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Investigation on Factors Affecting Cognitive Skills in Detection of Driving Fatigue

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ABSTRACT

Road safety is a worldwide concern where a high number of fatalities and injuries are caused by traffic accidents. One major issue contributing to these incidents is driving while fatigued, which has been recognized as a contributing factor to accidents in many countries. Being tired while driving is a state that encompasses both physical and mental exhaustion and can greatly impair a person's ability to drive safely. Fatigue negatively affects a driver's cognitive abilities, resulting in decreased performance behind the wheel. The aim of this study is to analyse the effect of driving duration, body mass index (BMI), types of roads and gender factor in causing fatigue while driving. Cognitive skills of drivers while driving was measured through the electroencephalogram (EEG) signal gathered from Emotiv EPOC device to measure brain activity. Relationship between cognitive skills and fatigue signalling is then analysed using regression analysis in Design-Expert software. Results indicated that as mental fatigue increases, there is a noticeable decrease in the relative power of beta rhythm, supporting previous research findings. Results on correlation show that the longer the drivers drove, the wearier they become. Obese people experience more fatigue when driving than those with a normal or overweight BMI. Driving on straight roads resulted in greater fatigue compared to driving on winding ones, with female participants indicating higher levels of tiredness than male participants. These insights are crucial for road safety authorities to tailor their supervision methods based on individual characteristics and to design effective driver fatigue warnings.

1. Introduction

Road safety issues has become a serious public health problem especially related to deaths and injuries from road traffic crashes. World Health Organization's Global status report on road safety in year 2018 reported that the annual number of road traffic deaths has reached 1.35 million, or approximately 3,700 deaths per day [1, 2]. In Malaysia, it is required that all road accidents to be

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reported to the Royal Malaysian Police (RMP) for investigation. According to data from MIROS Crash-team for the years 2007-2010, risky driving and fatigue were among the leading causes of road accidents [2]. Fatigue is defined as the awareness of a decreased capacity for physical or mental activity due to an imbalance in the availability, utilization, and restoration of resources needed to perform an activity [3]. Driving fatigue is a state of physical and mental fatigue that can impair a person's ability to drive safely. Fatigued drivers exhibited impaired decision-making skills, resulting in increased errors and decreased responsiveness to critical driving situations [4].

Various methods are used to measure the brain activities or the cognitive skills during driving to predict the mental condition of the driver and ensure safe driving. In this present study, the cognitive skills of car drivers are measured using an electroencephalogram (EEG) device. At this moment, there is a dearth in current research on real-time brain activity during driving in real road conditions which leaves a gap in our understanding of the cognitive states and neural mechanisms involved. Therefore, research that specifically look into brain activity while driving on various types of roadways are required. Effective fatigue management is also hampered by the absence of validated predictive models that can quantitatively quantify fatigue based on cognitive variables. Furthermore, little is known about how variables like gender, body mass index (BMI), road types, and driving time affect decision-making processes. High-level cognitive functions including perception, attention, and memory are the foundation of decision-making [5].

EEG is a non-invasive technique used to measure brain activity by recording electrical signals from the scalp. A driver’s fatigue level can be judged by detecting EEG, which will provide a basis for the development of on-board, real-time driving fatigue alarm devices [6]. The EEG signals are analyzed by decomposing them into time-frequency representations. This process yields wavelet coefficients in four specific wavebands: alpha (α), beta (β), theta (θ), and delta (δ).

Fatigue was found to have detrimental effects on risk perception and decision making in simulated driving scenarios. The findings revealed that fatigued drivers exhibited reduced risk perception and engaged in riskier decision-making behaviours compared to non-fatigued drivers [7]. The duration of driving had a notable impact on both subjective fatigue and driving performance [8]. Oxygen saturation when drivers also differ according to gender while driving as women have higher oxygen saturation level than men [9]. Factors such as road curvature, slope, roadside environment, and visual complexity also influence a driver’s behaviour, fatigue, and overall driving experience [10].

This study addresses significant gaps in current research by investigating the real-time brain activity of individuals while driving under real-world road conditions. Existing literature lacks comprehensive exploration into how factors such as road types, driving duration, BMI, and gender collectively influence decision-making processes during driving. By exploring the impacts of various road types, diverse driving durations, BMI ranges, and gender differences on decision-making, this research seeks to provide nuanced insights into the cognitive processes inherent in driving tasks. Understanding these dynamics has the potential to inform targeted interventions and strategies aimed at enhancing road safety and optimizing driving performance. Hence, this study aims to delve deeper into the factors contributing to driver fatigue, specifically examining the relationships between driving duration, BMI, road types, and gender with cognitive functions, particularly decision-making, and fatigue indicators. Through rigorous regression analysis, this research aims to uncover the nuanced interplay between these variables and cognitive fatigue, offering practical implications for mitigating fatigue-related risks during driving.

2. Methodology

The experimental methods conducted in this study is depicted in Figure 1. A real road experiment was conducted with the participation of twenty-six (26) individuals, which were thirteen (13) males and thirteen (13) females. The age range of the participants was from 20 to 25 years old. The selection of participants was based on their BMI categories, encompassing individuals with normal, overweight, and obese categories. All participants must be healthy during the experiment with no chronic health conditions and had a minimum eight hours of sleep on the night before. An EEG device; the Emotiv EPOC was employed to capture the brain's electrical signals during the participants' driving sessions. This device was mounted on the participant’s head. Experiments were conducted on two types of road conditions: monotonous and winding roads. The collected EEG data signals then underwent filtering using the Brain Vision Analyzer software. The EEG signals must be continuous to ensure a smooth filtering process. After filtration, the EEG signals were analyzed using Design-Expert software.

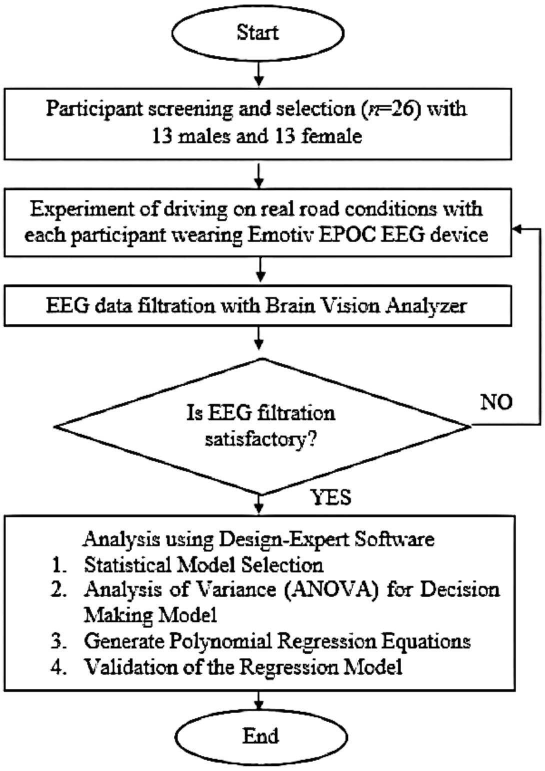

Fig. 1. Flow chart of experimental activities for this study

The Emotiv EPOC X14 represents a wireless neuroimaging headset meticulously engineered for the precise quantification and analysis of neural activity. Emotiv headsets have been utilized in research since 2013 and it has more electrodes than other headsets [11]. Characterized by a sophisticated array of 14 electroencephalography (EEG) sensors and dual reference points, this apparatus is adept at capturing and discerning the intricate electrical signals emanating from the cerebral cortex. Capitalizing on its superior spatial resolution and multi-channel architecture, the device facilitates nuanced detection and interpretation of diverse cognitive and affective states. Throughout the experimental trials, participants were outfitted with the Emotiv EPOC X14, enabling the acquisition of EEG signals across 14 scalp-mounted channels.

The experimental protocol involved participants navigating both homogeneous and winding roadways, thereby eliciting two discrete datasets per subject. Concurrent with the driving task, neural oscillations were elicited and stratified into distinct frequency bands. Previous literature underscores a conspicuous decrement in beta rhythm power relative to escalating mental fatigue, observed during both rest intervals and task engagement. This phenomenon is attributable to the potential onset of driver fatigue consequent to prolonged vehicular travel.

3. Results

3.1 Statistical Model Selection

The fit model sequential model sum of square (SMSS) was the statistical tool used to assess the suitability of a regression model for decision making. SMSS indicates how well a regression model fits the decision-making process, allowing for an assessment of its appropriateness and enabling informed decisions regarding its application and refinement. Table 1 presents the fit model of SMSS analysis that identifies significant factors that affect the observed variation in the decision-making process based on the data collected from 26 participants driving on real road conditions. Figure 2 shows a participant driving during the experiment.

Fig. 2. One of the participants in the study driving with the Emotiv headset headband mounted on her head

The SMSS analysis indicates that the quadratic term, with a sum of squares of 2.73, two degrees of freedom, a mean square of 1.37, and a significant F-value of 3.73 ($p = 0.0328$), shows a strong association with the model. Therefore, it is recommended to include quadratic term in the model to enhance its ability to capture the relationship between factors influencing driving fatigue.

Table 1
Sequential model sum of square (SMSS) analysis for the decision-making model

Source	Sum of squares	DF	Mean square	F value	Prob >F	
Mean	2016.33	1	2016.33			
Linear	61.56	4	15.39	36.22	< 0.0001	
2FI	2.97	6	0.49	1.19	0.3291	
Quadratic	2.73	2	1.37	3.73	0.0328	Suggested
Cubic	4.64	10	0.46	1.40	0.2308	Aliased
Residual	9.63	29	0.33			
Total	2097.87	52	40.34			

3.2 Analysis of Variance (ANOVA) for Decision-Making Model

The stability and efficacy of the quadratic model were validated through an analysis of variance (ANOVA), which assessed the interaction of input variables with the output response. ANOVA is a statistical method used to compare mean values across different groups or factors, identifying significant differences and analysing each factor's influence on overall data variability. Table 2 presents the ANOVA results for the four factors affecting cognitive skills: A (driving duration), B (BMI), C (types of roads), and D (gender).

Table 2
ANOVA analysis for the decision-making model

Source		Sum of squares	DF	Mean square	F-value	Prob > F	
Model		67.27	12	5.61	15.32	< 0.0001	Significant
	A	22.20	1	22.20	60.69	< 0.0001	
	B	17.12	1	17.12	46.80	< 0.0001	
	C	15.24	1	15.24	41.65	< 0.0001	
	D	7.00	1	7.00	19.12	< 0.0001	
	A2	2.43	1	2.43	6.65	0.0138	
	B2	7.480E-003	1	7.480E-003	0.020	0.8870	
	AB	0.78	1	0.78	2.14	0.1512	
	AC	1.61	1	1.61	4.40	0.0424	
	AD	1.365E-003	1	1.365E-003	3.731E-003	0.9516	
	BC	0.037	1	0.037	0.10	0.7522	
	BD	0.18	1	0.18	0.49	0.4891	
	CD	0.36	1	0.36	0.98	0.3289	
Residual		14.27	39	0.37			
Lack of fit		7.23	23	0.31	0.71	0.7746	Not significant
Pure error		7.04	16	0.44			
Cor total		81.54	51				

The model demonstrates statistical significance, supported by an F-value of 15.32, indicating a substantial impact of predictors on the response variable. Specifically, factors A, B, C, D, A2, and AC show significance with "Prob > F" values less than 0.05. This indicates that driving duration, BMI, types of roads, and gender significantly influence drivers' decision-making. Overall, these findings underscore a robust model where the four experimental parameters contribute significantly to the response variable.

The lack of Fit F-value of 0.71 suggests that the lack of fit is not significant compared to pure error, indicating a satisfactory model fit. This implies that the model effectively captures the relationship between parameters and decision-making. The Lack of Fit probability of approximately 77.46% further suggests that any observed lack of fit is likely due to random noise rather than systematic inadequacies in the model. Furthermore, correlation analysis derived from Design-Expert elucidates the relationship between each factor and participants' decision-making during driving, quantified through beta (β) wave activities obtained from EEG data results.

3.2.1 Driving duration

Limited research has been conducted on the effect of driving duration on decision-making processes. It was found that the impact of driving on fatigue and performance is connected to the duration of time spent behind the wheel [8]. Experimental results in this study show that there is a negative correlation between driving duration and beta wave activity, indicating that as the duration of driving increases, there is a decrease in beta wave amplitude as illustrated in Figure 3. Beta waves are related to a strongly engaged mind, indicating that the brain is actively involved in mental activities. Beta waves in EEG indicates that a person is awake, affective, and the brain is carrying out cognitive processing [12]. Meanwhile, a decline in beta power suggests a decrease in brain arousal levels. Therefore, the fluctuating tendency of the EEG rhythm provides an objective indication of mental fatigue caused by prolonged driving and can serve as a potential marker for mental fatigue during driving [13]

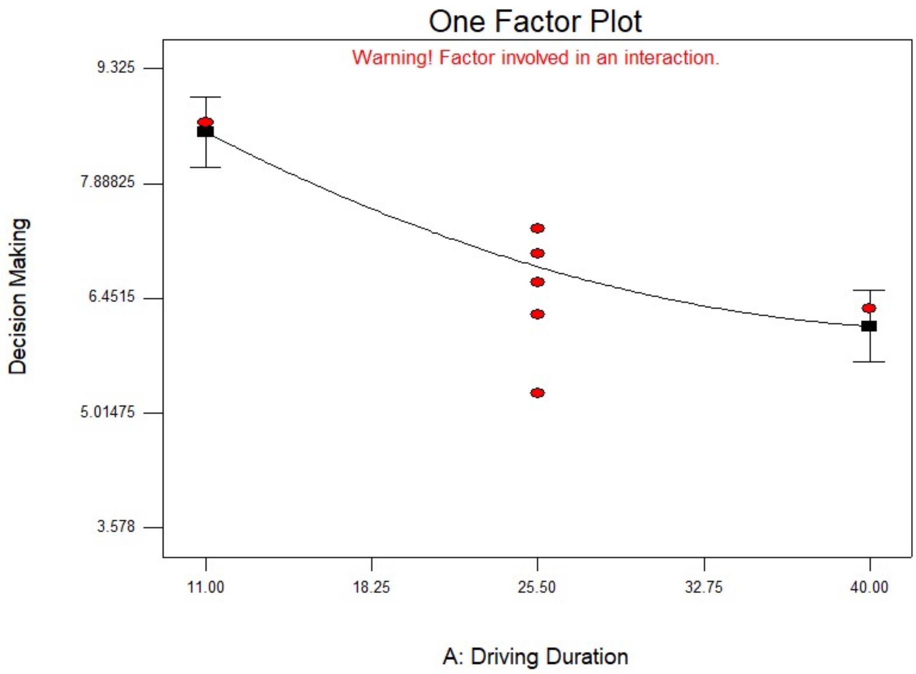

Fig. 3. Correlation between driving duration and decision-making when driving

3.2.2 Body mass *index (BMI)*

Figure 4 shows that participants with a higher body mass index (BMI) recorded lower decision-making compared to participants who are overweight or have a normal BMI. Obese is classified for participants with BMI of more than 30 kg/m^2, overweight is BMI from 25 to 29.0 kg/m^2 and normal is within 18.5 to 24.9 kg/m^2. Obese participants experience more fatigue while driving compared to participants with a normal or overweight BMI. This is supported by a finding that fatigue is a common concern among individuals who are obese [14]. An excessive amount of body fat has negative effects on the immune system, which is mediated through an increase in inflammatory cytokines [15, 16].

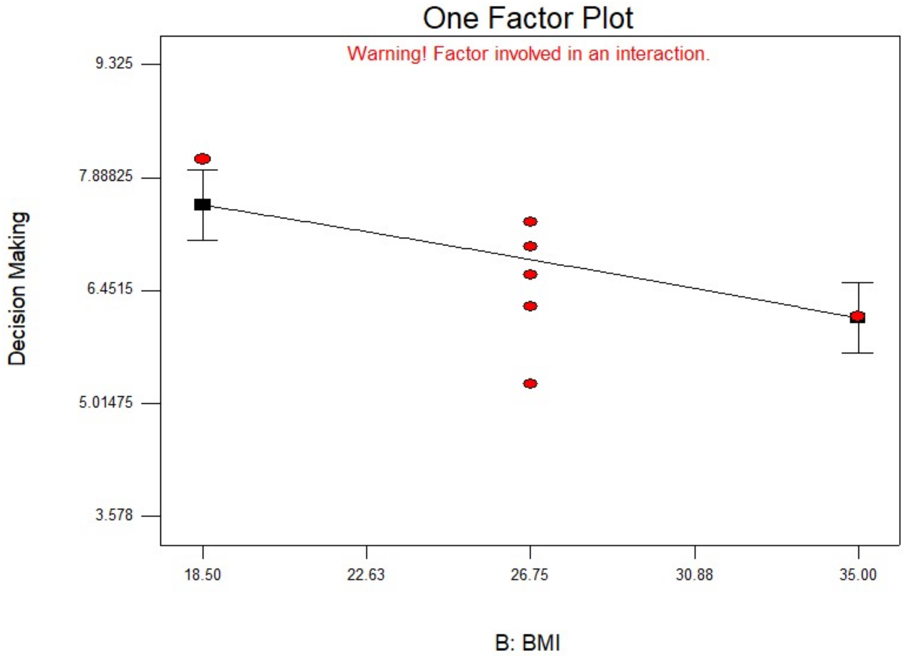

Fig. 4. Correlation between BMI and decision making when driving

3.2.3 Types of roads

The characteristics of road winding and monotony can influence driving fatigue. Figure 5 shows the relationship between types of roads and the decision making of the participants when driving. Monotonous roads are associated with lower decision-making abilities compared to winding roads. However, driving in a monotonous road environment, characterized by less variety and stimulation, could lead to increased levels of fatigue and diminished vigilance [17].

Figure 5 illustrates that winding roads with frequent bends and curves, demand increased attention and decision making from drivers, this can lead to heightened fatigue over time. Both winding and monotonous roads can lead to reduced alertness and fatigue when driving duration increases.

According to a study by Ibrahim *et al.,* [9], the characteristics of road geometry and the road-side environment were found to have a significant impact on driving performance. The study revealed that these factors influenced driving performance by affecting oxygen saturation levels. Another study conducted by Farahmand and Boroujerdian [10], researchers examined the effects of factors such as road curvature, slope, roadside environment, and visual complexity on driver behaviour, fatigue, and overall driving experience.

3.2.4 Gender

Figure 6 shows that female participants recorded lower scores on decision making. This shows that female drivers experienced higher levels of fatigue compared to male participants, which was reflected by their lower decision-making and lower beta wave activity. This finding is supported by a previous study where female participants exhibited notably reduced Heart Rate Variability (HRV), indicating heightened stress levels that correlated with inferior driving performance [18]. In relation to this, females have a higher percentage of body fat content (lower proportion of lean mass) which may increase the rate of quadriceps fatigue [19].

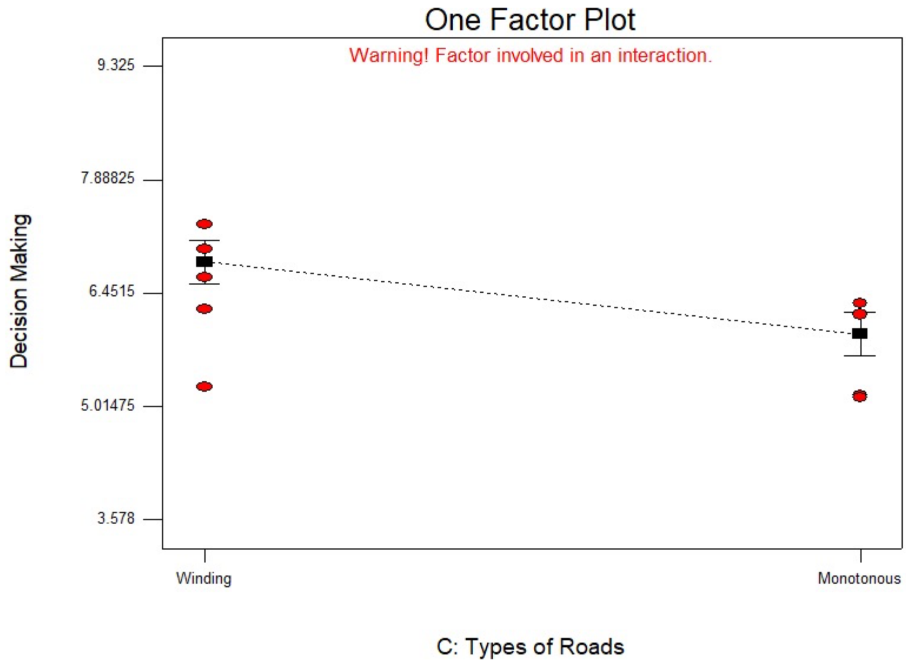

Fig. 5. Correlation between types of roads (winding and monotonous) with decision making when driving

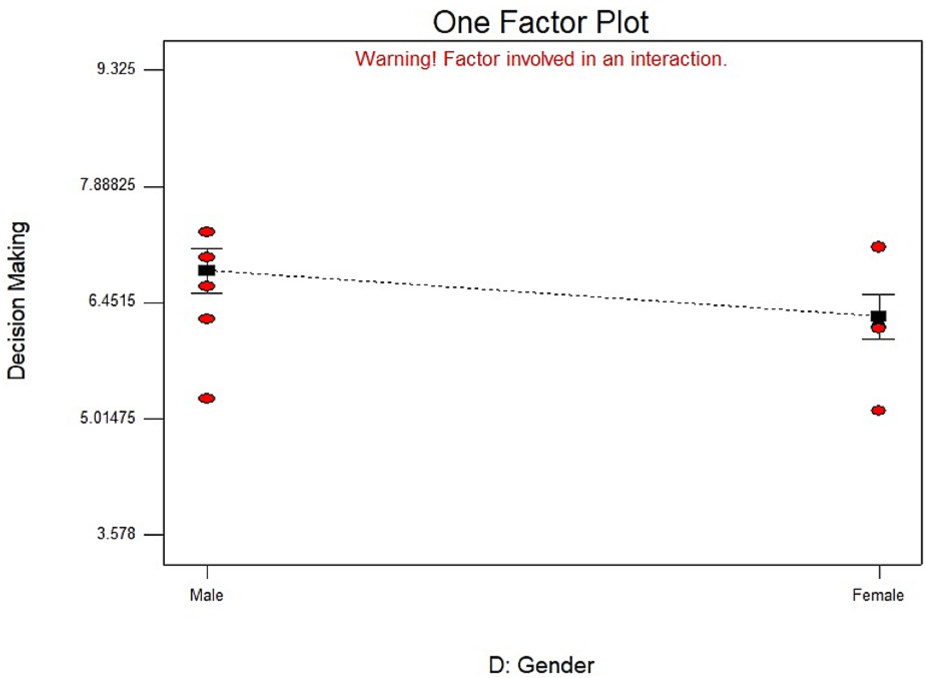

Fig. 6. Correlation between gender with decision making when driving

3.3 Polynomial Regression Equations

After obtaining the correlation of each factor with the decision-making, the next stage was to construct the polynomial regression equations according to gender and types of roads. Table 3 presents each of the polynomial regression equations from Design-Expert to determine the relationship between the input and output variables. The provided equations enable the estimation of decision-making levels by considering the real values of driving duration (in minutes) and BMI of the driver.

For example, in the equation for "Male, Winding" roads: +13.75321 - 0.24699 * Driving Duration - 0.11391 * BMI + 2.23141E-00 * Driving Duration² - 3.82306E-004 * BMI² + 1.85057E-00 * Driving Duration * BMI, this equation suggests that for male drivers on winding roads, the decision-making score decreases as driving duration and BMI increase. The quadratic terms (Driving Duration² and BMI²) and the interaction term (Driving Duration * BMI) further modify this relationship.

These equations allow you to predict the decision-making score for male and female drivers on winding or monotonous roads based on their driving duration and BMI. The coefficients provide insights into how these variables interact and influence decision-making in different road conditions. These polynomial regression equations provide a detailed understanding of how driving duration and BMI, along with their interactions, impact decision-making scores, tailored by gender and road type.

Table 3
Polynomial regression equations for decision-making model

Gender	Types of roads	Equation
Male	Winding	+13.75321 -0.24699 * Driving Duration - 0.11391 * BMI +2.23141E-00 * Driving Duration2 -3.82306E-004 * BMI2 +1.85057E-00 * Driving Duration * BMI
Male	Monotonous	+12.17986 -0.21126 * Driving Duration -0.12343 * BMI +2.23141E-00 * Driving Duration2 -3.82306E-004 * BMI2 +1.85057E-00 * Driving Duration * BMI
Female	Winding	+13.77123 -0.24803 * Driving Duration -0.13482 * BMI +2.23141E-00 * Driving Duration2 -3.82306E-004 * BMI2 +1.85057E-00 * Driving Duration * BMI
Female	Monotonous	+11.86616 -0.21230 * Driving Duration -0.14433 * BMI +2.23141E-00 * Driving Duration2 -3.82306E-004 * BMI2 +1.85057E-00 * Driving Duration * BMI

3.4 Validation of the Regression Model

Data validation is crucial to ensure accuracy and credibility of the polynomial regression model. Design-Expert calculates the predicted decision-making values using the regression equations and provides corresponding 95% prediction interval values. To evaluate the effectiveness of the regression model, the %Error metric is used, which quantifies the percentage disparity between the predicted values and the actual values for each equation. When the residual error of each equation falls below 10%, the model is deemed validated and accurate [20].

Table 4 displays the validation data for the decision-making model, showcasing the input parameters of driving duration, BMI, types of roads, and gender obtained for the experiment. The actual value is the observed value obtained from the real experiment, while the predicted value is the estimated value generated by the regression model equations using the same input variables. Additionally, Table 4 provides error percentages, representing the percentage difference between the predicted and actual values. A lower %Error is considered better as it indicates a smaller discrepancy between the predicted and actual values. The tabulated data shows that the %Error values range from 0.33% to 2.84%, indicating that the model's predictions are relatively close to the actual values. Hence, the polynomial regression equations are considered validated and accurate as the residual errors are below 10%.

Table 4
Data validation for the polynomial regression equations

Input parameters				Predicted value	Actual value	Error (%)
Driving duration	BMI	Types of roads	Gender			
11.00	35.00	Monotonous	Male	6.05	6.13	1.32
25.50	18.50	Winding	Male	5.10	5.21	0.33
25.50	18.50	Monotonous	Female	5.98	6.15	2.84
11.00	18.50	Winding	Female	9.13	9.06	0.77

4. Conclusions

Electroencephalography (EEG) serves as a technique for capturing the electrical activity of the brain by utilizing electrodes strategically positioned on the scalp [21]. This non-invasive method allows for the detection and analysis of neural signals, providing valuable insights into brain function and activity patterns. By measuring the fluctuations in electrical potentials generated by neuronal activity, EEG enables researchers and clinicians to investigate various cognitive processes.

This study presents EEG experimental data regarding factors contributing to driver fatigue. Utilizing a regression analysis model, it enables the examination and prediction of how certain variables impact cognitive skills, particularly decision-making while driving. The research underscores the importance of experimental parameters such as road types, duration of driving, BMI, and gender in influencing decision-making, as indicated by beta (β) wave activities derived from EEG data. Findings reveal that prolonged driving durations correlate with increased driver fatigue. Moreover, individuals with obesity experience heightened fatigue compared to those with normal or overweight BMIs. Fatigue levels are also influenced by road monotony, with participants reporting more fatigue on monotonous roads compared to winding ones. Additionally, female participants exhibit higher levels of fatigue compared to their male counterparts.

These findings contribute to long-term improvements in regulations on road conditions and by guiding upcoming investigations on road safety. Future works could involve expanding the participant sample size, exploring additional EEG features for fatigue prediction, developing educational programs, and investigating the influence of supplementary factors on decision-making. More experiments are needed to verify the relationship between the different factors in driving fatigue.

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