimental runs, the PSD of  $\beta$ -waves (DMS) decreases. This tendency corresponds to earlier research findings, as 13 studies out of 19 demonstrated a

decrease in  $\beta$ -waves as a person fatigued (6). This shows that the investigated factors (driving duration, BMI, types of roads and gender) cause cognitive impairment while driving.

### Independent Variable Significant

The Analysis of Variance (ANOVA) by Design Expert software was employed to determine if the driving duration, BMI, types of roads and gender would have a significant impact on the  $\beta$ -waves (DMS) and how the independent variables would affect the DMS. The model has a significant effect on the output response if the Prob>F value is less than 0.05. Table II shows that the model was significant because the sum of squares value of 73.49 was less than 0.05. The Prob>F values for A= Driving Duration, B= BMI, C= Types of Roads and D= Gender was all less than 0.05, indicating that the covariates had significant effects on the  $\beta$ -waves (DMS).

Table II: ANOVA

Source	Sum of Squares	DF	Mean Square	F-Value	Prob > F	
Model	73.49	4	18.37	221.80	< 0.0001	Significant
A	21.35	1	21.35	257.70	< 0.0001	Significant
B	22.70	1	22.70	274.01	< 0.0001	Significant
C	17.68	1	17.68	213.42	< 0.0001	Significant
D	11.77	1	11.77	142.05	< 0.0001	Significant
Residual	3.89	47	0.083	-	-	-
Lack of Fit	2.36	31	0.076	0.79	0.7208	-
Pure Error	1.54	16	0.096	-	-	-
Cor Total	77.38	51	-	-	-	-
Std. Dev.	0.29	R-Squared				0.9497
Mean	13.36	Adj R-Squared				0.9454
C.V.	2.15	Pred R-Squared				0.9393
PRESS	4.70	Adeq Precision				66.655

### Relationship Between $\beta$ -Waves (DMS) and the Significant Independent Variables

According to a review study (6), 13 studies out of 19 demonstrated a decrease in  $\beta$ -waves as a person fatigued. Fig. 4(a) and 4(b) display the decline in  $\beta$ -waves as driving duration rose within the 40 minutes of driving and BMI increased from 18.50 kg/m (healthy) to 35.00 kg/m (obesity). Hence, the DMS were diminished under these circumstances. The similar tendency was acquired, as shown in Fig. 4(c) as the  $\beta$ -waves decreased when the road shape changed from winding to monotonous. According to these tendencies, the driver's DMS was significantly impaired when driving on less-demanding, monotonous roads, suggesting fatigue. Meanwhile, Fig. 4(d) demonstrates how  $\beta$ -waves decreased when male drivers were replaced by female drivers. This pattern shows that female driver's DMS were significantly impaired when driving.

The ANOVA also generates series of polynomial equations as follow:

i. Road: Winding / Gender: Male  
 $19.23224 - (0.065040 \times \text{Driving Duration}) - (0.11787 \times \text{BMI})$

(1)

ii. Road: Monotonous / Gender: Male  
 $18.06613 - (0.065040 \times \text{Driving Duration}) - (0.11787 \times \text{BMI})$

(2)

iii. Road: Winding / Gender: Female  
 $18.28090 - (0.065040 \times \text{Driving Duration}) - (0.11787 \times \text{BMI})$

(3)

iv. Road: Monotonous / Gender: Female  
 $17.11478 - (0.065040 \times \text{Driving Duration}) - (0.11787 \times \text{BMI})$

(4)

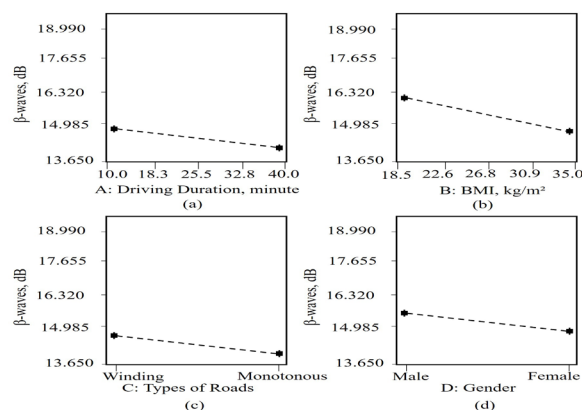


Fig. 4: Interaction between independent variable and  $\beta$ -waves (DMS) (a) driving duration; (b) BMI; (c) types of roads; (d) gender

## DISCUSSION

### Relationship between $\beta$ -waves (DMS) against the independent variables

#### Driving Duration

Fig. 4(a) demonstrates the change in DMS when driving duration increased and  $\beta$ -waves decreased. Therefore, the longer the driving duration, the more drivers experience a significant decrease in DMS, indicating fatigue. The considerable decrease in DMS seen as driving duration increased could be attributed to the stress experienced while driving. Driving a car is a stressful activity that entails a variety of risky and unpredictable events, such as driving during rush hour, becoming stuck in traffic and feeling out of control. Drivers must also be aware of traffic signs and signals, the speed of their own vehicle and the activities of other vehicles. Stress occurs when the need for mental workload exceeds the driver's capabilities. As a result, the longer a driver drives, the more likely they are to encounter stressful situations. A study investigated the effects of a social stressor (Trier Social Stress Test) on the subsequent performance of

24 male and 32 female college students on a decision-making task and discovered that the presence of a stressor may generally result in failure to attend to the full range of possible consequences of a decision (21). The stress is known as "allostatic load," and it has been shown to affect brain regions like the medial prefrontal cortex and the caudate nucleus (22). Cumulative stress can have a negative impact on brain areas involved in stress response and neurocognitive functions, resulting in decreased structural integrity and cognitive capacities, including DMS.

**Body Mass Index (BMI)**

Fig. 4(b) illustrates that when BMI increased from 18.50 kg/m (healthy) to 35.00 kg/m (obesity), the  $\beta$ -waves pattern reduced, implying that high-BMI drivers have severely impaired decision-making skills. The findings are consistent with a study (23), as people with obesity are less capable of making risky decisions than those who are not obese. Obese adults with severe cognitive impairment may be due to obesity-related health problem. Obese people (those with a BMI of 30 kg/m or more) are more likely to suffer from cardiovascular issues such as high blood pressure (hypertension). Previous studies found that people with a high BMI have lower oxygen saturation levels and a faster heart rate than healthy people, which increases hypertension (24). Hypertension contributes to cognitive impairment by promoting acute and chronic brain injury, hastening brain atrophy and activating neuroinflammatory processes. A study backs up this claim, stating that those with high blood pressure have a faster deterioration of their ability to think, make judgements, and recall information than those with normal blood pressure (25). As a result, obesity-related health issues such as hypertension may result in substantial impairments in DMS.

**Types of Roads**

Fig. 4(c) indicates that  $\beta$ -waves dropped when the route design changed from winding to monotonous. The findings show that driving on less-demanding, monotonous roadways significantly reduced the driver's DMS, indicating fatigue. DMS drops while driving on a monotonous road, which may be linked to a physiological signature of boredom when interest is lost due to a lack of geometrical variety and task effort. Boredom is characterized as an uncomfortable experience of fatigue, restlessness and constraint that is related to both unstimulating environments and individual characteristics. Decision-making is directly linked to boredom because boredom is associated with poor self-regulation, which leads to poor decision making and/or increased risk-taking. A study studied the impact of boredom on risk-taking in decision making and discovered that people who were more prone to boredom took more risks in financial, ethical, recreational, and health or safety domains (26). According to the study, increased risk-taking could be

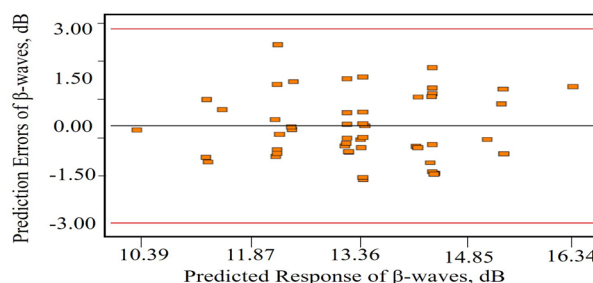
attributable to the deterioration of self-control caused by boredom. The physiological hallmark of boredom may result in substantial impairments in DMS due to a lack of geometric diversity and task effort.

**Gender**

Fig. 4(d) shows how  $\beta$ -waves decreased when female drivers took the place of male drivers. According to the findings, female drivers' DMS decreased substantially during driving, indicating fatigue. The variation in sex hormones may help explain the decrease in  $\beta$ -waves. Men and women handle stressful tasks differently. Driving requires complex cognitive abilities like decision making, to accomplish many tasks such as speeding up, signalling, executing a lane change, maintaining the right following distance and proper lane positioning before a turn, all of which can cause stress. Women are more prone to stress when driving than men, according to a study, since they have a completely different hormonal system, and some of these gender differences occur throughout the reproductive years and gradually decrease after menopause (27). This type of stress is known as "allostatic load," and it has been linked to brain damage in places such as the medial prefrontal cortex and the caudate nucleus (22). Cumulative stress can have a negative impact on brain areas involved in stress response and neurocognitive functions, resulting in decreased structural integrity and cognitive capacities, including DMS.

**Regression Model Validation**

Fig. 5 depicts prediction errors (residuals) vs predicted response values plot. Prediction errors residual is the difference between an actual response value and a predicted response value in PSD (dB). Overall, the residuals "bounce randomly" around the zero line. This shows that the assumption of a linear relationship is plausible. Furthermore, the residuals create a "horizontal band" around the 0 line. This implies that the variances of the error terms are the same. Furthermore, all residuals are distributed evenly across the predictor ranges.



**Fig. 5: Prediction errors (residuals) vs predicted response values plot**

As shown in Tables II, there were slightly difference in  $R^2(0.9497)$  and  $Adj R^2(0.9454)$  [ $\Delta 0.0043$ ], where  $R^2$  is higher than  $Adj R^2$ . According to a study (28),  $R^2$  normally is slightly similar and often higher than  $Adj R^2$ , indicates an excellent reliability for the model to predict the

relationship between the dependent and independent variables. This indicates that the regression models have excellent reliability to predict the relationship between the dependent and independent variables. In other words, the dependent response values in PSD (dB) that were predicted from the multiple polynomial regression equations were closer to the actual dependent response values.

## CONCLUSION

The study's goal, which was to conduct a regression analysis to determine whether variables such as driving duration, body mass index (BMI), types of roads and gender influence DMS, and how these variables interact to signal driving fatigue was met. According to the ANOVA results, all input variables (A= Driving Duration, B= BMI, C= Types of Roads and D= Gender) have Prob>F values less than 0.05, indicating that all variables have significant effects on  $\beta$ -waves (DMS). Overall, the findings are consistent with earlier research, since  $\beta$ -waves diminish as the driver fatigues, indicating a decline in DMS. Because of the stress of dealing with unsafe driving situations,  $\beta$ -waves decline as driving duration increases. Meanwhile,  $\beta$ -waves decrease as BMI rises due to obesity-related health concerns. Because of physiological indicators of boredom caused by road geometry and sex hormone differences,  $\beta$ -waves diminish when road geometry changes from winding to monotonous and gender changes from male to female, respectively. This study was limited to investigate only four factors (driving duration, body mass index (BMI), types of roads and gender) that might significantly influence the DMS in indicating driving fatigue. The future research might consider other possible factors that might cause driving fatigue, such as weather, driving time, different age ranges, and other road types like uphill or downhill roads. The findings may serve as a helpful guide for professionals in the field of road safety to control the cause of driving fatigue and hence minimize fatigue-related road accidents.

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