Investigation of Bus Passenger Discomfort and Driver Fatigue: An Electroencephalography (EEG) Approach

Benjamin Oladele Afuye

Transport Research Institute

School of Engineering and the Built Environment

Edinburgh Napier University

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ABSTRACT

Efforts to improve urban bus transport systems' comfort and increase user satisfaction have been made for many years across the globe. Increasing bus users and reducing car users has an economic benefit. Whenever the urban bus share is larger than 25%, there are journey time savings due to lower congestion levels on the network. A driver's loss of alertness due to fatigue has been recognised to be one of the major factors responsible for road accidents/crashes for many decades. Comfort and fatigue are psychophysiological phenomena. Objective measures of human psychological and physiological factors must be defined, investigated, and evaluated in order to have an in-depth understanding of the cause-effect mechanisms regulating psychophysiological factors.

Electroencephalography (EEG) developed as bio-sensor equipment to interpret and collate bioelectrical signals was used to gather the time-series quantitative data of urban bus passengers and HGV drivers. This study's EEG data application was designed to link the brain activity dynamics to dynamic experimental design variables or tasks by correlating increased or decreased measured brain activity by using a baseline for comparisons. Two experiments were conducted in this study. The first sought to understand the influence of driving time and rest breaks on a driver's psychophysiological response. Therefore, the EEG data was collected, categorised and grouped based on two hours of driving before a 30 minute break, two hours of driving after a 30 minute break and four hours of driving with no break. The Samn-Perelli seven-point scale of fatigue assessment was used to evaluate the influence of the duration of driving time on a driver's performance decrements. The second experiment investigated bus passenger discomfort by examining experimental design stage-related changes in EEG measured by using a control experiment for comparison. Consequently, datasets in two stages were collected for each subject (passenger), including the stationary laboratory (control) and dynamic onboard bus environment experiments. A subjective evaluation of the average ride comfort on each stage of the experiments was conducted by using the recommended assessment scale of the International Standard ISO 2631-1. The ERP EEG oscillations were evaluated by decomposing the EEG signals into magnitudes and phase information, and then characterising their changes relative to the experimentally designed phases and variables. A two-way analysis of variance (ANOVA) was conducted to test the model's predictor under different experimental conditions for passenger discomfort and driving fatigue experiments.

The variability in the driver's psychophysiological responses to the duration of driving occurs systematically. The effects appear to be progressive and aligned such that the driving performance was worst during the last 60 minutes of driving for four hours without a break, but better during the first 30 minutes. Data analysis also showed that a pronounced psychophysiological response exists relative to the influence of the road roughness characteristics, the passenger's postures, and the bus type. Further analysis of passenger discomfort showed that passengers are more strained while in a standing posture than in a seated posture, irrespective of the bus type and the degree of the road's roughness. The results indicated that passenger comfort deteriorates as the road roughness coefficient increases. Furthermore, the results demonstrated that female passengers express more discomfort/dissatisfaction than males under the same experimental conditions. Therefore, female passengers are more sensitive than males to a deviation from optimal comfort conditions.

This study provides opportunities for future research applications of EEG in transport research studies. It also provides a platform for evaluating different Intelligent Transport System (ITS) technologies, particularly passenger's reactions in autonomous vehicles.

DECLARATION

I hereby declare that this thesis and any material contained in this thesis have not been submitted to award any other degree or professional qualification in any university. I declare that this thesis and all work contained in this thesis results from my independent work. This thesis contains no material previously published or written by another person except where due acknowledgement to others has been made to the best of my knowledge and belief.

Benjamin Oladele Afuye

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DEDICATION

This thesis is dedicated to the most beautiful and strong woman in my life

Mrs Esther Abosede Afuye

And

My Precious Father

Late Pa. Joshua Afuye

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CHAPTER 1 INTRODUCTION

1.1 Background

People currently living in urban areas accounts for 55% of the world's population, and this is expected to increase to about 68% by 2050 (United Nation, 2018). Consequently, many cities face significant transport and mobility-related challenges, such as traffic congestion, air quality, noise and many others. The desire to improve the bus transport system's quality and increase user satisfaction has been essential for many years across the globe. Increasing bus users and reducing private car users have economic benefits and journey time savings, along with congestion reduction and environmental benefits (JMP consultants limited, 2009). Passenger cars represent the majority of road transport in almost all cities in the UK, including Edinburgh. For example, statistics show that 72% of households in Scotland had access to one or more cars in 2017 (Scottish Transport Statistics, 2018). This estimation is similar to the 2011 Scotland population census results, which showed that 69% of households in Scotland had access to one or more cars, with 27% having two or more cars. Therefore, the public bus transport system should serve as an alternative mode of travel to passenger cars, which could significantly reduce the volume of vehicles on the road and serve as a means of managing urban traffic challenges.

Bus passenger comfort deteriorates due to road-vehicle interactions and passengers experiencing sensations that do not target specific organs of the body, but create potential harmful effects (stress) to virtually all parts of the body. However, such effects are not limited to tractor drivers, workers operating industrial vehicles and people travelling on a bus, train or car (Mansfield, 2005). Factors of human sensations in a dynamic environment(s) are often complex and change over time. Some occur in many directions, and exposure to them causes a complex distribution of oscillatory motions and forces within the body. Human stability in a dynamic environment is controlled and managed by the brain, and is supported by the cerebellum, basal ganglia and visual cortex (Powell and Palacine, 2015). As the human body responds to the effects of road-vehicle interactions, it could cause a series of negative sensations that may lead to performance decrements, impaired health and interference with activities, along with posing health and safety risks, such as pathological damage or physiological change (Griffin, 1990).

The human physiological abilities and competence are critical factors for maintaining productivity and safety in all transport industries (including truck driving). Fatigue is psychophysiological; therefore, human psychological and physiological factors must be defined, examined and evaluated in order to understand it (Phillips, 2015). A driver's loss of alertness due to fatigue has been recognised to constitute one of the major factors responsible for road incidents or accidents of intercity Heavy Goods Vehicles (HGV) for many decades. Prolonged driving affects the alertness of truck drivers operating on day-to-day schedules and unscheduled trips. HGV driver's unscheduled operations, prolonged driving time from the management or unforeseen circumstances (such as traffic congestions due to road accident or adverse weather), a changing schedule or other additional tasks, such as fuelling and loading/offloading of goods usually contributes to the level of fatigue on both local- and long-distance haul. A significant decrease in a driver's physiological arousal impaired reaction time, information processing, and slow sensorimotor functions could result in a driver's performance decrements and reduce the ability to respond effectively and efficiently to sudden and unexpected situations (Lal and Craig, 2002).

The human brain is characterised by vibrant spatiotemporal dynamics, and physical and emotional states influence the brain's activity. The human brain activates neuropeptide-secreting systems in response to internal or external stimuli (Makeig et al., 2010; Gwin *et al.*, 2010). Discomfort or fatigue indicates a psychophysiological response to perceived demands and pressures within and without that produce adverse emotional reactions. The application of electroencephalography (EEG) is well known to be an approach capable of characterising individual brain states in the processing of different semantic categories that make the application of real-time decoding systems possible (Muller et al., 2008). EEG can potentially be used to collate reliable data and use it as an analytical approach for detecting changes in psychological or physiological states due to its degree of temporal resolution (Lal and Craig, 2002). EEG is one of the best approaches to evaluate brain dynamics associated with perceiving comfort disturbance in motion mainly because of its portability (Yu et al., 2010). Most cognitive processes usually occur within tens to hundreds of seconds, and the events activating those cognitive processes occur in time sequences that span from hundreds of milliseconds to a few seconds (EEG Pocket Guide, 2016). Therefore, EEG directly measures and collates data on neural activity. This information has an excellent sub-second time resolution because EEG captures hundreds to thousands of neural activities across multiple electrodes within a single second.

1.2 Research Questions

This research framework aims to characterise HGV driver's fatigue and public transport passenger ride comfort by measuring the psychophysiological responses via EEG. The following research questions will be answered.

a. What are the factors affecting the fatigue of HGV drivers? In particular,
    a. How does the duration of driving and rest breaks affect the driving fatigue/performance decrement?
    b. How does a driver's gender and age influence driving fatigue/performance decrements?
b. What are the factors affecting the comfort of bus passengers? In particular,
    a. How do pavement and bus type affect the comfort of bus passengers?
    b. How does passenger posture under the same/similar real-life traffic conditions affect the comfort of bus passengers?
    c. What is the impact of gender and age on bus passenger comfort?

1.3 Research Objectives

The aim of this research is to investigate driver fatigue and public transport passenger ride comfort by measuring psychophysiological responses. In order to achieve this research aim, the following objectives are pursued.

1. To investigate change in the psychophysiological responses (from the state of focus or vigilance to the state of fatigue or performance decrements) of a group of subjects with different sociodemographic characteristics as a function of the duration of driving an HGV in a driving simulator.
2. To quantify changes in a passenger's psychophysiological responses in a group of subjects with different sociodemographic characteristics while riding a real bus, considering different types of buses, pavements, and postures.

1.4 Justification of the Study

Public transport systems must meet passenger's needs in order to offer maximum comfort desired, with more emphasis placed on the travel environment. Passenger comfort can be used to evaluate the quality of mass urban transit services and fundamental factors that influence a passenger's choice of their mode of traffic (Eboli and Mazzulla, 2011). The quality of public transport system services is influenced by many factors that are not limited to speed, convenience, travel time, cost, reliability, safety and accessibility. Due to the variety of contexts in which bus passengers may be exposed to sensations, there is a general conclusion that travelling can negatively impact a user's well-being. Therefore, improving bus transportation systems in urban agglomeration requires the investigation of a passenger's physiological and psychological feelings as well as their perceptions on comfort (Morton et al., 2016; Beurier, 2012).

Generally, in the UK, the transport sector contributes 34% of all carbon emissions (124.4 Mt) and the significant parts of this is from the road transport sector, mainly passenger cars (National Statistics, 2018). Passenger cars represent the majority of road transport in almost all cities in the UK. Increased car ownership was observed to go hand in hand with the general decline in the passenger's journey on a bus. Urban bus transport systems must have the tendency and potential to be used as policy tools in order to reduce the number of cars on urban roads, and thus, reduce urban traffic pollution and traffic congestion. Therefore, there is a need for constant research on the factors responsible for the continuous decline in an average journey on a bus in the country.

Driving fatigue is now generally recognised as a serious threat to road safety. Fatigue-related accidents are more common on motorways than on urban roads due to drowsiness and inattentive causes by monotony and constant speed. Research has found that driving fatigue is the main contributing factor in almost 3% of road transport accidents, and up to 20% of these accidents usually occur on motorways (Bener et al., 2017; Stein & Jones, 1987). It is essential to examine the physical and psychological antecedents of driving fatigue, along with its consequences; therefore, there is a need to conduct studies that will offer an exclusive and stimulating opportunity to examine and conceptualise driver engagement during fatigued driving.

1.5 Structure of the Thesis

The research thesis is organised into eight chapters. Chapter 1 presents the introduction to this research, and discusses the background of the study, research questions, aim and objectives. A critical review of literature on passenger comfort, driver fatigue and the application of EEG are discussed in Chapter 2. The research methodology is presented in Chapter 3, which discusses the research design, case studies, the data collection approach, data cleaning and analysis. Chapter 4 presents the analysis of laboratory studies (the HGV driving simulator). Chapters 5 and 6 present the general analysis of bus passenger ride comfort by using beta EEG frequency and the eSense metric for attention. An overview chapter then synthesises the knowledge and results into two chapters: general discussion and summary and general conclusion, which enable the accomplishment of the research aim and objectives.

INVESTIGATION OF BUS PASSENGER dDISCOMFORT AND DRIVER FATIGUE

Chapter 1: General Introduction

Chapter 2: Literature Review

Passenger comfort	Driver Fatigue	Application of EEG

Chapter 3: Methodology

Study Design	Experimental Procedure	Participant	Data Collection	Statistical Analysis

Chapter 4: Fatigue Responses of the HGV Driver: Influence of driving time and break

IV: Driving time, age and gender	DV: EEG brain activity (beta and attention)

Chapter 5: Urban Bus Passenger Ride Comfort: Application of Beta EEG Brain Activity

IV: Road roughness, posture, bus type, age and gender	DV: Beta EEG brain activity

Chapter 6: Urban Bus Passenger Ride Comfort: Application of eSense Metric of Attention

IV: Road roughness, posture, bus type, age and gender	DV: eSense metric for attention

Chapter 7: General Discussion

Chapter 8: Summary and General Conclusion

Where IV: Independent Variable (s) and DV: Dependent Variable(s)

Figure 1-1: Structure of the thesis

1.6 Chapter-by-Chapter Summary

Chapter 1 of this research presents the general background of bus passenger comfort, driving fatigue and EEG as well as the aim and objectives of the study. The second part of this research is a general review of buses' roles, mechanisms of human brain sensitivity, driving fatigue, and the application of EEG (Chapter 2). From this review, it was clear that numerous researches have been conducted relative to broad-range issues in this research area. Even with previous research, several vital issues were identified in which no works or very few works have been published. These issues are not limited to applying EEG on bus passenger comfort relative to the influences of road roughness characteristics, bus type and passenger posture. Chapter 3 outlines the experimental design, equipment, the data collection's designed layout, artefact removal, and analysis techniques of this research.

The first study involved a laboratory investigation conducted on HGV driving fatigue (Chapter 4). Measurements of participant brain activity were collated to quantify HGV driver's psychophysiological responses as a function of the duration of driving. The results of Chapter 4 were used to inform the bus comfort study. Based on the results presented in Chapter 4, the brain activity (beta EEG frequency band and eSense metric for attention) showed correlations between the duration of driving time and psychophysiological responses.

Chapters 5 and 6 involved a field investigation conducted on pre-determined Lothian Bus routes designed to investigate the extent to which variations in road roughness characteristics, passenger posture and bus type influenced a passenger's comfort. An EEG was used to collate human electrocortical brain dynamics (beta and eSense metric for attention brain activity) that were associated with cognitive processes during mobile activities or whole-body vibrations as a function of the effects of vehicle-road interactions. Chapter 5 presents the application of the beta EEG frequency band, which is aimed to access a passenger's posture influence on the psychophysiological response of individuals exposed to different road roughness characteristics in both single- and double-decker buses. On the other hand, Chapter 6 presents the eSense metric for attention by using the same experimentally designed variables in Chapter 5. Understanding these psychophysiological responses presented in Chapters 5 and 6 can provide a significant understanding of the mechanism that causes passenger discomfort in dynamic environments. The results of this research demonstrated that there are variations between male and female participants. Also, an individual's adaptation to the impacts of exposure varies, and people sustain a different level of discomfort, which usually occurs at the expense of magnitudes of the sensations. In general, the passenger's psychophysiological responses showed significant variations between the seated and the standing postures, asphalt and set pavements, and single and double-decker buses. The results of this research supported previous findings reported in the literature. However, many of the published studies have only used a subjective approach emphasising the seated posture. None or few reported investigations used objective data collated directly on the participants, which provided a direct comparison of a passenger's comfort while in a seated and in a standing posture. Chapter 7 discusses the overall results found in the various studies and literature review (Chapter 2). The study's conclusions and recommendations are summarised in Chapter 8. Chapter 8 highlights the study's contributions to research knowledge by referring to the aim and objectives of the research.

CHAPTER 2 LITERATURE REVIEW

2.1 Introduction

Chapter 1 provides an overview of the research background, research questions, research aim and objectives. This chapter describes the literature related to the context surrounding driving patterns, along with human responses to vehicle speed profile factors and vibrations. This chapter of the literature review focuses on building an understanding of the appropriateness and method of using EEG in a different area of study. It has been observed that the amount of literature available on the application of EEG has grown dramatically over the last three decades.

2.2 Bus Passenger Comfort

An urban bus public transport system is known to be one of the leading facilitators of maximising productivity. The socioeconomic benefit of buses is significant in every town and city, and the benefits are not limited to providing efficient connections of wealth and labour to the marketplaces, but also reducing traffic congestion. It also has significant benefits for low-income households and those with limited or no opportunity to have or use a car, such as the disabled and younger and older people (Lucas et al., 2019). Bus transport systems provide opportunities for private individuals, cooperate bodies, and governments to increase asset value and income (Tourism & Transport Forum., 2010).

Furthermore, urban bus transport systems benefit people by allowing access to health and education services and employment and recreation opportunities, and many of those that use public transport enjoy the benefits of being able to use their travel time more productively. For instance, Stradling et al. (2017) revealed that people travelling on a bus could sit back, chat, send and read emails or relax compared to those who drive a car, which requires a high level of concentration. Also, Litman (2015) revealed that the quality of public transport has many significant impacts on people’s health because the degree of public transport integration into the community influences travel activity. Urban bus mass transit is known for providing or improving people’s fitness by removing fatigue associated with driving a private car, most notably during peak hours.

2.3 Bus Transport System

Urban bus public transport system is known to be one of the leading facilitators of maximising productivity. The socio-economic benefit of bus is significant in every town and city. The benefits are not limited to providing efficient connection of wealth and labour to the marketplaces and reducing traffic congestions. It also has significant benefit for low-income household and those with limited or no opportunity to have or use a car such as disable, young and older people (Lucas et al., 2019). Bus transport systems provide private individuals, cooperate bodies, and government opportunities to increase asset value and income (Tourism & Transport Forum., 2010).

In the last few decades, related transport and environmental policies and strategic plans of the government and public transport operators to promote urban mass transit and reduce private cars focusing on creating, improving or promoting eco-friendly urban society, control traffic congestions or improve health and safety (Government Office for Science, 2019). In addition, using bus reduces the likelihood of being obese by a 6% increase compared to the driving car (Jacobson et al., 2011) and reducing fatality rate compared to the private car. For instance, public transport's fatality rate is accounted for only about 4% of what is associated with a private vehicle (APTA, 2007). London, Glasgow and Edinburgh are examples of the United Kingdom cities where public bus transport operators have strengthened their efforts to improve supply. However, the share of trips made by public transport system in Great Britain and Scotland continues to be lower than that of the private car. Despite all the benefits of the public transport system and continues increases in government and bus operator's (such as Lothian Buses) investment in Scotland and Great Britain, there is still a decrease in passengers' average journey across the country. For instance, the Scottish Transport Statistics, 2018 showed that total passenger journey made by bus in Scotland is about 388 million in 2017-18, which is a decreased of 1.5% of an average journey made in 2016-17 (394 million) and a 20% fall from the total peak journey made in 2007-08 (487 million). Therefore, there is need for constant research on the factors responsible for continuous falling in an average journey made by bus in the country.

In the UK transport sector contributing 34% of all carbon emission (124.4 Mt) and the significant parts of this is from the road transport sector, mainly passenger cars (National Statistics, 2018). Passenger car represents the highest road transport modes in almost all cities in the UK, including Edinburgh. Several countries invest in public transport systems to make them more comfortable, attractive, greener and more competitive than private cars (European Environment Agency, 2013). Nevertheless, a qualitative or quantitative increase in supply does not bring about a corresponding increase in public transport system acceptance than passenger cars (Scottish Transport Statistics, 2019). For example, the Scottish Transport Statistics, 2018 shows that 72% of household in Scotland had access to one or more car in 2017. The desire to improve the urban bus transport system's quality and quantity and increase user satisfaction has become essential for many decades. Increase bus users has an economic benefit because whenever urban busload more than 25%, there is net economic benefit such as journey time saving due to lower congestion levels on the network during the peak hours (JMP consultants limited, 2009). Therefore, urban bus mass transit should serve as an alternative mode of travel to the passenger car, reducing vehicles' volume on the road and managing urban traffic challenges.

Despite the significant roles of buses in rural and urban areas worldwide, their services in Scottish cities still require additional effort to meet passenger needs and satisfactions. For instance, there was a trend in the falling of bus speeds in Edinburgh for one decade between 1986 and 1996. The scheduled bus speeds increased by 5% due to better conventional Edinburgh's radical Greenways Bus Priority Scheme. This increase in bus speed was dissipated through weak enforcement, removing bus priority lane during off-peak periods and improper maintenance (failure to paint the lanes green). Therefore, since 1996 Edinburgh bus speed has reverted to the UK broad trend and declined by about 20% (Begg, 2016).

Human sensibility (ride comfort) and passenger satisfaction in the public transport system are currently more important than ever. In the last few years, the bus operators have made efforts to improve the qualities of buses and services, passengers' ride comfort, customer care initiative, and network modification (JMP consultants limited, 2009). Also, attempts have been made to improve driver and passenger ride comfort through research and design suspensions and seats that attenuate vibration. However, this may still not guarantee the desirable ride comfort when travelling on some road sections (rough road) and speed (Mashino et al., 2015). For intra-urban buses to keep and attract more passengers, urban bus transports system must possess high-quality service that satisfies and meet a broader range of different passenger needs (Ponrahono et al., 2016). Therefore, improving passenger satisfaction will increase the system's use and encourage new customers (passengers).

2.3.1 Passenger Discomfort in Public Transport

The primary approach to study passenger discomfort is to subject the passenger to different driving conditions in real traffic situation or special equipment (Hoberock, 1976). Comfort refers to the pleasant state of the person's relaxing feeling in reaction to the physical environment and forms part of people's daily experience; therefore, users interact with a product or services and share their satisfaction level (Mansfield et al., 2020). The road-vehicle interactions usually expose driver or passenger to factors of emotions. The feelings have significant impacts on their level of satisfaction (Beurier, 2012). Determining passenger comfort in public transport may be challenging and involve significant tasks because it depends on human perception and many factors that vary from person to person (Government Office for Science, 2019). Several studies have been carried out to evaluate passenger satisfaction and dissatisfaction and develop a public transport system that meets a wide range of commuters' needs.

Comfort perceived by passenger in-ground public transport system varies on the types of vehicle, road quality, posture or orientation of the body, and passengers' ability to withstand stress. These factors interact to cause short or long-time changes in passengers' psychological and/or physiological state. Evaluation of discomfort often depends on the objective quantifications of subjective judgment, due to the reference points, the sensitivity, the responsiveness and assessment based on the adaptation and motivation that varies from person to person (Fotios, 2015, Tan et al., 2008).

Many studies on passenger sitting comfort focused on passenger eats in public transport (De Looze et al., 2003) operator seats in cars, buses, and farm machinery (Tan et al., 2008). Passengers' comfort was associated with es in motion perceived from all directions and environmental factors (Powell and Palacine, 2015). The factors of motion (acceleration, deceleration and jerk) are continually making passengers lose their balance and balance in the human being are control and manage by the brain and supported by the cerebellum, basal ganglia and visual cortex (Powell and Palacine, 2015).

Bus passengers experience discomfort on transit that sometimes results in musculoskeletal disorders (MSDs) (Armstrong et al., 1993). Some of these disorders are usually referred to as repetitive trauma disorders, cumulative trauma disorders or repetitive strain injuries that can affect muscles, bones, and joints (Armstrong et al., 1993). Studies have shown that passenger responds differently on large vehicles than small-sized vehicles (Lima et al., 2015, Cooper at el, 1978). The correct designs of road pavement also depend on the type of vehicles using the route. Some road could effectively tolerate some vehicular types such as passenger cars, and that same road may penalise other vehicles such as PCVs. Lima et al., 2015 compared driver and passenger comfort of different vehicles (car, bike and bus) travelling on a speed bump. The authors concluded that heavy vehicles occupants such as bus or truck are subject to more considerable discomfort than occupants of light vehicles such as cars and motorcycles. In Edinburgh, some Lothian bus routes were primarily designed a long time ago to accommodate small vehicles. Using those roads or street as part of Lothian Buses route has significant influences on both driver and passenger perceive sensations. Driven by these conclusions, further study is needed to evaluate both the transit users' perceptions of the quality and adequacy of the public transport service and characterisation of different bus types' mobility patterns.

The ISO, 1997b describes comfort as "subjective state of well-being or absence of mechanical disturbance relative to the induced environment". Apart from using acceleration to estimate an urban bus passenger's comfort, other parameters such as the rate of acceleration (Jerk) and the root mean square (RMS) acceleration could also use. The ISO, 1997a recommends RMS value calculated from the weighted acceleration as a factor of estimating passengers comfort and defined comfort index (Table 2-1).

Table 2-1: Comfort index definition

Index	Range (G)	Comfort description
0	Greater than 0.229	Extremely uncomfortable
1	0.145 - 0.229	Very uncomfortable
2	0.092 - 0.145	uncomfortable
3	0.057 - 0.092	Fairly uncomfortable
4	0.032 - 0.057	A little uncomfortable
5	Less than 0.032	Not uncomfortable

Sources ISO, 1997b

Wu et al. (2009) used a brake comfort model based on the car-following model to evaluate the relationship between vehicle deceleration and passenger comfort. The emphasis on ride discomfort resulted from the influence of longitudinal acceleration. The study used the car's speed, the friction coefficient between the car and road and the distance between the two cars as the input parameter. The critical value of 2.0 m/s^2 was average comfortable longitudinal acceleration. Castellanos and Fruett (2011) developed an embedded system for monitoring passenger comfort in public transport using triaxial accelerometer and

GPS data collated. A threshold of 1.5g was set for Z acceleration, while ±0.5g for X and Y acceleration. The authors found that the maximum acceleration of 2.127 g in the Z-axis, while X and Y-axes' values did not exceed the threshold. They concluded that monitoring passenger comfort in public transport provides the opportunity to identify and quantify passenger discomfort sources relative to the vehicle longitudinal, lateral and vertical acceleration.

Castellanos and Fruett (2014) developed a system Hardware, Firmware and Software (LabVIEW™ interface) to determine the dynamic motion factors that affect passenger comfort in public transportation systems. An on-board data collection approach using tri-axial accelerometer and GPS in conjunction with algorithms permit the system to evaluate driver behaviours and defects on the pavement. The authors used Jerk-Acceleration Threshold Detection (JATD) and jerk levels above the comfort range, Comfort Index (CI) and the average ride comfort recommended by the ISO2631-1. Their findings revealed that comfort deteriorates due to fast turn, break manoeuvre, abrupt starts and imperfection or obstacles on the road.

The correlation of the participant's subjective assessment and average acceleration shows that 70% of the subjects experienced discomfort at the acceleration of 0.7 g, 0.8 g and 1.4 g for lateral, longitudinal and vertical respectively. Powell and Palacine (2015) examined the effects of regular operations of longitudinal acceleration of railways on passenger comfort and safety. The authors used the biological theory of balance in human and used a multi-channel data acquisition system. The authors found that the quasi-static accelerations are always close to 1.4 m /s^2, generally acceptable. Shen et al. (2016) used a two-day survey of bus passenger perceptions in Harbin in peak and off-peak hours to evaluate bus passenger comfort based on passenger load factor and in-vehicle time. The authors sampled 300 (seated) and 240 (standing) passengers who regularly used bus service 63. The study results demonstrated that as the comfort perception score increases, the in-vehicle time and degree of congestion (passenger load factor) increase for both seated and standing passengers.

Qualitative techniques such as questionnaire, focus groups and interviews with passengers as well as quantitative measurement alongside with applications of qualitative approach have used to enhance the understanding concerning the specific factors that influence the perceptions of passengers on service quality of public transport system (Morton et al., 2016, Shen et al., 2016, Zhang et al., 2014, Sumaedi et al., 2012 Eboli &

Mazzulla, 2009, Eboli & Mazzulla, 2007, Cascajo & Monzón, 2007). For instance, Lai & Chen, 2011 investigate people's intentions to use the public transport system. The authors used measurement scale of perceived service quality that identifies two scopes connected with core factors that affect bus transport system and services (fare, service coverage, frequency and real-time information) and physical environment (stability, safety and cleanliness). Integrating quantitative and qualitative factors of passenger ride comfort will improve an understanding of transit customers' perceptions of service quality. Bus service providers could use bus service providers to retain the existing customers and attract new customers from other transport modes, primarily passenger cars (Zhao et al., 2016, Li & Hensher, 2013, Eboli & Mazzulla, 2011, Eboli & Mazzulla, 2010).

2.3.2 Passenger Ride Comfort and Posture Influence

The quality of public transport system services is influence by many factors that are not limited to speed, acceleration/deceleration, safety and accessibility. In every automated or semi-automated vehicle such as urban bus transit (single or double-decker), sharp accelerations and decelerations are inevitable. It usually requires avoiding or reducing the vitality of incident/accident, obey traffic rules, or merge vehicles into high-speed traffic at close headways. Standing passengers in urban buses are not provided with any safety provisions, except for handholds, and the seated passengers are not required to wear seat belts (Rutenberg & Hemily, 2003). Standing passengers usually experience a significant amount of discomfort due to sudden accelerations/decelerations (George et al., 2013). Therefore, passengers' overall safety, most especially standing passengers, is based on the public transport system's regular operating conditions. However, higher longitudinal and lateral acceleration levels compromise passenger comfort safety if they are adequate to cause passengers to lose their balance (Powell & Palacin, 2015). Urban bus passenger comfort assessment/evaluation is essential to monitor and sustain the bus operators' services.

Passengers often stand in public transport for all or part of the journey while exposed to different rates of speed profile factors (speed, acceleration and deceleration) and vibration that could cause discomfort or inconvenience. Although Powell & Palatine (2015) highlighted the three basic strategies by which standing passenger could preventing severe discomfort/falling. First, ankle strategy, which is the contract of the leg muscles and bends the ankle to withstand external acceleration, keep body balance and prevent falling under the influence of small acceleration. The hip approach also applies to period when the degree of acceleration is higher; in this approach, there must be a change in body position to withstand the induced stimuli to the influences of vehicle speed and jerk. The final method is stepping strategy, in which one or more steps are required to prevent or avoid falling due to the influence of higher acceleration/deceleration or jerk.

Nevertheless, there is no universally acceptable approach(s) to evaluate bus passenger discomfort since the buses, road roughness characteristics and operations vary from place to place. Therefore, it is worth using a different method to examine the relationships between various ride comfort indices and compare them. For example, Munawir *et al.*, 2017 compared Sperling's Ride Index and BS EN 12299 to evaluation passengers of ride comfort of seated and standing subjects using Sperling's Ride Index. The authors find that standing posture discomfort shows a higher ride index value than the seating posture in both approaches. The International Standard ISO 2631-1, British Standard 6841 and European pre-standard ENV 12299 provide frequency weightings for evaluating vibration for standing discomfort. All the three standards advocate frequency weighting Wd for evaluating vibration discomfort of both seated and standing people relative to the influence of longitudinal and lateral vibration posture (Thuong & Griffin, 2011). However, there are limited studies on the standing bus passengers' dynamic comfort, especially for buses. Studies on seated passenger comfort have been carried out on discomfort from the vibrations (Beurier, 2012).

Suzuki et al., 2000 also pointed out that the evaluation of railway passenger discomfort is significantly different depending on the posture, seated or standing due to lateral acceleration. Also, Thuong & Griffin, 2011 used method of magnitude evaluation to investigate how the discomfort of standing people exposed to vertical and horizontal vibration. The authors found that the seated and standing people's responsiveness is similar for vertical vibration, but significant differences for horizontal vibration due to instability in standing posture. Furthermore, Hirshfeld, 1932 used a small car riding on a smooth track that could accelerate from 0 to 0.373 g in a laboratory experiment, to investigate the effects of longitudinal acceleration on the balance of standing passengers. The participants stood on a platform that moved with variable acceleration profiles. The author found that different levels of jerk influence passengers' ability to balance and the least tolerant for unsupported passengers facing forward to lose balance is 0.13 g. The corresponding proportions of average acceleration that an unsupported standing passenger used overhead strap and passenger supported with a vertical grab rail are 0.27

g and 0.15 g respectively. The study revealed that different acceleration or jerk produces a different level of discomfort related to experimental conditions (Table 2-2).

Table 2-2: Average acceleration to loss balance

S/N	Condition	Average acceleration attained (g)
1	Facing backward, unsupported	0.19
2	Facing sideways, unsupported	0.23
3	Facing forward, holding overhead strap	0.27
4	Facing forward, holding vertical stanchion	0.15
5	Facing forward, unsupported	0.15
	a. Males, high heels	0.15
	b. Males, low heels	0.16
	c. Females, high heels	0.16
	d. Females, low heels	0.10

Source: (Hirshfeld, 1932)

Wilson, 1940 investigated the deceleration distance of high-speed vehicles to understand the braking system of automobiles. He examined the average deceleration required for the vehicle to stop from the speed of 112.7k/h (70m/h) and its impacts on passenger comfort. The study demonstrated that 0.43 g is severe and uncomfortable to passengers because it can slide off objects from the seat (classify as emergence stop by the driver). Sudden jerks on starting or stopping of automobile causes standing passenger to lose balance (Gebhard, 1970). The author demonstrated that longitudinal and lateral accelerations/decelerations acceptable for passenger comfort based on rider rating range from 0.11 to 0.15 g and 0.06 to 0.22 g.

Hoberock (1977) investigate the discomfort of seated and standing passengers. The author found that the average acceptance rate of the seated passenger's acceleration can be as high as 0.5 g or more while standing passenger in public ground systems cannot exceed the acceleration value of 0.16 g before perceiving a significant level of discomfort (Figure 2-1). However, the study concluded that it is difficult to set a standard limit of acceleration or jerk at which passenger loss balance. The passenger's ability to retain balance varies from person to person. Therefore, the study suggested a range of 0.11 g – 0.15 g as the maximum permissible accelerations.

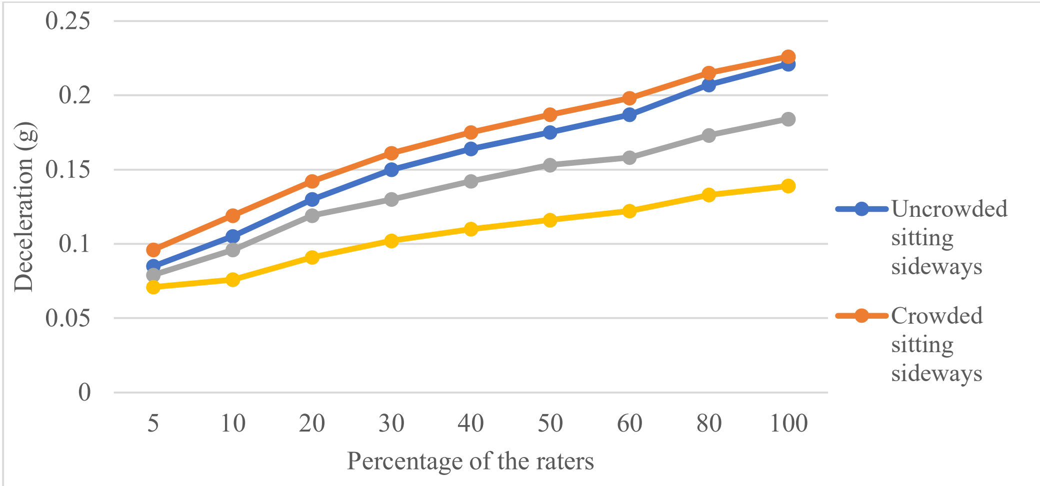


Figure 2-1: Average permissible deceleration for passenger comfort in ground transport
Hoberock (1977)

A sharp increase in acceleration/deceleration tends to increases the likelihood of injury to the passengers, thereby degrade safety (Abernethy et al., 1977). Abernethy et al., (1980) used an instrumented vehicle controlled by automatic brake system to determine the maximum deceleration and jerk level tolerated by the passenger sitting in an automobile. The participants were exposed to an average deceleration of 0.25g and 0.75g and average jerk of 1.25 g/s. Seat sensors and passenger ratings were used to collate the deceleration at which passengers began to move off their seat. The study results demonstrated that seated passenger facing forward or backwards feels discomfort at a deceleration of 2.45 m/s^2. In comparison, the limit longitudinal acceleration for a passenger seated and facing side is 1.4 m/s^2.

2.3.3 Passenger Ride Comfort and Road Surface Irregularity

The essence and significance of providing an even road surface on reconstructed and newly constructed roads have been recognised in the United Kingdom for a very long time recognised. The essence of even road surface documented in the standard of road profile attributes required by the Department of Transport specifications for constructing road and bridges (Cooper et al., 1978 part 1). Road roughness has been an essential factor in investigating and evaluating the roadway condition because it influences the driver and passenger ride comfort. Urban bus passengers are sometimes across some rough roads that could expose them to whole-body sensations higher than the action value set by European Union directive of 2002/44/EC. These could result in the suffering of stress-related heart diseases and even musculoskeletal poor conditions in the neck, back and shoulders (Sezgin and Arslan, 2012). Road vehicle's ride comfort primarily depends on the roughness of road surface, vehicle suspension system and vehicle speed. These factors combined to form or produce body sensations that could initiate a different form of passenger discomfort, cause pain or injuries to the passenger and driver (Austroads, 2007). Human response to vehicle speed profile, rough road, and other factors through the passenger's seat, the vehicle floor, and weight in the frequency range of human sensitivity. These sensations influence the level of perceived comfort, affects performance and could lead to long-term health effects of the subject (Nahvi, 2009; Swedish Road Administration, 2005).

The assessment of road roughness's influence on vehicle ride comfort depends on the vehicle's dynamic attributes and the travelling speed (Soliman, 2006). The degree of road roughness provides information about the road profile quality, without any direct measurement of ride comfort perceived by the vehicle occupants. Therefore, ride comfort is dependent on the interaction between the vehicle and road characteristics. Road pavement roughness causes vibration phenomena and usually reduces the driver and passenger ride quality. It increases user fatigue, discomfort and reduces vehicle load-transmission, particularly steering and braking actions (Cantisani & Loprencipe, 2010). The study of Soliman, 2006 investigate the effect of road roughness on the vehicle ride comfort and rolling resistance. The author developed a mathematic model to evaluate the vehicle ride comfort. The author found that the passenger ride comfort deteriorates as the road roughness coefficient increases. As the road roughness coefficient increases, the rolling resistance force induced by road roughness also increases. Road roughness is indirectly associated with urban bus passenger ride comfort (Swedish Road Administration, 2005). It is assessed by the International Roughness Index (IRI) and can be linked with induced detrimental effects in driver and passenger ride comfort (Loprencipe and Zoccali, 2017). However, the assessment quantity provided by IRI is different from ride vibrations perceived by the passengers. Therefore, IRI assessment cannot adequately evaluate ride comfort because the performance indicators were based on the vehicle axle and body (Blum, 2015). The result of several vehicle simulation studies revealed the driver/passenger ride comfort controlled by vehicle dynamics are the suspension stiffness and damping, tire pressure, and speed of the vehicle (Zehsaz et al., 2014).

Cooper et al., 1978, part 1 used a laboratory experiment to investigate the relationship between road surface irregularity and driving style and quantified in the form of comfort characteristics curve. The study results revealed that the ride comfort curves increase linearly with speed, vehicle types and road roughness characteristics. They concluded that variability associated with using the root-mean-square acceleration as an approach to evaluate comfort does not exceed 0.004g. Gomes and Savionek, 2014 investigate cyclist discomfort due to hand-arm vibrations on asphalt, precast concrete slab, and interlocking concrete blocks pavements. The correlation between objective and subjective evaluations demonstrated that riding on asphalt pavement is more comfortable than the interlocking concrete blocks. However, rough pavement causes road-vehicle dynamic interactions that vary from place to place as well as causing a significant decrease in the driver and passenger comfort. Comfort is difficult to evaluate objectively because the perception of the users' dynamic effects also needs to be considered. Therefore, the useful indications for the objective evaluation of both roughness pavements and passenger ride quality could be achieved solving equations that describe the mechanical system on a riding vehicle (Cantisani & Loprencipe, 2010).

2.3.4 Comfort Models

Discomfort could be interpreted as an unpleasant state of human body reaction to its physical environment. However, there is no generally accepted definition of comfort or discomfort (De Looze et al., 2003). However, it is a feeling or an emotional state that are subjective. Also, long man dictionary of contemporary English defines comfort as "*the absence of pain or suffering and having all one's bodily wants satisfied; discomfort is lack of comfort"*. Discomfort occurs as a result of people interacting with the environment that affects their physiological and psychological state. Presently, evaluation of comfort or satisfaction derived from products or services has developed to a stage that the end-users consider and producers or services providers also see comfort as a significant selling point. The level of comfort or satisfaction plays fundamental roles in product-buying and services-using decisions.

Generally, to formulate a hypothesis or build a conceptual framework or develop a comfort model that can evaluate discomfort for shape optimisation purposes, a model relates psychological, physiological or emotional response to induce experimental design variable or phenomena. Vink & Hallbeck (2012) pointed out three major stages that need to occur before discomfort can perceive (Figure 2-2). The stages are interaction (I), effect in the internal body (E) and perceived effects (P).

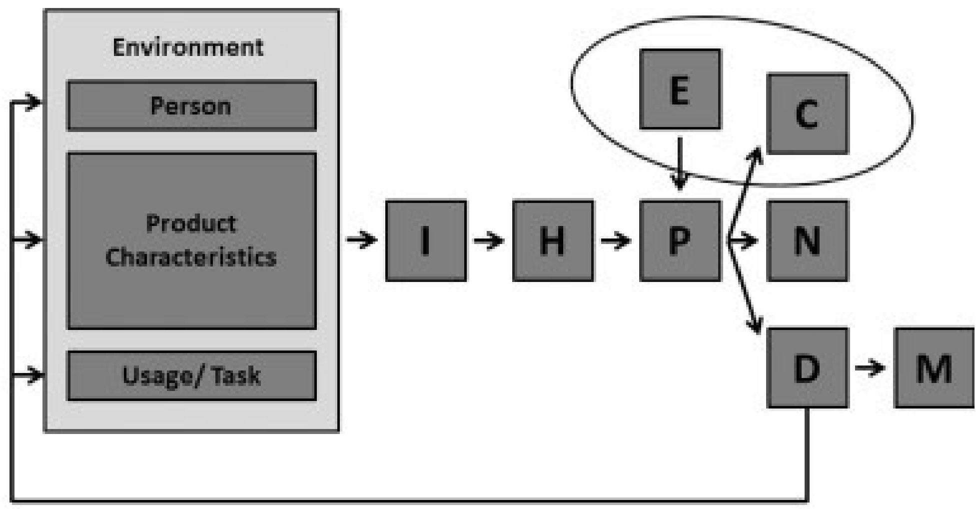


Figure 2-2: The proposed comfort model
Source: (Vink & Hallbeck, 2012)

The authors used the concept of interaction (I) between a person, product, and usage/tasks in an environment to propose a comfort and discomfort model, which was inspired by Moes's study, 2005 and Looze et al., 2003. The interaction produces an internal human body effect (H). As the body posture change, tactile sensations, muscle activation, and the perceived effects (P) influenced by the body affect and expectation (E). Therefore, this cause-effect could either results to comfort (C) or feel nothing (N) or interpreted as discomfort (D) that produce musculoskeletal.

The proposed dose-response model of Armstrong et al. (1993) is characterised by four sets of interacting variables (exposure, dose, capacity and response), such that the response at one phase can act as a dose at the next phase (Figure 2-3). In this model, exposure refers to the external factors that cause the disturbance of the individual's internal state (dose). This disturbance is classified as mechanical (tissue forces and deformation that occur due to exertion or movement of the body), physiological (such as consumption of metabolites, ion displacement and tissue damage) or psychological disturbance associated with anxiety resulting from workloads. On the other hand, the response refers to as changes that may occur in the psychophysiological state of individual due to the extent at which the external exposure leads to an internal dose such a change in temperature, ion concentrations or shape of tissues. The study reveals that one response can result or lead to the new dose that results in another response. For instance, an exertion in any part of the body can result from changes in tissue shape and metabolite levels, which in turn cause discomfort. The authors define capacity as the ability of the individual to resist the psychophysiological destabilisation.

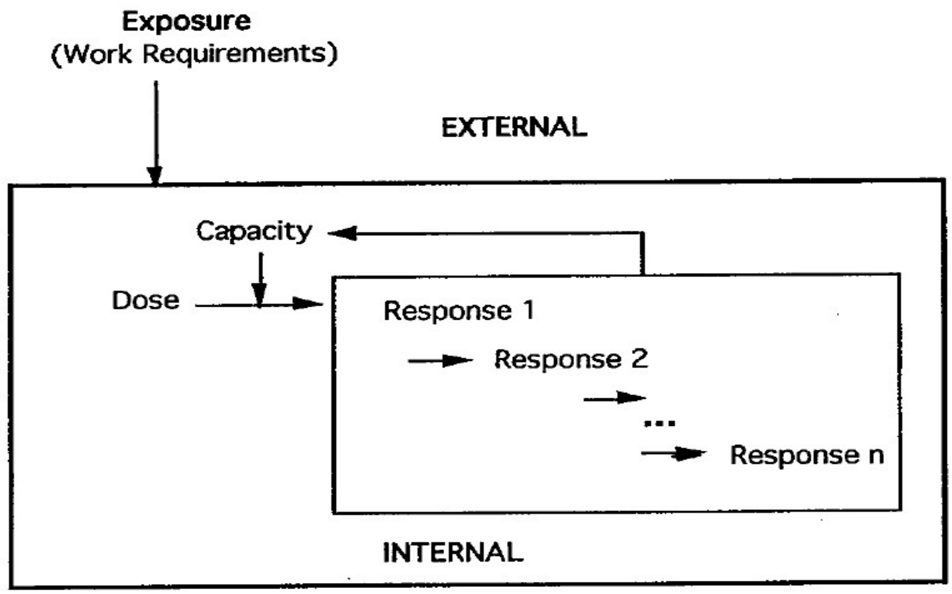


Figure 2-3: The proposed model of Dose-Respons*e*
Sources: Armstrong et al. (1993)

2.4 Assessment of Driver Fatigue

The constant advancement in technology and necessity to travel makes modern society rely on general twenty-four hours of operations in the transport sector (rail, aviation, haulage or bus), health care sectors, military and many public and private services. These factors expose many people to different working hours at a different time of the day, which could cause severe disruptions in sleep and circadian rhythms. The side effect is that it brings about fatigue, reduced waking alertness and impaired performance and ability (Bonnet, 1985). Three significant factors describe how and why sleep-related accidents: duration of time spent on a task, time of the day and rest deprivation. Therefore, there is evidence of performance decrements, when humans' continues performing a task over a long time (Parkes et al., 2009).

Driver's fatigue often arises from long hours of continuous driving or sleep debt, especially if a person has been deprived of sleep twenty-four hours before the driving task. Therefore, fatigue's psychological and physiological aspects need to be investigated to understand its causes-effects on the driver. The more the driver(s) continues, the more fatigued they become. Fatigue has modelled in both transport and non-transport researches. There are many fatigue-related incidents or accidents of the truck driver in both short and long-haul trucking across the globe (ROSPA, 2001). Fatigue in HGV drivers often causes significant risk to other road users. Its general consequence is impaired human efficiency, feeling extremely tired and generally unwell, and, most importantly, continuing the current task after becoming aware of fatigue (Phillips, 2015).

The human physiological abilities and limitations are critical factors in maintaining productivity and safety in all transport industries (including truck driving). Fatigue is psychophysiological; therefore, human psychological and physiological factors related to fatigue must be defined, examined, and measured to understand it (Phillips, 2015). Fatigue is a transition period between awake and sleeps that is gradual, cumulative in-process and capable of reducing efficiency, alertness and mental performance (Lal & Craig, 2001). It is abstract and multidimensional (Phillips, 2014). Furthermore, the study of Nilsson et al. (1997) described fatigue as an experience of tiredness that arises from a person psychophysiological state. For instance, the metabolic condition, level of attention, heart rate, and respiration could result from the disliking of the present duty/activity and unwillingness to continue. Phillips (2014) describes fatigue as the suboptimal psychophysiological disorder caused by physical or mental effort. The degree and dimension of the condition of fatigue vary and depend on the form, dynamics and context of exertion. Whereas, the context of exertion is the value and meaning of performance to the individual; rest and sleep history; circadian effects; psychosocial factors, spanning work and home life; individual traits; diet; health, fitness and other individual states; and environmental conditions (Phillips, 2014).

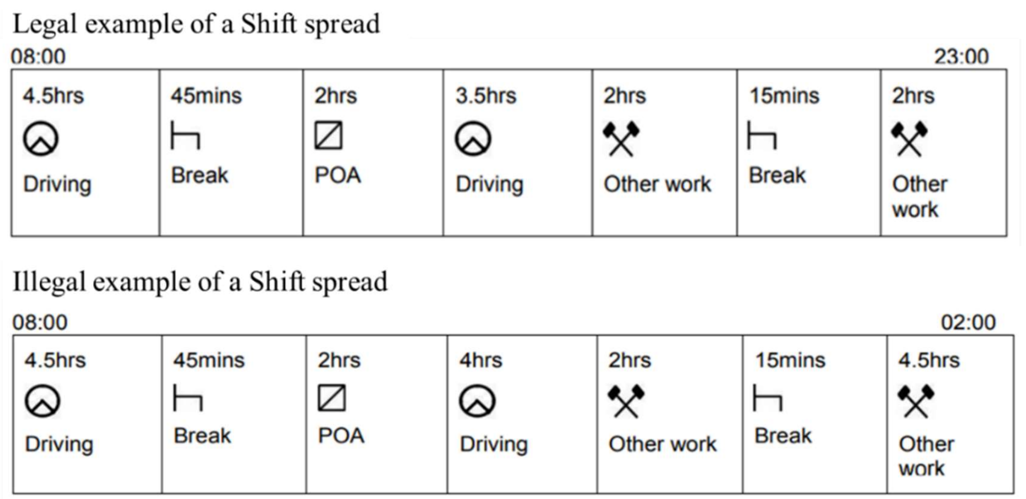
The length of working hours, the arrangement of duty, time available for rest, and the number of sleeping hours within each 24-h cycle interact to contribute to the human level of fatigue. Rosekind et al. (2000) revealed that an understanding of sleep and circadian rhythms play a fundamental role in evaluating fatigue. Asleep loss affects some aspects of the human system, which are not limited cognitive processes, physical coordination, vigilance, judgment, or decision-making. Therefore, factors that affect the circadian system and sleep are likely to affect fatigue. For instance, the study of Wu et al. (2017) used the combination of a subjective approach (KSS fatigue assessment) and video recognition technology to evaluate drives' level of fatigue. The experiment was carried out in a laboratory equipped with driving simulator, computers, cameras, projector and brain wave equipment. The authors found that the method based on the rough set theory fusing multi-index decision to judge the drive fatigue level is accurate than single index detection method.

Dorrian et al. (2011) demonstrated that sleeping less than five hours in twenty-four hours before work will negatively influence the likelihood of fatigue-related error at work. HGV drivers' activities are characterised by unscheduled operation(s) and extended duty time due to unforeseen circumstances resulting in prolonged driving time. Changes in schedule and other additional tasks such as fuelling and load/offload contribute to local and long-distance haul fatigue. The possibility of driving hours to cause fatigue has been identified long ago as a severe transport problem. It is known to be one of the significant factors contributing to road accidents across the globe. Prolong driving bring about the intensification of fatigue and affects driver cardiovascular and neurophysiological functions (Bonnet, 1985). It could also affect alertness and fatigue driver operating on day to day scheduled and unscheduled trips. It is driving fatigue limited drivers' ability to respond effectively to unexpected situations, whereas these pose a significant risk to the concern's drivers and other road users. Despite that studies highlighted the contributions of driving fatigue or performance decrement to road crashes/accidents, the relationship between driving fatigue and duration of driving it is still less clear (Parkes et al., 2009). Fatigue had different effects on driving. There is a significant relationship between drowsiness-related factors, factors that might counteract drowsiness, duration of driving and rest break and crash risk.

Cummings *et al.*, 2001 pointed out that fatigue is a major contributor to the road crash risk. The risk of accident increased exponentially relative to increases in driving time. The authors found that road accident risk was significantly less for drivers who used a highway rest to stop and drink coffee within the last two hours. Department for transport, 2014 points out that there is no daily limit on the amount of working time for drivers in one day. A total of nine hours daily driving limit can be increased to ten hours twice a week and maximum fifty-six hours weekly driving limit or maximum ninety-hour fortnightly driving limit. However, the driver has 45 minutes of rest break after 4 hours and 30 minutes of driving. The rest break can be split into two periods, the first being at least 15 minutes and the second at least 30 minutes that must be completed after four hours and thirty minutes of driving. The Department for Transport suggested that the driver could have included additional rest break of a minimum of 30 minutes in between the final four hours of driving If the driver had taken less than 45 minutes to rest on the journey. However, take an additional 30 minutes rest break at the destination would have complied with split breaks rules. Therefore, the day's work would become legal due to the splitting of a rest break before four hours and thirty minutes of continuous driving

(Department for Transport, 2014). The regulation (EC) No. 561/2006 and British domestic drivers hour regulations defined drivers of large commercial vehicles and passenger vehicles subject to EU driver rules limiting driving time and a rest break. The regulation exempts drivers who do not drive for more than four hours on each day of the week from the daily limit (Parkes et al., 2009).

The example in the figure below shows the legal and illegal spread of day shift. The illegal driving shows fifteen hours of a shift from the start of the shift to reduced rest of nine hours within the twenty-four hours from the beginning of the workday. While the illegal shift fifteen hours working time was recorded, and the shift spread of the shift is 18 hours leaving only six hours with the twenty-four hours from the start of the working day for a daily rest period.



Source: Department for Transport, 2014

Figure 2-4: European Union driving hours regulations

Duration of driving and rest break is closely associated with driver fatigue or performance decrement (Chai et al., 2017; Mu et al., 2017; Yin et al., 2016). However, there is inconsistency in the literature on the average time requires to drive to prevent road crash. For instance, Horne and Reyner, 1995 found that the majority of the sleep-related accident of HGV usually occurs in the first two hours of the driving time. Also, to some extent, the driver hours regulations are flawed. They have criticised increasing road crash occurrence because circadian rhythms are not incorporated with the studies; thereby, required driver rest when awake and drive when sleepy (ROSPA, 2001). Miller & Mackie (1978) point out in his study that there is a significant increase in the participants' coarse steering after four to five hours of driving. The previous study also shows that the driver must ensure that they take no less than 30 minutes of break after no more than four hours of driving (Parkes et al., 2009). Besides, Horne and Reyner, 1999 points out that the EU regulations on drivers driving hours do not seem to base on any evidence of safe driving times. The regulations were designed to checkmate the drivers for driving the unreasonable length of time without a rest break. The amount of time they can drive a day and the amount of time they are on duty with a reasonable rest period, the regulation still authorises drivers to drive for a long time (ROSPA, 2001). For instance, the EU drivers' hours regulations stipulated that drivers can drive up 4 hours and 30 minutes without a rest break or even more. There is a significantly flawed in drivers' hours' regulations (Department for Transport, 2014, ROSPA, 2001).

Several approaches have been used in space and time to investigate fatigue. A qualitative research technique (questionnaires and Focus Group Discussion) have used to investigate drivers and pilots fatigue (Rosekind et al. 2000, Hanowski et al. 2003, Naweed et al. 2015, Filtness and Naweed 2017). For instance, the study of Filtness and Naweed (2017), used data gathered from FGD to evaluate the contributions of fatigue to Signal passed at danger (SPAD) using the train driver's perception. Drivers with less than one year and those with more than ten years driving experience were sampled. There was an emphasis on why they experience fatigue, how fatigue impacted their work, and what they usually do to control its effects. The authors found that there is reliable evidence that fatigue increases the risk of safety in road transport. Hanowski et al. (2003) investigated fatigue in local/short-haul trucking. The drivers provided their view on issues of safety and fatigues. Data was gathered from eleven (11) FGD conducted in eight cities, across five states. Information on driver alertness, performance measures, attention and near-accidents or critical incidents was gathered and analysed. The study results demonstrated that drivers who perceived fatigue and involved in local haul driver at-fault incidents affected by their quantity and quality of sleep compared to those who do not show sign of fatigue. The actual length of continuous work and daily working hours, the arrangement of duty, time available for rest, and many sleeping hours within each twenty-four hours cycle interact to contribute to the human level of fatigue. A survey of fatigue factors was conducted in an aviation company in the US by Rosekind et al., 2000. The factors that can be measured to indicate fatigue were performance, perceptual, electro-psychophysiological and biochemical measurement. The authors used 107 questions questionnaire that targeted six main areas of the respondents (demographic characteristics, sleeping habit, flight experience, duty/rest pattern, fatigue and work environment). The results showed that 49% of the respondents believe that they usually experience fatigue during extended day duty, while 40% often experience fatigue during early morning departures. The corresponding percentage of the respondents that usually experience fatigue due to multiple flight legs, night flight, workload, consecutive duty days are 33%, 26%, 15% and 14% respectively. Also, 15% always experiencing fatigue whenever they cross time zone, while 10% are due to weather/turbulence, and 15% are usually due to long waiting.

2.5 Human Brain Activities and EEG

The brain is the most complex organ in the body that controls all body responses to internal and external stimuli through the nervous system (Namazi and Kulish, 2015). Scientists revealed that the human brain consists of a hundred billion neurons. It consists of right and left hemispheres and right hemisphere is associated with cognitive activities such as the ability to understand, think, remember, perceive and emotional feelings, while left side performing the language, arithmetic, analysis and speech (Fuad and Taib, 2014).

2.5.1 Mechanism of Human Brain Sensitivity

The brain fills the cranium and consist of four major parts; the brain stem, diencephalon, cerebellum and cerebrum. The thalamus is known to form part of the limbic system, which is associated with the emotions or feelings because it recognises to be the final transmit region for data or information before transfer to the cerebral cortex. The specific nuclei are responsible for scanning the cerebral cortex to determine the brain's active parts. Most importantly, those firing at around 40Hz and transferring this information to the rest of the thalamus. The brain electrical current generally comprises NA+, K+, Ca++, and Cl-ion regularly pumped through the neuron membrane channels (Souza et al., 2014). However, one way to understand the brain's activities and evaluate its response to stimuli is Brain-Computer Interface (BCT). BCI refers to a system that translates "brain signals into new kinds of outputs" (Daly & Huggins, 2016). BCI translates brain signal into messages relative to an external stimulus (Daly & Huggins, 2016). It is a process of collating the brain signal and extracts signal features that have proven useful for task performance. Souza et al. (2014) point out that the bio-potential electrical signals originated from the brain can be detected by invasive (surgery) and non-invasive (measurement from the surface).

The nervous system receives information relative to the human environment (sensation) and generates responses relative to the information's types and magnitudes (motor responses). The nervous system divided into parts responsible for sensation (sensory functions) and response (motor functions). Its detects, process and response to changes within the body system and external environment. (Mitsukura et al., 2009). For instance, homeostatic is an example of a nervous system that sense changes, interpret the changes and automatically adjust to the changes. The nervous system is divided into the Central Nervous System (CNS), consists of the brain and the spinal cord and the Peripheral Nervous System (PNS). The PNS consists of the Somatic Nervous System (SNS) and Autonomic Nervous System (ANS), including the sympathetic and parasympathetic. Changes in psychophysiological states influence the brain that rules the sensation centre (Mitsukura et al., 2009). This change could be in forms of internal or external body sensations transmitted by receptor to the CNS. Previous studies demonstrated that brain response to the stimulus is not limited to the pleasant and unpleasant olfactory stimuli, emotional stimuli, periodic simulations, silence and random noise, visual stimuli or auditory stimuli (Namazi & Kulish, 2015). However, the brain responses depend on the type, magnitude and the location of the stimuli.

2.5.2 Introduction to EEG

The EEG is a visual record of the bioelectrical activity of the brain. It was first measured and described in 1929 by Hans Berger. The cerebral cortex produces bio-electrical activity due to the body cells' electrical activity, which changes relative to the mental condition, cerebration and emotion (Mitsukura, 2016). The word electroencephalogram was first used by Berger to described humans brain electric potentials (Rahman et al., 2012). EEG records the brain's bio-electrical activity by placing electrodes on the scalp (Teplan, 2002). EEG is a non-invasive brain imaging modality that uses sensors characterised by time resolution to record brain activity on motor behaviours' time scale. It is portable for subject locomotive or vehicle on-board survey (Gwin et al., 2010). The degree of the portability and weight (light) of the EEG systems allows for flexible data collections in real-world stable or dynamic environments (Imotion Users Guide, 2019; Cohen, 2011). An excellent temporal resolution of EEG makes it widely used as an experimental technique to investigate human brain function by tracking the temporal neural dynamics (brain activity) correlated to experimental events (Mognon et al., 2011). Winkler et al. (2011) revealed that EEG reflects the brain's spontaneous electrical activity and activity specific to a well-defined experimental event(s).

EEG is a sophisticated device in neurology and neurophysiology due to its ability to reflect the normal and abnormal electrical activity. Previous neuroscientific research conducted to establish the relationship between EEG signals and cognitive processing or behavioural changes has led to neurology theories (Cohen, 2011). According to Souza et al. (2014), brainwaves usually form sinusoidal shapes in nature, ranging from 0.5 to 100 µV in amplitude and lower in about 100 times than EEG signals. Most cognitive processes usually occur within tens to hundreds of seconds, and the events activating cognitive processes occur in time sequences that span hundreds of milliseconds to a few seconds (Imotion Users Guide, 2019; EEG Pocket Guide, 2016). Therefore, EEG is one of the best approaches to evaluating brain dynamics associated with perceived comfort disturbance in a motion environment mainly because of its high temporal resolution and portability (Yu et al., 2010). EEG is characterising with high time resolution and capable of captures cognitive, perceptual emotional and others within the time frame which the cognition processes occur.

Furthermore, it can capture the physiological changes underlying the cognitive processes better than other brain imaging techniques such as Magnetic Resonance Imaging (MRI) and Position Emission Tomography (PET) scanners). However, MRI has a significant spatial resolution, but measures neural activity indirectly, therefore MRI requiring an in-depth understanding of the relationship between what is measured and how it relates to cognitive processing (Cohen, 2011, Imotion Users Guide, 2019). These qualities make EEG the right tool for collating data for research that require precise timing of cognitive, attentional and emotional processing (Cohen, 2011).

The Mandalay is one of the first research-grade customisable EEG Neurofeedback headsets incorporated directly into Visual Reality (VR) headsets, which allowed brainwave activity to go beyond the lab screen into the real world. It is characterised by a dry sensor on the forehead and two sensors on the ear to measure brainwave activity at 512Hz (Rahman, 2012). The collected data transmitted via Bluetooth to a window base device in real-time. Generally, Myndplay (EEG) measures the brain's electrical potential responses that flow during the dendrites' synaptic excitations in the cerebral cortex (Rahman, 2012).

2.5.3 EEG Frequency Bands

The event-related models, which focus on EEG activity evoked by sensory stimuli or bodily movement onsets, frequency-based EEG analysis methods allow the oscillatory activity of specific frequency bands related to the cognitive-affective states, engagement and motivation (Cohen, 2011). EEG signal has a wide range of frequency bands, though clinical and physiological studies interest is concentrated on the frequency of 0.5 to 30 Hz. The EEG Frequency refers to the oscillation speed and has the unit Hertz (Hz), the number of oscillations per second (Imotion Users Guide, 2019; EEG Pocket Guide, 2016). This frequency range is divided into delta, theta, alpha, beta and gamma frequency bands (Yildirim & Varol, 2016). Delta waves are characterising by frequencies range of 0.5 - 4 Hz and an amplitude of 20 - 400 µv. It is encountered when the brain shows very low activity. Theta brain waves frequencies range from 4 to 8 Hz, and amplitudes vary from 5-100 µv. Delta frequency band usually encounters healthy individuals whenever there is low brain activity such as dreaming sleep, medium depth of anaesthesia and stress. Alpha wave frequencies range from 8 - 13 Hz, and amplitudes vary between 2 - 10 µv. They appear in the state of the physical and mental rest state, absence of external stimulus, closed eyes of individuals in the awake state. At the same time, beta waves frequencies are more than 13 Hz and characterised with amplitudes vary from 1 - 5 µv. Beta EEG frequency band is encountering in the phase of focused attention, mental work, sensory information processing and tension (Figure 2-5).

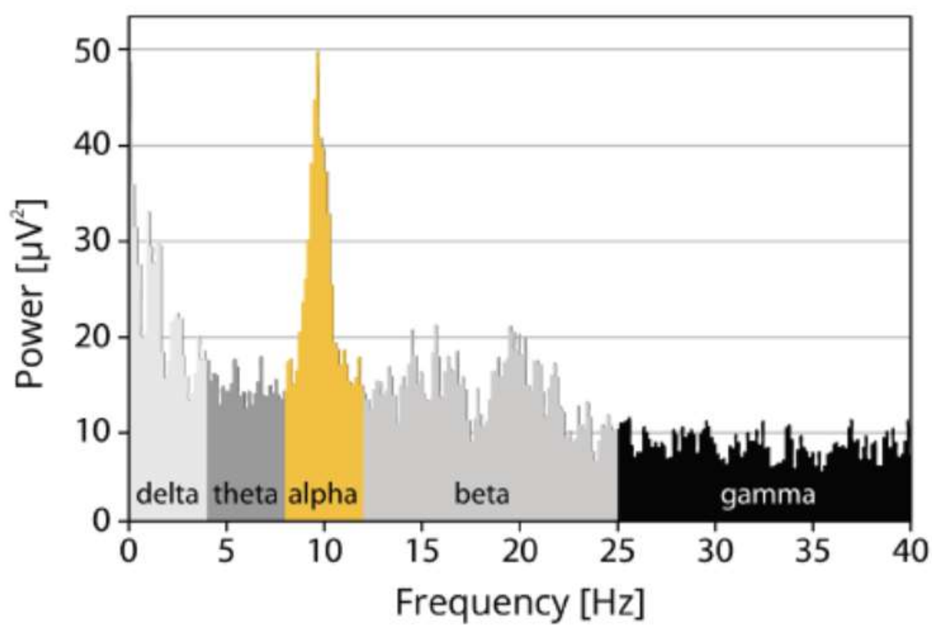


Figure 2-5: EEG brain frequency bands
Sources: (Imotion Users Guide, 2019, EEG Pocket Guide, 2016

Although EEG frequency bands classification varies over time, for example, the study of Taghizadeh-Sarabi, et al., (2013) presented the EEG power spectrum as delta (1–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz) and gamma (from 30 HZ). The EEG frequency bands are delta 0.5–3.5 Hz; theta was 3.7–7.5 Hz; alpha was 7.5–13.5 Hz; and beta was 13.5–22 Hz (Shulman et al., 2006). EEG frequency bands are classified into; delta: <4 Hz; theta: 4-8 Hz; alpha: 8-12 Hz; beta: 12-30 Hz; and gamma: 30-70 Hz or higher (Stelt and Belger, 2007; Teplan, 2002). Neurosky, 2011, point out that EEG power data value represents the current magnitude of 8 commonly recognised types of EEG frequency brainwaves. The frequency bands includes eight 4-byte floating-point numbers of delta (0.5 - 2.75Hz), theta (3.5 - 6.75Hz), low-alpha (7.5 - 9.25Hz), high-alpha (10 - 11.75Hz), low-beta (13 - 16.75Hz), high-beta (18 - 29.75Hz), low-gamma (31 - 39.75Hz), and mid-gamma (41 - 49.75Hz). Whereas, Fuad and Taib, (2014) revealed that the neural oscillations could be measured with EEG. The frequency ranges from gamma (40 – 80 cycles per second), beta (13 – 39 cycles per second), alpha (8 – 13 cycles per seconds) theta (4 – 7 cycles per seconds) to delta (0.5 – 4 cycles per seconds). Also, Imotion Users Guide, 2019 and EEG Pocket Guide, 2016 distinct the EEG frequency bands as delta band (1 – 4 Hz), theta band (4 – 8 Hz), the alpha band (8 – 12 Hz), the beta band (13 – 25 Hz) and gamma band (> 25 Hz) see (Figure 2-6). However, the EEG phase values have no units or scale of measurement; it will be only meaningful compared to each other and themselves in terms of their relative quantity and temporal fluctuations or oscillations (Imotion Users Guide, 2019; EEG Pocket Guide, 2016).

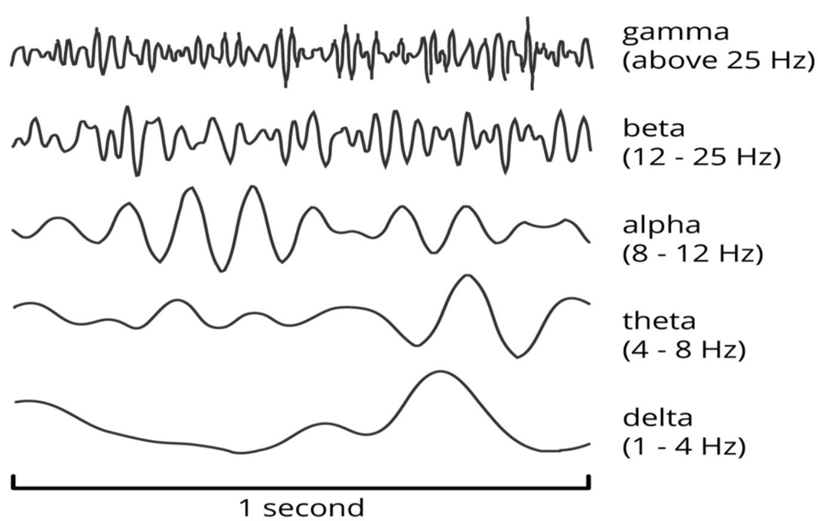


Figure 2-6: Brain frequency bands (ranges)
Sources: (Imotion Users Guide, 2019; EEG Pocket Guide, 2016; Rahman et al., 2012)

The EEG is a complex quasi-rhythmical signal within a time-frequency band of 0.1 - 100 Hz and hundreds of microvolts' amplitude at the scalp. The frequency range is 0.5 - 50 Hz and divided into five bands for clinical reasons (Zamora, 2001a), which the power is;

I. Delta (δ) activity: [0.5 - 4] Hz
II. Theta (θ) activity: [4 - 8) Hz
III. Alpha (α) activity: [8 -13] Hz
IV. Beta (β) activity: [15 - 25] Hz
V. Gamma (γ) activity: [30-50] Hz

2.5.4 Beta EEG Frequency Band

The beta EEG frequency band integrates the multi-modal cerebral cortex responses relative to the experimental design phases and variables. Beta EEG frequency band is one of the four periodic rhythms recorded in the EEG. Its amplitude range between 5 and 10 μV (Yao et al., 2009). The beta EEG frequency band integrates the multi-modal cerebral cortex responses relative to internal or external stimuli. ERPs are known to be a suitable approach for investigating both normal and abnormal aspects of cognitive processes. The fluctuations in power (amplitude) of EEG frequency bands are associated with diverse brain states, such as increased beta brain activity associated with alertness or cognitive demands (Mavros et al., 2016). Also, a significant increase of EEG power spectra in the beta band demonstrates an increase individual level of arousal and alertness (Borghini et al., 2014, Okogbaa et al., 1994), and following this stress has found caused an increase EEG beta band power (Saeed et al., 2018; Saeed et al., 2017). Previous studies indicate that single-channel EEG can be used to examine emotion at the front region and cortical activation in the brain during the induced stress stimulus indicated a significant increase in beta brain activity (Al-Shargie et al.; 2016). Another study found that the negative linear relationship between the power ratio of beta brain activity and the subjective score indicates stress (Abdul-Hamid et al., 2010). Therefore, beta brain activity varies (increased) relative to stimuli difficulty (Saeed et al., 2018; Al-Shargie et al.; 2016). However, an interpretation of significant changes in beta EEG brain wave ranges from the optimal (baseline) to too little or too much as detailed in Table 2-3.

Table 2-3: Interpretation of EEG frequency bands

Brain wave	Too Much	Optimal (an idea or best)	Too little
Gamma	Anxiety, High arousal and stress	Information processing, learning perception and rem of sleep	Depression, learning disability
Beta	Anxiety, high arousal and inability to relax and stress	Conscious focus, memory and problem-solving	Daydream, depression and cognition
Alpha	Inability to focus and too relax	Relaxation	Anxiety, high stress, insomnia
Theta	Depression, hyperactivity, impulsivity and inattentiveness	Creativity, emotional connection, intuition, relaxation	Anxiety, poor emotional awareness and stress
Delta	Brain injuries, learning problem, inability to think	The immune system, natural healing, restoration or deep sleep	Anxiety, poor emotional awareness and stress

Source: NeuroSky, 2011

2.5.5 eSense(cm) Meters (Attention and Meditation)

Attention and meditation eSenses, the meter value is presented on a relative eSense scale of 1 to 100. The unsigned one-byte value reports the user's eSense attention meter indicated the user's mental focus level during intense concentration and directed (but stable) mental activity (Zhu et al., 2015). However, distractions, wandering thoughts, lack of focus, or anxiety may lower the attention meter levels (Baltar & Filgueiras, 2018; Chow, 2014; Neurosky., 2009). Meditation eSense, on the other hand, refers to as the unsigned one-byte value reports the current eSense meditation meter, which indicates the level of user's mental calmness or relaxation. Meditation is the extent of a person's mental levels, not physical levels; therefore, simply relaxing all the body muscles may not immediately result in a heightened meditation level (Chow, 2014; Eberth & Sedlmeier, 2012). However, relaxing the body often helps the mind to relax. Meditation is related to reduced activity by the brain's active mental processes, and distractions, wandering thoughts, anxiety, agitation, and sensory stimuli could reduce meditation eSense meter (EEG Pocket Guide, 2016).

The signal processing was conducted using the NeuroSky's MindSet Research Tools (MRT). The eSense metric of attention interpreted following the NueroSky eSense meter scales. The eSense metric value of attention reported on a relative ***eSense scale of 1 to***

100 (Neurosky., 2009), in which any values between ***40 and 60*** are considered "neutral", and is similar in notion to "baselines" that are established in conventional EEG measurement techniques. The value from ***60 to 80*** considered slightly elevated. It may be interpreted as levels being possibly higher than normal levels of attention or meditation. Also, values from ***80 to 100*** considered elevated, indicating heightened levels of the eSense. The values between ***20 and 40*** indicate reduced levels of the eSense. In contrast, the value between ***1 and 20*** represent strongly lowered levels of the eSense, which could be interpreted as an indication of the states of distraction, agitation, or abnormality (Imotion Users Guide, 2019; Neurosky, 2010). An eSense meter value of 0 is a unique value indicating the Myndband cannot calculate an eSense level with a reasonable amount of reliability that might occur due to excessive and uncontrollable noise levels.

2.5.6 Event-Related Potential (ERP)

Brain frequencies provide an avenue to combine analysis of sensory and cognitive functions of EEG or MEG at the level of a single neuron and the field of potentials (Basar et al., 1999). Changes in ongoing or spontaneous EEG brain activity that term as oscillatory responses temporally associated with a specific event(s) (Zhu et al., 2015; Başar et al., 1999). The evoke ERP oscillations in the EEG frequency ranging from delta to gamma represent a group of neural population responses to an event in superposition manners due to transition from a disordered to ordered state (Basar et al., 2000). The practical application of oscillatory neural activity begins to emerge from analysing the relationship between responses to well-defined events such as event-related oscillations and phase-or time-locked to a sensory or cognitive (Başar et al., 1999). Basar et al., 1999) point out that brain theory's oscillation shows that EEG oscillations permit analysis and interpretation of sensory and cognitive functions in thinking and feeling in the human brain and any other freely behaving organism. Evaluating detail frequencies of EEG provides an understanding of the signals' functional cognitive relationships (Başar et al., 1999). The most common approaches are to concentrate on ERPs by averaging and applying event-related oscillations (EROs). The hemodynamic response to neural activity in response to specific events (Cohen, 2011). Therefore, brain activity can be investigated by frequency domain analysis of event-related potential.

In contrast, David et al., 2006 depict that the cortical reactions can be investigated in the time domain to evaluate ERPs or in the time-frequency domain to examine the oscillation activity. However, the evoked power of the EEG can be estimated by average the EEG signal over trials and subject it to time-frequency analysis to produce an event-related response (EER). In contrast, the induced oscillation, on the other hand, can be estimated by apply time-frequency decomposition to each trial and average the power across the trials (David et al., 2006).

The local field potentials (LFPs) and EEG record cortical oscillatory activity as an evoked oscillation that reflects different neuronal processes. Operationally, evoked and induced oscillation phase-relationships with stimulus by the processes of trial averaging and spectral analysis/estimation. The event-related oscillations evaluated relative to a cognitive event(s) can be categorised as an evoked oscillation directly phase-locked to the event or non-phase-locked induced oscillation (Başar et al., 1999). The ERP or evoke potential is a significant fluctuation in brain activity result from induced neural activity in the Central Nervous System (CNS) either from the internal or external stimulus (Teplan, 2002) and known for their high temporal resolution (Zhu et al., 2015). ERPs is a suitable approach for investigating both normal and abnormal aspects of cognitive processes.

2.5.7 EEG Data and Artifacts

One of the most common problems associated with EEG application is that EEG signals usually consist of artefacts with an amplitude that are sometimes higher than those generated by neural sources. Therefore, artefacts in EEG study or experiment refer to the potential difference due to an extracerebral source activity initiating from others tissue (Anderer et al., 1999) and non-phase locked signals non-neural artefacts (Jung et al., 2000). Winkler et al., 2011 revealed that typical artefacts of the EEG data are causing by the non-neural physiological state of the subject such as eye blink and movement, muscle activity and heartbeat, or external technical and mechanical sources (Figure 2-7). Mechanical artefacts in EEG signals are generally associated with a head swing during locomotion or vehicles on-board survey, which may sometime be characterised by amplitude larger in magnitude than the underline EEG signals (Gwin et al., 2010).

This unsigned one-byte integer value that ranges in value from 0 to 200 defines the fidelity of the signal measured by the Myndband (Neurosky, 2010). Any non-zero value indicates that noise is detected and the higher the value, the lesser the data's fidelity. The value is usually output every second and indicates the degree of the most recent measurements (Imotion Users Guide, 2019; Neurosky, 2010). The value of 200 has a special meaning specifically that the Myndband contacts reference does not touch the user's skin. The poor contact could be due to hair in the way, excessive motion of the wearer, when used in some environments characterised by strong electric signals or static electricity build-up in the person wearing the sensor (Neurosky, 2010).

EEG data is highly prone to noise (Gwin et al., 2010) and contaminated by different artefacts such as muscle activity, eye movements and blinks, and several other line noise (Li and Principe, 2006), see Table 2-7. Artefacts also affect the correct analysis and interpretation of ERP (Jung et al., 2000). Therefore it is essential to remove artefacts from experimental data, without altering the underlying brain activity, because artefacts are sometimes characterised by amplitude higher than the EEG signal of interest (Gwin et al., 2010, Li and Principe, 2006). Tran et al., 2009 pinpoint that artefact is always overlapping with brain activity and influences the analysis of ERP(s) EEG data. Therefore, there is a need to understand and identify different artefacts against event-related brain activity to minimise artifactual components. Neurosky, (2010) points out that EEG data filtering technology and eSense™ algorithm were designed to detect, correct, compensate for, account for, and tolerate different types of non-EEG artefacts. However, users interested in using the eSense values (Attention and Meditation) do not need to worry too much about the EEG data-poor signal (Imotion Users Guide, 2019; EEG Pocket Guide, 2016; Neurosky, 2011).

Artefact removal strategy to adopt depends on the aim and objective of the study and data availability. Moreover, careful handling of artefacts is crucial for EEG data processing because what defined as artefacts in some research may sometime become or contain valuable information in another study (iMotions, 2016). One of the most common strategies is to reject all EEG epochs contain artefact higher than some selected EEG voltage value or above the voltage threshold (Jung et al., 2000). Nevertheless, in some cases, data rejection may not be acceptable because it can potentially result in the loss of a large volume of data (Jung et al., 2000). Kerick et al., 2009 investigated the assessment of EEG signal in motion environment to quantify EEG signals' integrity as a function of diverse motion artefacts in the real-life study. The experiment was carried out in three different ambulatory and three-vehicle motion environments. The authors used spectral analyses to characterise the nature and the degree of the artefacts present in each condition of the experiments. They found that brain-related EEG signals could be measured under different conditions, even within moving vehicles which are more dynamic and real than the simulated laboratory settings. The authors concluded that the brain's electrical activity could be reliably recorded in operational environments, such as driving on paved or washboard surfaces. They concluded that advanced artefacts reduction algorithms are required to improve signal fidelity in both ambulatory and vehicle motion environments.

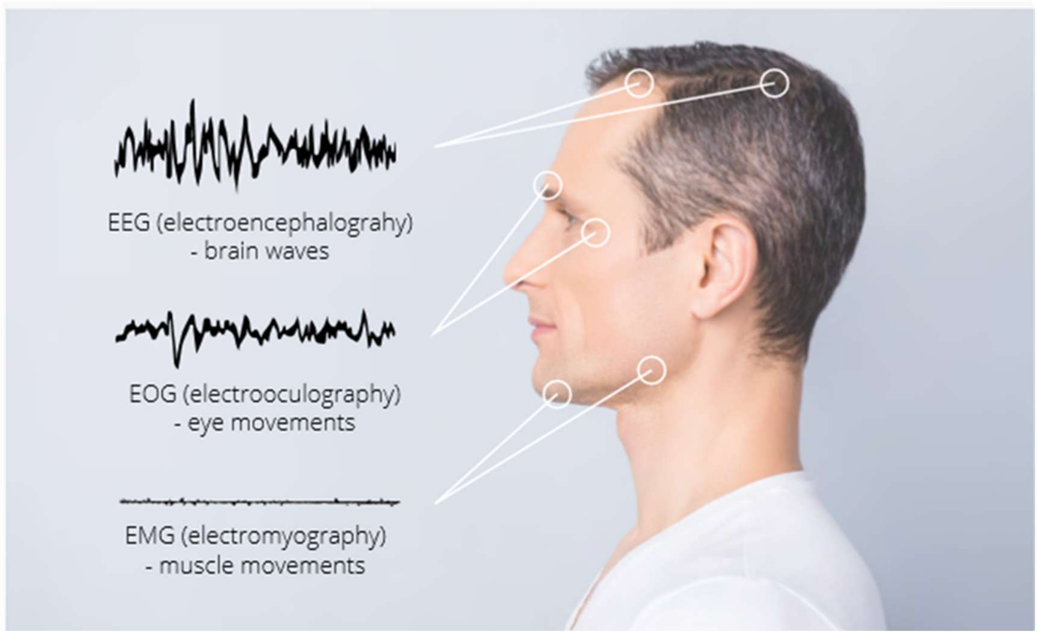


Figure 2-7: External sources of artefacts
Source: (iMotions, 2016)

An approach based on regression in either time domain or frequency domain has been proposed for removing ocular artefacts (Li & Principe, 2006). The authors pointed out that using any of the regression approaches can result in a considerable alteration of relevant brain activity or ERPs, mainly because the electrooculogram (EOG) contain both eye and brain activity.

2.6 Application of EEG

EEG has been used to investigate the systematic change(s) that arises from the specific external or internal event(s), which are temporally related to a sensory, cognitive or motor event. EEG a powerful non-invasive tool for recording bio-electrical signal to obtain data for study brain mechanisms of attention and information in health and disease (Stelt and Belger, 2007). Although recording psychological and physiological response is not a perfect neurocognitive function measurement (Cohen, 2011). However, EEG can provide a direct and real-time index of neuronal activities at a millisecond scale resolution which is relatively easy and inexpensive to utilise (Rahman et al., 2012; Oken and Chiappa, 1988). Despite the limitations of EEG application, it is more preferred to study rapid changes in the pattern of brain activities that underline human cognitive function and dysfunction due to its degree of temporal resolution (Stelt and Belger, 2007). Apart from using EEG in experimental psychology, clinical psychology, and biomedical engineering, it has also been widely used in different application areas such as consumer neuroscience, marketing research, transport research and advertisement, trailer and media testing (iMotions, 2016).

Advancement in technology and interest of many researchers has brought about the recent development in the context of Brain-Computer Interfaces (Biomedical Engineering). The study of Yasui (2009) used two experimental phases to understand the brain's psychophysiological states. An EEG sensor with a dry electrode was used to obtain subjects' brain wave of a 22-year-old student in awake and sleeping states in real-life situations. The morning was characterised by higher frequency due to regular school activities, more low frequencies shown after lunch and higher frequencies observed again during the afternoon class until the end of all school activities. The same author compared the brain activity of 32 years driver, in a condition of driving without using a phone and another condition of driving and receiving a phone call. The author ensures uninterrupted data collection of baseline and post-intervals of the phone conservation (Yasui, 2009). The study demonstrated that using a cell phone while driving created high-frequency components data compared to pre and post driving (without using a cell phone).

Landström and Lundström., 1985 used EEG to monitored change in wakefulness during exposure to whole-body vibration. The authors exposed the subjects to three vibration stimulus sections, and four paused sections for 15 minutes each. An increase in theta and decreased alpha brain activity was found to reduce wakefulness, as the average value of theta activity during exposure always exceeded that of paused. The authors concluded that the sensation evokes during exposure to vibration are transfer to the brain and integrate to produce a subjective response to the stimulus.

2.6.1 Application of EEG for Motion Sickness

The common sickness in real life is carsickness, airsickness, space sickness and seasickness. Motion Sickness (MS) occurred in the occipital, parietal and somatosensory part of the brain, unusually high amplitude and frequency brainwaves pattern of the theta frequency band (4 – 7 HZ) and alpha frequency band (8 – 13 HZ) (Chen et al. (2010; Lin et al., 2007). Yu et al. (2010) used EEG data collected in a realistic driving environment to simulate real-life motion stimuli that consist of seven identical Personal Computers synchronised by Land Area Network. The EEG brainwaves are related to MS in the occipital, parietal, and somatosensory part of the brain and observed a general increase in both theta and alpha bands when the baseline is compared to the MS stage induced stimulus. The authors concluded that the proposed approach could predict the subject's MS level in real-life conditions because it shows the classification performance is greater than 95%.

A VR-based dynamic 3D system consists of a six-degree-of-freedom motion platform that can impose a real-life traffic conditions stimulus to the subject's wad developed. An EEG was used to monitor ten healthy subjects (six males and four females) with no history of gastrointestinal, vestibular disorders and cardiovascular were sampled (Lin et al., 2007). The subjects are not also on any medication and had normal or corrected to normal vision. The experiment was divided into three stages of baseline stage of a straight road, motion sickness stage of consecutive-curve road, and the straight road's final stage for 10 minutes, 40 minutes and 15 minutes respectively. The study results demonstrated that theta brain activity increased relative to motion sickness in the brain's parietal and motor area. A similar approach to Lin et al. (2007) was used by Chen et al. (2010) to examines motion-sickness-related brain response. A VR-based driving simulator that consists of a 32-channel EEG system and a joystick were used for the study. A total of twenty-four subjects with no history of gastrointestinal, vestibular disorders and cardiovascular, no drug or alcohol abuse, and not on any medication and had normal or corrected to normal vision were sampled. The subjects' EEG brain activity was monitored under three different driving conditions (pre-MS, stage of MS and recovery stage of post-MS). A significantly increased alpha power band was found in the somatosensory areas, reflected the dominance of vestibular inputs to eliminate the conflict with subjects' visual perception.

2.6.2 EEG and in-vehicle Driver and Passenger Responses

Human sensitivity induced by vibration factors in a dynamic environment is sometimes challenging to investigate and evaluate due to variation frequency, intensity, and direction. The sensations transfer to the brain and integrate to produce a subjective response to the stimuli and cause a disturbance, unpleasant, annoying, alarming and fatiguing (Landström & Lundström, 1985). The application of EEG is well known to be an approach that is capable of characterising individual brain states in the processing of different semantic categories that makes the application of real-time decode system possible (Muller et al., 2008). The study of Chin-Teng et al., 2005 proposed a system that incorporates EEG spectral estimation, ICA and fuzzy neural network model to evaluate cognitive driver states in a dynamic environment. Chin-Teng et al., 2006 investigate the relationship between driving behaviours and driver ERP responses. The authors classified the drivers into a group of gentle and aggressive driving based on the analysis of ERP variations using analysis of the power spectrum of ICA. Also, in 2008 the research group of Chin-Teng investigated changes in EEG power spectral to examine the dynamic brain responses to the influence of experimental design variables in both time and frequency domains (Chin-Teng et al., 2008). The authors studied changes in EEG response to distraction during simulated driving and found a significant impact of dual tasks on ERP theta EEG brain activity.

Muto et al., (2013) used EEG and electromyogram (EMG), speed profile factors and questionnaire to estimate riding comfort changes of subjects riding a bicycle in a stable experimental room. The authors found that there are variations between subjects EEG patterns relative to riding comfort changes. Chang and Hwang (2011) used EEG data and sensory questionnaire to improve vehicle ride comfort. The result of the statistics obtained from EEG data used to modify the suspension parameters of the vehicle. The authors found a significant relationship between EEG brainwaves and subjective comfort assessment, and they concluded that EEG could assist in understanding and evaluating passenger comfort.

Furthermore, researches showed that human sensations influence the psychophysiological patterns of the brain. Using EEG allows to measure and evaluate human response to external stimulus objectively. EEG and a sensory questionnaire were used to evaluate car ride comfort based on the different vehicle tire types (Mitsukura et al., 2009; Fukai et al., 2009). The authors found a cross-correlation between the subject's EEG brain activity and subjective comfort assessment, which verified the proposed approach's effectiveness. Koizumi et al., (2006) evaluate ride comfort of rail passenger using brain waves and questionnaire. The author used comfort contours measured from EEGs and four patterns of how discomfort was perceived differently by each subject. The author found that the coefficient of determination of multiple regression analysis demonstrated the adequacy using EEG to investigate ride comfort.

2.6.3 EEG and Driver Fatigue

Driving fatigue is one of the leading factors of the road traffic accident, accounting for 14% - 20% (Ma et al., 2019). Fatigue is a transition period between awake and sleeps that is gradual, cumulative in-process and capable of reducing efficiency, alertness and mental performance (Lal & Craig, 2001). It is abstract and multidimensional (Phillips, 2014). The study of fatigue is complicated because of dissociation that sometimes occurs between the experience of fatigue and the presence of psychophysiological indicators of fatigue. For instance, some may feel fatigued even though their psychophysiological state and indicators are normal. Simultaneously, some may not perceive fatigue even though their performance is impaired, and psychophysiological level is an imbalance (Lal and Craig, 2002). Therefore, EEG is capable of measures overall inhibitory and excitatory postsynaptic potentials of nerve cells at different frequencies of delta waves associated with sleepiness and theta waves that associated with low alertness and decreased processing activity (Lal and Craig, 2002).

Several studies have investigated EEG's ability to examine driving fatigue, and it is likely effects on road crash. For instance, Wei et al. (2012) used a self-assessment driving simulator to estimate driving fatigue. EEG was used to collate bio-electric signals of twenty subjects in an experiment conducted in dawn (02:00 – 06:00) afternoon (13:30 – 16:30) and evening (19:00 – 22:00). The authors found that the approach can evaluate the drivers' fatigue level with an accuracy of about 92.3%.

Lal et al. (2003) developed an algorithm for an EEG based driver fatigue countermeasure. The authors used nineteen channels EEG on a sensory-motor driver simulator. A total of ten male subjects with valid truck drivers, licences and with no medical contraindications were sampled. The driving task consists of a 10 minutes familiarisation stage, followed by two hours driving less than 80 km/h until they showed physical signs of fatigue. The observed changes in subjects' brain activity were used to develop the algorithm to identify fatigue levels. The results revealed that the subjects were in the alert phase for about 40% of the study durations. The corresponding average percentage of the durations that the subject was in the transitional phase, transitional to post-transitional and post-transitional are 25%, 20% and 15% respectively. Lal and Craig (2002) study to investigate psychological factors associated with fatigue and the EEG frequency bands most sensitive to psychological factors. Subjects were instructed to sleep for two hours a night before the study to boost the chance of fatigue during the experiment. The authors used data obtained from simultaneous physiological driving task conducted in a temperature-controlled laboratory on a standardised sensory-motor simulator using EEG, electrooculogram (EOG) and video. The video image that showed the physical characteristics and EOG signs of fatigue was used to validate the changes in subject brain activity (EEG) relative to fatigue. Lal and Craig classified the EEG fatigue as drowsiness transitional to post-transitional phase and the early stage of sleep, followed by an arousal phase. The authors found that fatigue is significantly associated with delta, theta and beta brain activity and observed persistent increases in delta and theta brain activity as fatigue progressed from the baselined through transitional to post-transitional phase. The video analysis revealed the changes in EEG associated with the physical sign of fatigue. The more the level of fatigue, the higher the propensity of subjects driving-related error and accident.

2.6.4 EEG and Stress

Stress is known as physical and psychological responses to internal and external emotion/stimuli that usually produces negative body reactions. Stress occurs whenever the body system cannot adapt successfully to environmental conditions changes (Noor Hayatee Abdul-Hamid, Sulaiman et al., 2010). Human discomfort/stress is a form of psychophysiological response to perceived demands and pressures within and without that produces a negative emotional reaction (Subhani et al., 2011). Discomfort is associated with psychophysiological response to any situation(s) that requires homeostasis imbalance, which occurs when there is any significant variation(s) between what it is and what ought to be (Subhani et al., 2011). The extent of stress can be evaluated from the cortical responses using non-invasive neuroimaging approach. The human brain activates neuropeptide-secreting systems in response to stress and demonstrated by changes in EEG power spectral (delta, theta, alpha and beta brain activity) (Subhani et al., 2011). Al-shargie et al. (2018) used bio-electrical activity collated by EEG to evaluate mental stress. The results showed dominant right prefrontal cortex (PFC) to the influence of mental stress (reduced alpha rhythm); therefore, the EEG Power Spectrum ratio could be used to determine human stress.

Acute and chronic stress create functional change in some brain regions such as the hippocampus, prefrontal cortex, amygdala and many other brain parts. In neurology, researchers use stress stimuli to induce mental stress. EEG was used to monitor and evaluate psychophysiological stress (Subhani et al., 2011). An objective EEG (alpha and beta) brain activity and subjective stress assessment questionnaire were used to monitor stress. The results showed a negative linear correlation between the power ratio of beta and alpha EEG brain activity and subjective stress assessment scores. Also, there is a correlation between mental stress and suppression of alpha EEG brain activity, whereas, beta EEG brain activity varies by the task difficulty. Therefore, alpha brain activity becomes dominant in the absence of stress.

2.7 Driving Pattern and Vehicle Acceleration Characteristics

In the last few decades, researchers have used different parameters to describe driving patterns, in which average speed is the most common one (Ericsson, 2000). The driving pattern and all the test procedure were laid out to provide a realistic representation of vehicles' real-life driving conditions on the road (Franco et al., 2014). It has been widely used in different parts of the world to evaluate driver behaviours, traffic management and environmental studies. Over the years, several approaches and different parameters have used to model factors influencing variability in the driving pattern. For instance, Ericsson's (2000) study examines the cause-effect model on variability in urban areas' driving patterns. He identified 26 parameters that are hypothetically affecting driving pattern under the influences of street environment, driver, vehicle, traffic, weather and driving behaviours factors.

Time-speed profile factors are often complex, changes over time, some occur in many directions, and exposure to them causes a complex distribution of oscillatory motions and forces within the body (ISO2631–1, 1997b). The human body responds to these parameters may also cause sensations (e.g. discomfort or annoyance), influence human performance ability and fitness or present a health and safety risk (e.g. pathological damage or physiological change). Several studies have been conducted to quantify the comfort of public ground transport (train or bus) and car with changes in the vehicle rate of acceleration (George et al., 2013; El Sayed et al., 2012). Very few of such studies considered the urban bus mass transit (Delton and Dale, 2008). The typical acceleration rates of vehicles in motion are not often up to the maximum level, because drivers rarely apply the maximum acceleration of their vehicles except when there is an emergency. Although whenever vehicle velocity reaches zero and does not reverse, the acceleration displays a very sharp or sudden change. It imposes a large jerk to all elements in motion with the vehicle loads, including the passengers (Delton and Dale, 2008). About 90% of all drivers, deceleration rate, is more than 3.4 m/s^2, which is still within their ability to maintain lane and steering control during the braking manoeuvre even on wet roadways. Therefore, a comfortable deceleration rate of 3.4 m/s^2 is recommended as the threshold for determining to stop sight distance (Maurya & Bokare, 2012; AASHTO 2001).

The study of Kuhler and Karstens (1978) used a set of 10 parameters to described, developed and accessed driving pattern; the average acceleration (for all acceleration stages, when $a > 0.1$) and average deceleration (for all acceleration stages when $r < -0.1$) see Table 2-4. The average speed of the entire driving, average driving speed (excluding the period of the stop) and proportion of time of acceleration time ($a > 0.1\ m/s^2$). In addition, the proportion of time of deceleration time ($a < 0.1\ m/s^2$) and proportion of time at constant speed ($|a| < 0.1\ m/s^2$). The average number of acceleration-deceleration changes (and vice versa) within one driving period, mean length of a driving period (from a start to a standstill) and the proportion of the standstill time ($v < 3$ km/h, $|a| < 0.1\ m/s^2$).

2.8 Gaps Identified in the Literature

The primary approach to study passenger discomfort is to subject the passengers to different driving conditions in real traffic situation or special equipment (Wang et al., 2020; Hoberock, 1976). Urabe & Nomura, 1964 indicated that evaluating a vehicle's ride comfort requires data on passenger's sensations and quantitatively evaluates them under various conditions. Studies used questionnaire survey, interview and FGD, in which the subjects were asked to make a subjective evaluation on riding experience during or after the journey (Shen et al., 2016; Zhao et al., 2016; Zhang et al., 2014; Kottenhoff & Sundström, 2012; Eboli & Mazzulla, 2011; Lin et al., 2010; Cascajo & Monzón, 2007; Hoberock, 1977; Hoberock, 1976). The subjective approach to evaluating passengers' discomfort of most of these studies is characterised by the problem of indistinctness of the evaluation criteria'. Some authors established the relationship between vehicle motions parameters and passengers' subjective comfort assessment, characterised by the evaluation criteria' indistinctness (Muto et al., 2013).

The questionnaire survey, interview, and FGD have no spatial and temporal relationship with the vehicles' operations. Therefore, the relationship between passenger discomfort and vehicle motion parameter, road roughness characteristics and probably posture cannot be fully investigated. Other studies based on verbal rating using digital comfort assessment score method, in which the passengers were required to rate their perceived comfort/discomfort per minute (Wang et al., 2020). Although the approach provides a possibility to record passenger discomfort in-vehicle time, this approach's limitation is that passengers' comfort/discomfort and the evaluation criteria cannot be investigated in relation with vehicles' operations characteristics specific moment.

Some previous studies are limited by the passenger's inability to evaluate the discomfort in real-time, which result to inability to accurately analyse the impacts of vehicle speed profile factors, road toughness characteristics, in-vehicle time, posture or bus type on passenger discomfort. Evaluation of discomfort often depends on the objective quantifications of subjective judgment, due to the reference points, the sensitivity, the responsiveness and assessment based on the adaptation and motivation that varies from person to person (Tan et al., 2008, Fotios, 2015). Consequently, there is a need for evaluation methods based on biological signals that can directly reflect human psychophysiological states or sensations (Muto et al., 2013). Therefore, an objective measure that can relate the qualitative assessment of road users' response (perception) to the influence of road surface irregularity characteristics, posture and bus type on passenger comfort is needed.

Furthermore, the interpretation of emotions and how they are perceived vary from person to person. Therefore, a subjective evaluation may not provide adequate evaluations since people verbal reports or perception seemingly determined by the awareness of their inner mind, verbal proficiency, norm and culture. Using physiological measures that are general and quantified than the subjects' verbal report, or perception will provide reliable information about the subject matter. For instance, the assessment quantity provided by the International Roughness Index (IRI) is different from ride vibrations perceived by the passengers. It cannot indicate the ride comfort because the performance indicators were based on the vehicle axle (Blum, 2015; Cantisani & Loprencipe, 2010). The common subjective approach of evaluating driving fatigue does not always reliably reflect objective performance measures. Many studies have investigated the driver's fatigue. However, no or very few studies have used EEG to investigate driving fatigue/performance decrement with driving and rest break duration.

Several studies have proposed the method and application of EEG on a vehicle's ride comfort. However, very few have used EEG to investigate or evaluate urban bus passenger comfort in a real-life situation. A significant change in postsynaptic neurons instantly reflected in the EEG, making this approach outstanding for examining the rapid shift in brain activity relative to the influence of experimental design variables (Bell & Cuevas, 2012). The ability of EEG to monitoring the rapid shift in brain activity induced by the influence of dynamic vehicular motion conditions (real-life) due to its portability, time-series data capture capability and high temporal resolution (Yu et al., 2010; Chen et al., 2010). These attributes make the EEG approach a unique method of monitoring any significant changes in driver and passenger psychophysiological responses to experimental design variables compared to baseline.

CHAPTER 3 METHODOLOGY: STUDY DESIGN, EXPERIMENTAL PROCEDURE AND DATA COLLECTION

3.1 Introduction

Chapter 2 discussed the literature review on urban bus passenger comfort, EEG rhythms and oscillations, and the application of EEG, which are the main factors affecting bus passenger journeys. The review of data collection techniques in transportation research and subsequent analytical approaches is used in data analysis. Chapter 3 discusses the research methodology used for this study. This chapter provides an outline of experimental design, the equipment and the data collection technique.

3.2 Lothian Buses

Lothian Buses is the largest urban bus transit operator in the United Kingdom and the primary bus service provider in Lothian that operates buses from Annandale Street, Longstone and Marine at Seafield depots. The City of Edinburgh Council owns 91% of the Transport for Edinburgh Company while the remainder belongs to East Lothian, West Lothian and Middle Lothian councils. The buses operate mainly in Edinburgh by providing services to nooks and crannies of the city, and also providing feeder services to train or tram stations as well as many parks and rides. It also extends services to some suburbs, towns and villages.

Figure 3-1: Lothian buses

There are also limited-stop express routes, night bus services, park and ride services, airport services and many tourist services. Lothian buses run several bus trips daily, between 1200 midnight and 0500 to different parts of the city, and the frequency of the bus to each location varies according to land use and the total population of that geographical location (Figure 3-1).

Lothian Buses Route Map

Bus services in Lothian form the core of the Lothian Buses group, and most buses still follow the same route since the beginning of the operation of trams in the 1950s. However, some modifications have occurred in space and time, which have created confusion in details, such as letter-suffixed routes and clockwise/counter-clockwise circular services. Presently, most of the routes pass through the city centre to the various locations (Figure 3-2). These made Lothian Buses' operations unique and user friendly (cost-effective) because services are not terminated at the city centre. It is worth noting that Lothian Buses are equipped with CCTV cameras for driver and passenger safety. One of the recent improvements in the Lothian Buses' services was the introduction of the 42 Alexander Dennis Enviro400 XLB-bodied Volvo B8L 13.4 buses that began operation in early 2019. These buses seat 100 passengers and are equipped with front and middle doors to reduce waiting time at the bus stops.

Figure 3-2: Spatial distribution of Lothian bus route

3.3 Ethical Approval

Ethical approval for the experimental techniques/conditions used in this thesis was obtained from the School of Engineering and Built Environment (SEBE), Edinburgh Napier University Ethical Advisory Committee before the study's commencement.

3.4 Equipment

3.4.1: GPS-based Performance Box

The GPS-based Performance Box (PB) device (Figure 3-3) can measure vehicle speed, throttle position, time, distance of travel and driver performance accurately, and it is used for data collection. The Global Positioning System (GPS) depends on the satellites' signals to give the moving vehicle's geographical locations in second-to-second intervals. The device is a high performance 10Hz GPS that measures 10Hz logging of time, distance, speed, position, lap times and split times. The time-scale resolution of this data acquisition system is 0.1 seconds. The system designed for data collection contained non-contact 10Hz speed and distance measurement with the aid of GPS, internal and external GPS antennas, g-force measurement of lateral and longitudinal acceleration and an internal yaw sensor. There is also an RS-232 socket for connecting to a PB Mini Input Module, a USB interface for reading an SD card, streaming data and upgrading firmware (Figure 3-3). The 256Mbyte removable SD card can store up to about 200 hours of continuous logging (VBOX User Guide, 2014).

Figure 3-3: The GPS device (PB) keypad

The average speed is defined as (V2-U2) / (2 x S), where V is the final velocity, U is the initial velocity and S the distance travelled (VBOX User Guide, 2014). The PB software is based on a Graphical User Interface (GUI) and a Command-Line Interface (CLI) that permit data analysis and presentation, using Racelogic software and Microsoft excel. The software also comprises the part that allows communication with a GPS receiver, a yaw sensor and a 2-axis accelerometer. The PB aids the organisation and configuration of data in terms of routes names and types, bus type and ID, time of the day, day of the week and weather conditions. It could also organise and delete data from the SD card and permit analysis and presentation of acceleration and jerk threshold.

Furthermore, whenever the 'Write Results File' option is enabled, the PB creates two results files on an SD card. The first file, 'RESULTXX.TXT', produces the test results every time data is appended onto the file's end. The second file, 'BESTXX.TXT', displays only the best result of every test by overwriting previous results in order to increase data quality assurance.

3.4.2 Myndplay Electroencephalography (EEG)

An excellent temporal resolution of EEG makes it widely used as an experimental technique to investigate human brain function by tracking the temporal neural dynamics (brain activity) correlated to experimental events (Mognon et al., 2011). Presently, fewer channel EEG devices are available, and the study conducted by Saeed et al., 2018; Saeed et al., 2017 and Van Der Wal & Irrmischer, 2015 showed that a single-channel headset could be used to investigate emotion recognition at the frontal region. The Myndplay's MindBuilder (MB)-EEG equipment has been developed as bio-sensor equipment to interpret and collate the brains' electrical activity, and was used to gather the time series quantitative eSense metric power spectrum data in this study. The (MB)-EEG device is a single channel produced by MyndPlay and consists of five main parts: an ear clip, a battery area, a power switch, an adjustable headband, and an internal Myndband chipset. MyndPlay EEG is technology that is used in this study, and it enables a device to interface with the user's brainwaves. It is characterised by a sensor that touches the participants' forehead. The contact and reference points are located on the ear pad, and the onboard chip processes all data (Saeed et al., 2018; Bright & Nottage, 2018; Saeed et al., 2017; Borghini et al., 2014). The principle of operation of MyndPlay EEG used in this study is relatively simple; the two dry sensors are used to detect and filter the EEG signals. The sensor tip detects electrical signals from the brain's forehead and ambient noise generated by human muscles and electrical devices (Crowley et al., 2010; Yao et al., 2009; Yasui, 2009). The second sensor, the ear clip, is ground and reference that allows the Myndband chip to filter out the electrical noise. The MyndPlay EEG measures the raw signal, power spectrum (delta, theta, alpha, beta and gamma), attention level, mediation level and blink detection. The raw EEG data is received at a rate of 512 Hz while other measured values are on a second-by-second basis (Figure 3-4). The Myndplay is significantly different from the typical EEG in size, the number of electrodes, the complexity, the resolution capabilities and the cost. The Myndplay comprises software that allows easy connection, recording, viewing, and presentation of data in real-time, and the MATLAB module gives the user the ability and opportunity to define custom MATLAB scripts and functions for data processing and analysis. It is wirelessly connected to a computer that includes all-new mentally-driven capabilities in supported software.

Figure 3-4: The NeuroSky Mobile MindSet (MYNDPLAY) and the display screen on Window tablet during EEG data collection

Myndplay EEG Software

The MyndBand EEG technology comprises software that permits recording electrical data at the precise time-course of cognitive and emotion processing, underlying behaviour. Besides, the EEG technology used for data collection is characterised by the excellent time resolution of receiving hundreds to thousands of electrical activity information within a second (it has a temporal resolution on the order of milliseconds). In recording data from the brainwaves, the transmission part of the EEG is connected to a window tablet via Bluetooth. The NeuroView software was used to process the signal (data) received while the information was stored in a spreadsheet. The MyndBand software allows easy connection, recording, viewing and presentation of data in real-time, and it gives users the ability and opportunity to define custom MATLAB scripts for data processing and analysis. This study's collated data was exported to a Comma-Separate-Values (CSV) file and opened in Excel software for data processing, analysis, and presentation. The bio-electrical signals obtained were converted into numeric values (attention and meditation) that range from 0 to 100 and the power spectrum of the delta, theta, alpha, beta and gamma. It consists of two specialised applications (NeuroView and NeuroSkyLab) in which the NeuroView is designed for the beginner and intermediate EEG researchers wishing to view and record EEG data in real time. The measurement of bioelectrical signals can be taken in the form of:

- Raw signal
- EEG Power spectrum (delta, theta, alpha, beta and gamma)
- eSense metric for attention
- eSense metric for meditation

3.4.3 The EURO Truck Driving Simulator

Inexpensive and relatively realistic EURO Truck simulator equipment consists of the steering wheel, accelerator, brake, clutch, and gears to function with a personal computer and a speaker (Figure 3-5). The HGV driving simulator Logitech Software runs on Windows 7, Windows 8, Windows 8.1, Windows 10 and Xbox One. The wheel is characterised by 270 mm height, 10.94 mm width, 260 mm depth and 2.25 kg weight. The digital environment in which subjects were driving was created by the software, Euro Truck Simulator 2. The corresponding proportion of pedal height, width, depth and weight is 167 mm, 311 mm, 428.5 mm and 3.10 kg, respectively.

Figure 3-5: Participant in TRIL, Edinburgh Napier University

3.5 Sample Size Estimation

The purposive sampling method, which is synonymous with a type of non-probability or non-random sampling technique that does not require underlying theories was applied in this research. In this approach, the participants' selection is based on the researchers' judgment (Palys, 2008; Tongco, 2007) with the willingness (readiness to wear the EEG) of the participants that meet the details of the experimental conditions. Several approaches, including power analysis, cost or return on investment (ROI) analysis or local standards are used to determine the number of participants required for a study (Caine, 2016; Bacchetti et al., 2011). A feasibility analysis conducted in the study consisted of the number of experiments, the cost, the duration of the study and the willingness of the participants that meet the experiment's conditions (Caine, 2016; Bacchetti et al., 2011; Tilburt & Kaptchuk, 2008). These constraints form part of the basis of guidelines for determining the sample size used in this research. Therefore, a local standards guideline was used to determine this study's sample size, and it was obtained through a systematic literature review. It manually extracted information, such as research method, sample size, the gender breakdown of the participants, the contribution type and the paper status of studies that have already been published on the application of EEG on passenger discomfort and driving fatigue (Jing et al., 2020; Saeed et al., 2017; Al-Shargie et al., 2016; Al-shargie et al., 2015; Taghizadeh-sarabi et al., 2013; Lin et al., 2013; Ko et al., 2011; Sulaiman et al., 2010; Yu et al., 2010; Chen et al., 2010; Kerick et al., 2009; Huang et al., 2009; Lin et al., 2007; Philip et al., 2005; Lal et al, 2003; Teplan, 2002; Landström and Lundström, 1985). The summary information and average manually extracted sample size were used to generate the typical sample sizes used in this study (Caine, 2016; Bacchetti et al., 2011).

3.6 Experimental Design

3.6.1 Drivers Fatigue Experiment

An experimental function-related analysis that permits a multi-level method of data collection was used in this study. The participant's psychophysiological response (EEG) and subjective fatigue assessment data were collated relative to the influence of the duration of time spent in driving. The driver fatigue assessments tasks were performed by using the Transport Research Institutes Laboratory (TRiL), Edinburgh Napier University. The section of TRiL used for this experiment comprised of an HGV driving simulator, The NeuroSky Mobile MindSet (MYNDPLAY), Window Tablet with Bluetooth and computers that run the NeuroSky Mobile MindSet research tool (software) as part of NeuroSky's MindSet Research Toolkit (MRT). This section of TRiL was designed to investigate changes in psychophysiological states and other brain-event-related tasks at the quality level specified in the NeuroView user's guide of 2009. The trial (driver fatigue assessments) study was designed so that, where possible, the approach, result and conclusion would inform the design and strategy of the next stage of the study. The driver fatigue assessments observed (see Chapter 4) were used to understand the equipment's performance (e.g., Electroencephalography). For instance, it aided in the understanding of the application of EEG. It provided adequate information, proper understanding and interpretation of various EEG frequency bands, along with an attention eSense meter. It also enabled the understanding of the various types of artefacts and their influences on the actual EEG data (ERP). These procedures were used in data processing and artefacts removal as well as delimiting the scope of field study (passenger ride comfort) presented in Chapters 5 – 6.

3.6.1.1 Participants

The experiment was carried out on healthy male and female subjects between 22 and 42 years of age. Nine subjects (five males and four females) were sampled. All the participants were healthy and not suffering from any illnesses or taking any medication, with no history of brain malfunction or mental illness (Saeed et al., 2018). All the participants had no record of cardiovascular or gastrointestinal disorders (Lin et al., 2013; Ko et al., 2011; Chen et al., 2010). Each participant received information regarding the experimental conditions and protocols for at least seven days before the day of the experiment. They were instructed to avoid smoking, drinking alcohol and caffeine for at least 12 hours before the experiment (Ko et al., 2011, Chen et al., 2010). Besides, they must have a good sleep for one night preceding the experiment, and they were not allowed to use a mobile phone or any other electronic gadget because all these factors could cause additional significant activity of the brain. The willingness to participate in the experiment was obtained from all the participants. All the participants that met the specified conditions are permited to particiate in the experiments. Participants were trained to know the study's scope, and they were given adequate time to practice and understand the EURO Truck driving simulator system before starting the actual experiment. The participants drove HGV-simulated urban roads and highways characterised by other road users (vehicles and pedestrians). The experimental protocol was approved by the Edinburgh Napier University Ethical Advisory Committee.

Duration of driving and rest break is closely associated with driver fatigue or performance decrement (Chai et al., 2017; Mu et al., 2017; Yin et al., 2016). Since the study seeks to understand the influence of driving time and rest break on the driver's psychophysiological response, this research was designed to collect data for driving time long enough to cause significant changes in cortical activation (psychophysiological response) of the participants (Mu et al., 2017; Lal & Craig, 2005). Consequently, four hours of driving with no break and four hours of driving with a break of 30 minutes after two hours of driving were used in this study. This was based on the conclusion of previous studies. For instance, Lal et al., 2003 developed an algorithm for an EEG-based driver fatigue countermeasure in which the participants were engaged in two hours of continuous driving to induce physical signs of fatigue. In addition, Williamson et al. (1996) demonstrated that there was significant changes in the magnitude of steering wheel deviations at the beginning of the second hour and the third and last hour of the driving task. Also, the study of Miller & Mackie, (1978) demonstrated a significant increase in coarse steering and decreases in fine steering of the participants after four to five hours of driving. The previous study also shows that the driver must ensure that they take no less than 30 minutes of break after no more than four hours of driving (Parkes et al., 2009).

Furthermore, a significant increase in beta brain activity indicated increased cortical activation of participants who drove for four to five hours. Finally, the regulation (EC) No. 561/2006 and British domestic drivers hour regulations defined that drivers of large commercial vehicles and passenger vehicles are subject to EU driver rules that limit driving time and ensure adequate breaks, and exempts drivers who do not drive for more than four hours on each day of the week from the daily limit (Parkes et al., 2009). This study examines the impacts of time spent driving and rest breaks on the participants' psychophysiological responses. Therefore, four hours of driving each with 30 minutes of break and without a break were used as the minimum requirements for this study because it is enough to cause changes in the participants' cortical activation (psychophysiological response).

3.6.1.2 Driving Fatigue Data Acquisition

The subjects were assessed during an HGV simulator task to investigate and evaluate EEG changes during baseline measure as well as early or extreme fatigue stages. The collected data was transmitted via Bluetooth to a Windows-based device in real-time. The experiment was conducted in a laboratory under the controlled temperature of (18^{0}C) and light, with a noise level below 60 dB. The EEG data was measured between 11:00 and 17:00 hours with speed ranging from 20 – 60 km/h with few road stimuli. During the data collection, an observer who was seated two to three meters away from the subjects monitored the subject's behaviour without causing any distractions. Factors such as the circadian cycle and fatigue or performance decrements could be quickly induced and were controlled by ensuring that all the participants had a normal sleep one night before the experiment because sleeping less than five hours within 24 hours before work will negatively influence the likelihood of fatigue-related error at work (Dorrian et al., 2011). During each experiment, the subjective fatigue assessment was reported in real time based on the participants' experience relative to the influence of the duration of driving and the break's impact. The Samn-Perelli seven-point fatigue assessment scale shows that human sensations and functionality were used in this study. The fatigue assessment scale ranges from fully alert and wide awake to completely exhausted and unable to function as detailed below.

1. Fully alert and wide awake.

2. Very lively and response, but not at peak.

3. Okay, somewhat fresh.

4. A little tired, less than fresh.

5. Moderately tired, let down.

6. Extremely tired, very difficult to concentrate.

7. Completely exhausted, unable to function effectively.

The researchers explained the questionnaire to the subjects before the commencement of the experiment. During the driving task, if the participants felt more fatigued compared to the last condition (30 minutes), they were prompted to pick a number that best defined their level of perceiving sensations and functionalities at the interval of every 30 minutes.

Changes in fatigue level were reported in real time without interrupting the experiment. The Samn-Perelli seven-point fatigue assessment scale was applied and synchronised with EEG data after each experiment in order to provide overall fatigue and performance decrement rating information.

Table 3-1: Summary of fatigue-phase instrumentation in the TRiL

Phase 1		
EEG component	**Range**	**Duration**
Spectral power	Beta brain activity that ranges from frequency of between 15 – 25Hz	four hours no break
Attention	User' level of mental focus that ranges from 0 – 100	four hours no break
Phase 2		
EEG component	**Range**	**Duration**
Spectral power	Beta brain activity that ranges from frequency of between 15 – 25Hz	four hours with 30 minutes break after two hours of driving
Attention	User' level of mental focus that ranges from 0 – 100	four hours with 30 minutes break after two hours of driving

During the fatigue driving task, the EEG data was categorised and grouped based on two hours of driving before a 30 minute break, two hours of driving after a 30 minute break and four hours of driving with no break (Table 3–1). After the noises are filtered out of the driving fatigue assessments' experimental EEG data, a total of 238,717 data points (second) was obtained from all of the nine sampled participants in all phases of the experiment. The corresponding proportion of data points for driving two hours before a 30 minute break, two hours after a 30 minute break and four hours with no break are 59,663, 59681 and 119,373, respectively (Table 3-2). Independent variables were designed to compare the participants' performance and psychophysiological responses to the influence of driving with a break and without a break. A comparison between the participant's age and gender influence was made to compare the amount of performance deterioration and psychophysiological evidence of fatigue experienced by each age and gender group. The details of the driving fatigue data point per subject on each phase of the experiment can be found in table 1 in appendix I.

Table 3-2: Driving fatigue data points

Time	Before break	After break	No break
30 minutes	14,891	N/A	14,899
60 minutes	14,909	N/A	14,907
90 minutes	14,947	N/A	14,916
120 minutes	14,916	N/A	14,924
150 minutes	30 minute break	30 minute break	14,930
180 minutes	N/A	14,899	14,915
210 minutes	N/A	14,908	14,929
240 minutes	N/A	14,962	14,953
270 minutes	N/A	14,912	N/A
Total	59,663	59681	119,373

3.6.2 Urban Bus Passenger Ride Comfort Experiment

3.6.2.1 Sampled Rroute

The psychophysiological signal measurement was conducted in the laboratory (control experiment) and on Lothian Buses routes in the urban part of Edinburgh, UK (Figure 3-6). Onboard data collections were carried out during the regular off-peak hours to control the influence of noise, temperature, overcrowding and in-vehicle time on passenger comfort. The bus passenger comfort experiment was conducted on selected Lothian bus routes characterised by asphalt and sett pavements. This study investigated passenger discomfort on bus service 36 and 21 from Morningside to Ocean Terminal and Ferry Road to Royal Infirmary Edinburgh, respectively (Figure 3-7).

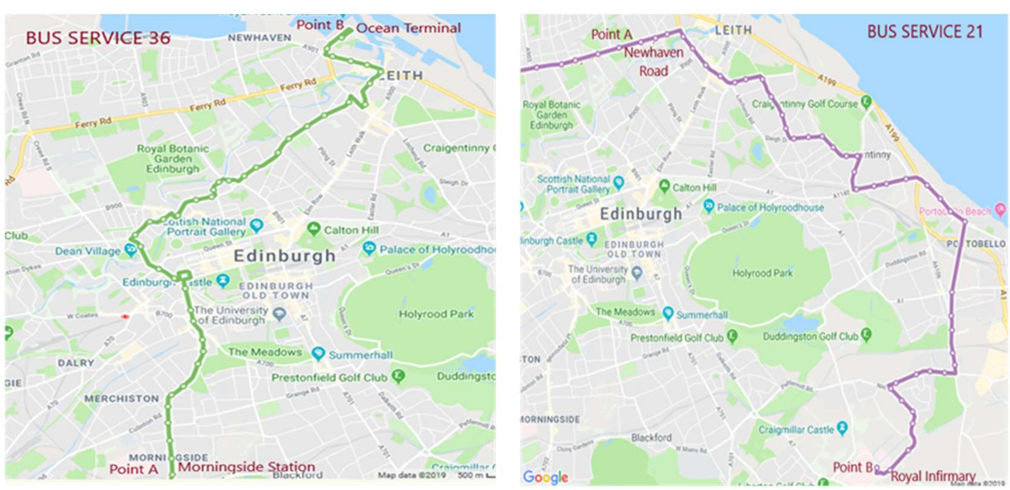


Figure 3-6: Map of the sampled pre-determined Lothian Bus routes

Figure 3-7: Lothian Buses and route pavement types

3.6.2.2 Participants

The general participant information, such as gender and age, was collected before the study's commencement. The experiments involved twenty healthy volunteers (12 males and eight females aged from 21 to 50 years). All the participants were healthy and not suffering from any illnesses and not on any medication, with no history of brain malfunction or mental illness. The participants had no record of cardiovascular or gastrointestinal disorders (Lin et al., 2013; Ko et al., 2011; Chen et al., 2010). The volunteers had normal sleep the previous night of the experiment because these factors could significantly arouse the subject's cognitive state (Taghizadeh-sarabi et al., 2013; Lal & Craig, 2005; Lal & Craig, 2002). Also, all the participants had normal or corrected-to-normal vision. Before the start of the real experiment, participants were trained to know the scope of the study. Each participant reported total compliance with the experiment's standards and regulations and adhered to instructions, such as not to move, not to restrict the motion stimulus and not to fall asleep, but rather concentrate on the reading task. The MyndPlay headset was placed on the subjects, and the experiment began when the participants were set and ready for the onboard reading task.

3.6.2.3 Bus Passenger Discomfort Data Acquisition

A significant change in postsynaptic neurons instantly reflected in the EEG, making this approach outstanding for examining the rapid shift in brain activity (Bell & Cuevas, 2012). Using the EEG is one of the best approaches for monitoring the rapid shift in brain activity induced by the influence of dynamic vehicular motion conditions (real-life) due to its portability, time-series data capture capability and high temporal resolution (Yu et al., 2010; Chen et al., 2010). This study was interested in bus passenger discomfort and experimental design stage-related changes in measured EEG by using baseline periods for comparisons. Consequently, datasets in two stages were collected for each subject (passenger) in this study, including the stationary laboratory (control) and dynamic onboard bus environment experiments (Bell & Cuevas, 2012; Ko et al., 2011). The control experiment for the passenger comfort study was conducted in a laboratory under the control temperature of 18^0C and light, with a noise level below 60 dB (Figure 3-8). Each participant was informed about the scope of the experiment, and gave their written consent for participation. The participants arrived at the laboratory at 09:00 after a regular night's sleep and had breakfast, and the investigators ensured that they all met the experiment's conditions.

Figure 3-8: Participants in the laboratory and onboard bus experiments

The EEG data started at 09:30 in the laboratory. All the participants were instructed to sit, relax in a stable laboratory environment and read on their mobile phone for the experiment's duration (10 minutes). The control experiment was designed to evaluate or test the effects of independent variables (road roughness, posture and bus type) on the participant's level of discomfort as it was used in the studies of Azizan et al., 2016; Lin et al., 2013; Ko et al., 2011; Yu et al., 2010; Chen et al., 2010; Kerick et al., 2009; Huang et al., 2009; Lin et al., 2007; Lal et al, 2003.

The second stage of the study demonstrates real-life urban bus passenger discomfort that comprises of an EEG system and the recommended passenger comfort assessment scale of the international standard ISO 2631-1 for public transport. Afterward, the laboratory experiment and the subjects were conveyed to the starting point of the real-life onboard bus experiment by a car and were allowed to settle down for 15 minutes before the experiment commenced. An instrumental vehicle data collection approach was adopted. The installed system on the bus was a prototype designed by Suryawanshi et al., 2015 and Castellanos et al., 2011. The PB was mounted close to the subjects' feet in a fixed position that made the PB active with the vehicle's speed. The system collected different real-time speed profile data, such as the peak-to-peak value of velocity, acceleration, and deceleration. The investigators were seated in a passenger seat to monitor the data collection processes (Figure 3-9).

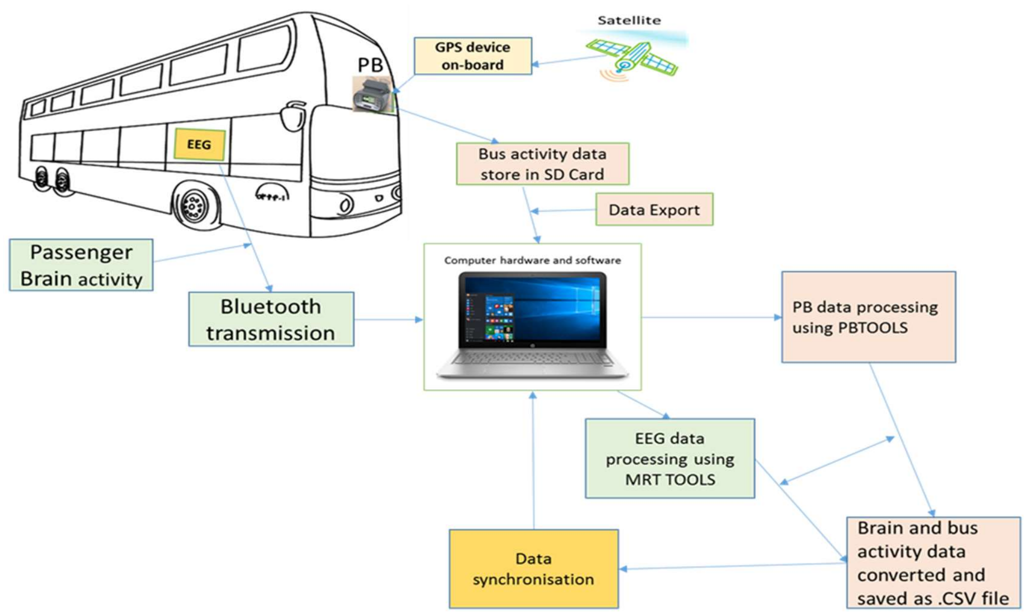


Figure 3-9: Data collection system layout

EEG brain activity is sensitive to any environmental change (Chen et al., 2010). Consequently, this study stage focused on road roughness characteristics, passenger posture and bus type on the participant's psychophysiological responses. The psychophysiological signal was measured on this stage of the experiment with two dynamic vehicle motion conditions with participants seated for 15 minutes and standing for 10 minutes on asphalt pavement in single- and double-decker buses. Secondly, two dynamic vehicle motion conditions of five minutes each for seated and standing on sett pavement in both single- and double-decker buses, the psychophysiological signal was measured (Table 3–3). Therefore, the onboard urban bus passenger discomfort-related beta EEG, and the eSence metric of attention brain activity (psychophysiological response) were collated in the following eight stages of the experiments: (1) seated on asphalt pavement in a single-decker bus, (2) standing on asphalt pavement in a single-decker bus, (3) seated on asphalt pavement in a double-decker bus, (4) standing on asphalt pavement in a single-decker bus, (5) seated on sett pavement in a single-decker bus, (6) standing on sett pavement in a single-decker bus, (7) seated on sett pavement in a double-decker bus and (8) standing on sett pavement in a double-decker bus.

Table 3-3: Passenger comfort experimental phase

Phase	Experiment
1	Stationary seated condition in laboratory.
2	Dynamic vehicle motion condition: seated and standing conditions on asphalt pavement.
3	Dynamic vehicle motion condition: seated and standing conditions on sett pavement.

The subjective comfort assessment was based on the participant's experience on each stage of the experiments by using the recommended passenger comfort assessment scale of the international standard ISO 2631-1 for public transport (ISO2631–1, 1997b). The researchers explained the questionnaire to the subjects before the commencement of the experiment. This questionnaire has perceived levels of discomfort, which include not uncomfortable, a little uncomfortable, fairly uncomfortable, uncomfortable, very uncomfortable and extremely uncomfortable (ISO2631–1, 1997b). The questionnaire was administered immediately after the onboard bus experiment by using a self-administered survey technique because any experiment where the subject's cognitive state is monitored, interrupting the experiment to administer the questionnaire could significantly arouse the subjects (Chen et al., 2010). The questionnaire was designed to capture the perception of passenger-level discomfort on each experiment phase.

The EEG data recorded during urban bus passenger discomfort was categorised and grouped based on the baseline and eight stages of the onboard experiment. After data cleaning, 11,169 and 65,607 data points were obtained from all the 20 sampled participants in baseline and onboard experiments, respectively. The corresponding proportion of data points of single decker-seated-asphalt, asphalt-double-standing, sett-single-standing and sett-double-seated are 15,500, 9,339, 3,997 and 4,034, respectively (Table 3–4). The details of each participant's data points in all stages of the experiment are in appendix II. The independent variables were designed to compare the participants' performance and psychophysiological responses to the experimental design variables' influence. Also, the comparison between the participant's age and gender influence was incorporated to evaluate the variations in the level of discomfort experienced by each of the age and gender groups.

Table 3-4: Passenger discomfort data point

Variable	Data point (second)
Baseline	11,169
Asphalt-single-seated	15,500
Asphalt-single-standing	9,369
Asphalt-double-seated	15,464
Asphalt-double-standing	9,339
Sett-single-seated	3,939
Sett-single-standing	3,997
Sett-double-seated	4,034
Sett-double-standing	3,965

3.6.3 Speed-Time Data

A series of approaches have been used to collect data to develop vehicle driving patterns and estimate passenger comfort disturbance (Kottenhoff & Sundström, 2012). Presently, driving patterns or cycles are developed with data collected by using the onboard data collection approach that is usually stratified by vehicle type, road type, and level of speed and time. Second-by-second speed data was collected for this study on selected Lothian bus routes. In this study, an instrumented vehicle approach that permits quantitative assessments of vehicle performance under actual road conditions was used to gather time-series data (Bosetti et al., 2014). The speed data logging device (PerformanceBox) was installed on selected single- and double-decker buses on selected Lothian bus routes. The real-life traffic situations linked directly with the real-time speed-time measurements, which were based on the instantaneous driving conditions of speed, acceleration, deceleration, cruise and idle.

3.7 Data Preparation and Analysis

The degree of portability and weight (light) of the EEG systems allows for flexible data collection in real-world stable or dynamic environments (Imotion Users Guide, 2019; Mavros et al., 2016; Cohen, 2011). The recorded EEG signals were fed to the MindSet

Research Toolkit (MRT) before the Fast Fourier Transform (FFT). The data was filtered and grouped based on the experimental independent variables. The event-related beta EEG oscillations were evaluated by decomposing the signals into magnitudes relative to the experimental designed phases and variables. The magnitudes were determined by obtaining the average of all the amplitudes (EEG activity) of the beta band's frequency range to a data point per second for each subject across all the experimental conditions (Bell & Cuevas, 2012). Urban bus passenger discomfort evaluation includes two parts: the statistical analysis by using both objective and subjective methods, and the ride quality models that are developed to establish the relationships between dependent variables (beta EEG frequency band and eSense metric for attention) and independent variables (road roughness, posture, speed profile factors and bus type). The data provided the model of a human's feelings to the influence of road characteristics and driving behaviours in both single- and double-decker buses in different postures (seated and standing). The ERP beta and eSense metric of attention brain activity were exported as American Standard Code for Information Interchange (ASCII) to Statistical Package for Social Sciences (SPSS) for statistical assessment (Delorme & Makeig, 2004). Statistical analysis was performed by using ANOVA, the post hoc test and testing of the subject-effect via the SPSS. Estimating the marginal mean of beta brain activity and eSense metric for attention was used to determine the relationship between the dependent and independent variables.

3.7.1 Factors of Data Dnalysis (dependent variables)

In this study, the advance EEG data view software (license) MRT produced by Myndplay Ltd., which gives the most control over the raw data by exporting the data into CSV or MATLAB format was used. The bioelectrical signals obtained were converted into numeric values of eSense metric of attention and meditation that ranged from 0 to 100 and the power spectrum of the delta, theta, alpha, beta and gamma. The EEG measures the brain's electrical potential responses that flow during the dendrites' synaptic excitations in the cerebral cortex (Rahman et al., 2012). The EEG frequency brainwaves (activity) consists of five-byte floating-point numbers of delta (δ) activity [0.5 - 4] Hz, theta (θ) activity [4 - 8) Hz, alpha (α) activity [8 - 13] Hz, beta (β) activity [15 - 25] Hz and gamma (γ) activity [30-50] Hz (Escobar et al., 2020; iMotions, 2016; Zamora, 2001). These values have no units, and therefore, are only meaningful compared to each other and themselves in terms of their relative quantity and temporal fluctuations or oscillations (Mitsukura, 2016; iMotions, 2016; Liu & Sourina, 2014; NeuroSky, 2011; Lewis, 2000). In this study, the dependent variables are eSense of attention, and the beta EEG frequency band, which are found to be associated with the experience of stress and fatigue (Saeed et al., 2018; Al-Shargie et al., 2016).

3.7.1.1 EEG eSense Metric Value of Attention

Brain response to external or internal stimulus is a function of different patterns of neural interaction. The unsigned one-byte value reports the eSense metric of attention of the subject(s) and indicates the users' degree of mental focus during intense concentration and focus. The prolongation of the theta EEG spectrum correlates with the selective level of attention, and a coordinated response that indicated arousal, alertness or readiness is associated with theta oscillations during motor behaviour (Basar et al., 1999) (Basar et al., 1999). Although brain oscillations are correlated with multiple functions depending on sensation and event(s), the descriptions are informed of sensory registration movement and cognitive processes that are associated with attention (Basar et al., 1999). Also, attention-related responses were found in humans over the frontal and central electrophysiological changes in the frontal cortex and in the parietal cortex. The ERP stimuli gave rise to high states of induced focused attention in subjects (Başar et al., 2001).

In this study, the ERP eSence metric of attention signal processing was conducted by using the NeuroSky's MindSet Research Tool (MRT). The eSense metric of attention interpreted following the NueroSky eSense meter scales ***of 1 to 100*** (NeuroSky Inc., 2009). Any values between ***40 and 60*** is considered "neutral" and is similar in notion to "baselines" that are established in conventional EEG measurement techniques. A value from ***60 to 80*** is considered slightly elevated. It may be interpreted as a level of being possibly higher than a normal level of attention or meditation. Also, values from ***80 to 100*** are considered elevated, indicating heightened levels of eSense (Table 3-5). Values between ***20 and 40*** indicate reduced eSense while values between ***1 and 20*** represent enormously lowered levels of eSense, which could be interpreted as an indication of the states of distraction, agitation, or abnormality (iMotions, 2016; NeuroSky, 2011). The interpretation of the eSense metric of attention values between 1 and 39 makes it suitable as the dependent variable in the driving fatigue and passenger discomfort study.

Table 3-5: Interpretation of the eSense metric for attention

Value	Interpretation
81 - 100	Considered as elevated, which strongly indicates heightened levels.
61 - 80	Considered as slightly elevated and may be interpreted as levels being possibly higher than normal levels.
41 - 60	Neutral (similar in notion to baseline).
21 - 40	Distraction, agitation, or abnormality.
1 - 20	Distraction, agitation, or abnormality.

Source: (iMotions, 2016; NeuroSky, 2011)

3.7.1.2 EEG Power Spectrum and Interpretation of the Beta Frequency Band

The ERP or evoke potential is a significant fluctuation in brain activity that results from induced neural activity in the Central Nervous System (CNS) either from internal or external stimuli (Teplan., 2002). ERPs are known to be a suitable approach for investigating both normal and abnormal aspects of cognitive processes. Beta EEG frequency bands [15 - 25] were chosen from the five-byte floating-point values of EEG frequency bands as the second dependent variable because it is found to be associated with stress, anxiety and the inability to relax when there are significant changes relative to the influence of the experimental design variable or event (Subhani et al., 2011; Sulaiman et al., 2010; NeuroSky Inc., 2009). The beta EEG frequency band is associated with integrating the multi-modal cerebral cortex responses relative to internal or external stimuli. The fluctuations in power (amplitude) of the EEG frequency bands are associated with diverse brain states, such as an increase in beta brain activity associated with alertness or cognitive demands (Mavros et al., 2016). Also, a significant increase in the EEG power spectra in the beta band demonstrates an increase in individual arousal level (Borghini et al., 2014; Okogbaa et al., 1994), and an increase in motion sickness (Chen et al., 2010).

Stress has also been found to cause an increase in EEG beta band power (Saeed et al., 2018; Saeed et al., 2017). Al-Shargie et al. (2016) indicated that a single-channel EEG could be used to examine emotion at the front region and cortical activation in the brain during induced stress stimulus as an indication of change (increase) in beta brain activity. Another study found the negative linear relationship between the power ratio of beta brain activity and the subjective score as an indication of stress (Abdul-Hamid et al., 2010). Furthermore, other studies have shown that beta brain activity varies (increased) relative to stimuli difficulty, demonstrating that workload and stress can be successfully monitored via a single-channel EEG device (Escobar et al., 2020; Saeed et al., 2018; Al-Shargie et al., 2016). A significant change in beta EEG brain waves ranges from the optimal (that could be termed as baseline) to too little or too much as detailed in Table 3-6, making the beta EEG frequency band suitable for investigating driving fatigue and passenger discomfort.

Table 3-6: Interpretation of the EEG band to mental and emotional feeling

S/N	Brain wave	Interpretation		
		Optimal	Too little	Too much
1	Beta	Conscious focus, memory, problem solving	Depression, poor cognitiveability, Attention Deficit Hyperactivity Disorder (ADHD)	Anxiety, high arousal, inability to relax, stress

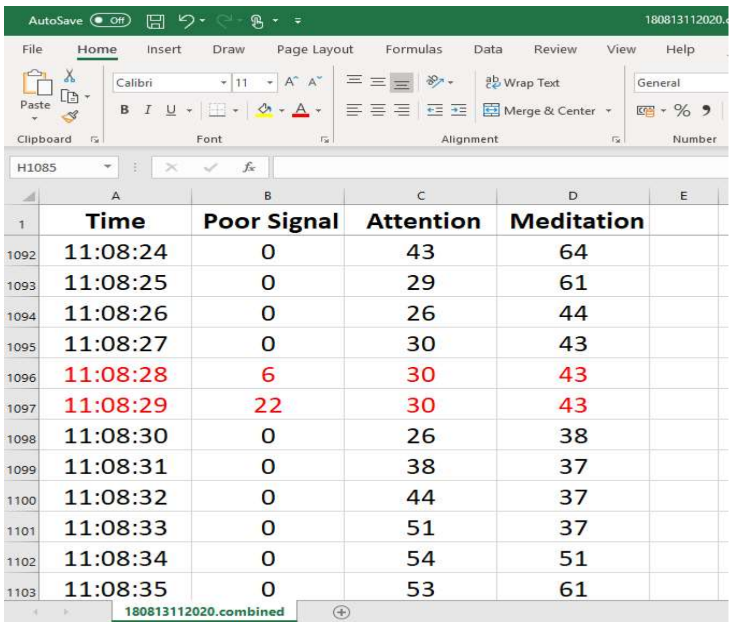
Source: NeuroSky, 2011

3.7.1.3 Artefact Removal

EEG data/signals are sensitive to noise that does not originate from the brain and usually mixes with the data. The noise sources in EEG data are not limited to technical error, subject behaviour and physical activities. EEG signals are also liable to artefacts whenever there is insufficient contact of the sensors or reference contacts to a person's skin due to hair in the way or excessive motion of the wearer. According to the ThinGear manual 2010, the NeuroSky's EEG data filtering technology and eSense™, the algorithm was designed to detect, correct, compensate for, account for, and tolerate different types of non-EEG artefacts.

In this study, the following approaches were used to denoise data to the minimum level. The first attempt to minimise artefacts from EEG signals started from the time of data collection in which the manufacturer's user guide and data collection procedures were followed by ensuring that the headset fit snug on the head and the electrodes and ear clip were securely attached to the skin. Secondly, an artefact rejection method was applied in which the contaminated signals were discarded (Subhani et al., 2011). The artefact removal was based on the unsigned one-byte integer value that ranges in value from 0 to

200 and defines the fidelity of the signal measured by Myndband. This value is usually output every second and indicates the degree of the most recent measurements' poorness. Any non-zero value indicates that some noise contamination is detected in the process of data collection (Figure 3-10). The higher the number, the more noise is detected. The value of 200 has a special meaning, and it shows that the Myndband contacts (sensors) are not touching the user's skin. In this study, any section of the data where the noise signal is more than five units was filtered out since physiological noise can rarely be avoided.



	Time	Poor Signal	Attention	Meditation
1092	11:08:24	0	43	64
1093	11:08:25	0	29	61
1094	11:08:26	0	26	44
1095	11:08:27	0	30	43
1096	11:08:28	6	30	43
1097	11:08:29	22	30	43
1098	11:08:30	0	26	38
1099	11:08:31	0	38	37
1100	11:08:32	0	44	37
1101	11:08:33	0	51	37
1102	11:08:34	0	54	51
1103	11:08:35	0	53	61

Figure 3-10: Data sample of the EEG used for analysis

The participant's psychophysiological measurements were characterised by noisy values, which made the extraction of the temporal features of the data challenging (Guo et al., 2020; Luck & Gaspelin, 2017). Since the raw EEG data for both driving fatigue and passenger discomfort were skewed, an outlier analysis was conducted by using individual box plots for each driving fatigue and passenger discomfort beta EEG brain activity in order to identify extreme data points (Caine, 2016). Based on this analysis, simple negative and positive amplitude thresholds of 2.5 and 97.5 percentiles, which enclosed the 95% of the beta brain activity and eSense metric of attention were defined and applied separately to all the subject's psychophysiology responses on each stage of the experiment (Pollet & Meij, 2017; Adil & Irshad, 2015). Values smaller than the 2.5% percentile or larger than the 97.5% percentile were considered outliers and were removed as artefacts. There were 20,483 data points (7.9%) of driving fatigue and 19,224 data points (20%) of passenger discomfort experiments that were identified and removed as noise, leaving 238,717 and 76,776 data points as the final dataset processed for analysis and modelling for the driving fatigue and passenger discomfort study, respectively.

3.7.2 Data Analysis

This study's valuable point of data analysis and discussion is to evaluate ERP from the modern event-related time-frequency analysis of EEG. The logical oscillatory deflections are evident in the averages of the EEG epochs phase, or are time-locked to a group of repeated stimulus or response events (Guo et al., 2020). Several approaches have been used for representing psychophysiological time-series data (minimum or maximum observation, mean, mode or median). For example, a median sample can be determined from aligning experimentally designed variable data. The median values on each stage of the experiments were determined in order to form the representative data for experimental conditions (Voith & Milwaukee, 2002). The most common method for representing the psychophysiological time series is to summarise the data by determining the average features of data points containing independent variables and concatenating them as a representative of the participant(s) (Guo et al., 2020, Luck & Gaspelin, 2017; Cohen, 2011). The average values often reflect the fluctuation range of the participant's psychophysiological response for the experiments' conditions or events (Hoormann *et al.*, 1998). In this study, the data segments on each stage of the experiments are aligned; the average representative data on each stage of the experimental conditions is generated by using the SPSS data aggregate function. The mean value of the ERPs for each stage of the experimental condition in this study was obtained by computing the average value of the total psychophysiological responses on each stage of the experimental conditions per subjects in order to form the representative data for each of the experimental conditions (Campos *et al.*, 2020, Guo et al., 2020, Hoormann *et al.*, 1998). The computed ERP average values represent the subjects' responsiveness on each stage of driving fatigue and passenger discomfort experimental conditions (Campos et al., 2020).

Statistical Analysis

This research used regression analysis to model the ERP responses of urban bus passenger discomfort and driver fatigue. This study examined the effects of road roughness, passenger posture and bus type on passenger comfort as well as the influence of time spent driving on driver fatigue. A two-way analysis of variance (ANOVA) was conducted to test the predictor in the model under different conditions of the experiments (independent variables) (Kim et al., 2019; Luck & Gaspelin, 2017; Dien, 2017). Statistical significance and interaction effects were accepted at $p < 0.01$. The statistical method was used to determine whether there were significant differences between different conditions of the experiment and the nature of the relationship between dependent and independent variables. The F test of significance of effects of the data analysis and the eta-squared measure of the effect size of GLM univariate in the Tests of Between-Subjects Effects was used to compare and evaluate the predictors in the model. The partial eta-squared or correlation ratio is a fundamental procedure for analysing ERP responses, which has been widely used as effect size measures for ANOVA to evaluate the relationship between the dependent and independent variables (Shen et al., 2016). Also, a parametric method was used to analyse objective performance, and the subjects' inter variabilities were evaluated (Table 3-7). The researcher ensured that before the parametric tests were used, the assumptions of normality were met. Statistical analyses were used to assess any significant variations or effects between the control experiment (a stationary seated condition in the laboratory) and dynamic vehicle motion conditions of seated and standing passengers on asphalt and sett pavements in single- or double-decker buses. The graphical analysis of interactions (profile plot) was plotted across each group to demonstrate the trends and effects by using Graphically Univariate GLM-predicted mean cell values. The X-axis shows the independent variables, and the Y-axis is the estimated means.

Table 3-7: The parametric approaches used for statistical analysis

Experimental study	**Dependent variable (factors)**	**Experimental Design variable**	**Statistical Method**
Study 1 Simulator trial	EEG power spectrum (beta band)	Driving time, age and gender	GLM Univariate (ANOVA)
Study 2 Simulator trial	eSense attention	Driving time, age and gender	GLM Univariate (ANOVA)
Study 3 Bus comfort study	eSense attention	Speed profile factor, bus type, pavement type, posture, age and gender	GLM Univariate (ANOVA)
Study 4 Bus comfort study	EEG power spectrum (beta)	Speed profile factor, bus type, pavement type, posture, age and gender	GLM Univariate (ANOVA)

3.8 Summary

In this chapter, the study design, the experimental procedure, data collection, and data analysis were discussed. Also, the equipment and data cleaning/artefact removal were discussed. The Lothian Bus routes characterised by asphalt and sett pavements were identified and selected as primary data collection routes. In chapter 4, the general analysis of the dataset obtained for the driving fatigue trial is presented and discussed. The influence of duration of driving on driver fatigue or performance decrements are also discussed.

CHAPTER 4 PSYCHOPHYSIOLOGICAL RESPONSES OF THE DRIVER: INFLUENCE OF DRIVING TIME

4.1 Introduction

Chapter 3 presents the research design, experimental procedure and data collection system layout. It also highlights the case study, sample size and details of the equipment used for data collection. Driver fatigue could lead to a reduction in a driver's alertness and performance decrements over short- or long-term driving. In the transport system, cumulative fatigue due to driving time could have strong impacts on a driver's vigilance and performance; therefore, a better understanding of the cause and effect of fatigue in the transport system is required. Generally, vigilance is known to be the central factor of safety for all transport operators, and there is also a significant relationship between vigilance and sleepiness or circadian factors (Filtness & Naweed, 2017). Also, the natural circadian cycle in psychophysiological response could have significant impacts on a driver's level of alertness and fatigue (Philip et al., 2005; Miller & Mackie, 1978). Consequently, the data collection and analysis for this study was performed within the framework of time spent driving. The investigation of fatigue underwent some refinement, and all the likely influence of equipment and environmental and operational factors were controlled.

Therefore, chapter 4 aims to investigate the cumulative fatigue of driver relative to the influence of time spent driving. In this chapter, the average beta EEG frequency band and eSence metric for attention brain activity were computed, filtered and integrated to produce the psychophysiological response of the participants to the influence of duration of time spent on a driving task. The psychophysiological response of the participants with the influence of four hours of driving with no break, two hours of driving before a 30 minute break and two hours of driving after a 30 minute break were computed. During the data collection, the investigators ensured that all the participants had a good sleep the night before the experiment. Furthermore, issues related to participants' lives outside of work, such as driving experience, health disorders and individual proneness were considered when designing the approach to data collection. For instance, all participants had more than three years of driving experience, and they were all healthy adults with no display of any symptom of brain malfunction or mental illness. They had no record of mental therapy nor a history of mental health-related issues. None of them was on any prescribed medication because all this could influence brain activity.

4.2 Processing the Driving Datigue Psychophysiological Time Series Data

The EEG data was partitioned into 30 minutes of periodic variations (stages) in order to evaluate the variance that is associated with each periodicity separately. Therefore, the impacts of the duration of driving and breaks on the psychophysiological activation on participants' sense of fatigue and performance decrements were investigated. The psychophysiological response of the subjects in each of the conditions were summarised by averaging the underlying data (brain activity) spanning the entire epoch, called principle ERPs (pERPs). The algorithms for estimating the underlying EEG brain activity were used to reduce data not only across the subjects, but also across all the experimental conditions (independent variables). A total of 238,717 data points was obtained for each of the beta EEG brain activities and eSence metrics of attention. The value of data points and the assignment of subjects to the conditions of the experiment for each of the subjects in relation to the study's experimental conditions are detailed in appendix I.

The mean values of the dependent variables (beta and eSence metric of attention) were obtained by using the SPSS aggregate data function. The variable participant and independent variables (experimental stages, age and gender) were used as the break variables to obtain the aggregated mean value of the dependent variables across cases. Therefore, new variables in the active dataset that contain aggregated (mean) data were created to replace the active dataset with aggregated results. Consequently, the data was reduced to a smaller set that explained variations between subject effects within the framework of subject and experimental conditions. Therefore, the aggregated mean of the ERPs was computed across all the conditions of the driving fatigue experiment (Luck & Gaspelin, 2017, Hoormann *et al.*, 1998). The computed ERP is the average of all the psychophysiological response epochs of each of the subjects and conditions of the driving fatigue experiments. The experimental conditions (independent variables) and the obtained aggregated mean data (psychophysiological responses) were used for data analysis and modelling. The data points and assignment of subjects to the conditions of the experiment is detailed in Table 4-1.

Table 4-1: Driving fatigue data point

Time	Before break	After break	Time	No break	Total
30 minutes	9	N/A	30 minutes	9	18
60 minutes	9	N/A	60 minutes	9	18
90 minutes	9	N/A	90 minutes	9	18
120 minutes	9	N/A	120 minutes	9	18
30 minutes break	30 minutes break	30 minutes break	150 minutes	9	9
150 minutes	N/A	9	180 minutes	9	18
180 minutes	N/A	9	210 minutes	9	18
210 minutes	N/A	9	240 minutes	9	18
240 minutes	N/A	9	N/A	N/A	9
Total	36	36	-	72	144

A fundamental approach and procedure for ERP that generates datasets and presents chances for some basic analyses, such as repeated measure analysis of variances, was applied. In the analysis of typical ERP in this study, an ANOVA with within-subject factors was applied for conditions, and between-subject factors was also used to test group differences (Dien, 2017). The driver vigilance and alertness decrement in this study were evaluated and validated by using the correlations between psychophysiological response (EEG brain activity) and the Samn-Perelli seven-point scale of fatigue assessment relative to the influence of driving time. The details of the Samn-Perelli seven-point scale of fatigue that asked about human sensations and functionality are:

1. Fully alert, wide awake.
2. Very lively, responsive, but not at peak.
3. Okay, somewhat fresh.
4. A little tired, less than fresh.
5. Moderately tired, let down.
6. Extremely tired, very difficult to concentrate.
7. Completely exhausted, unable to function effectively.

4.3 Relationship between a Driver's Psychophysiological Response (Fatigue) and Duration of Driving

Driving time forms an integral part of the operation, planning and understanding of driving fatigue. This section of the study focused on investigating the effects of prolonged driving on the level of fatigue and performance decrements of a driver. The amount of time driving could cause adverse effects on a driver's performance, attention, vigilance and reaction time (Parkes et al., 2009; Nilsson et al., 1997). Reducing the undesirable impact(s) of long-duration driving requires an in-depth understanding of the average driving time that is needed before a break is essential. The neuronal brain activity for this study was collated by using an EEG in response to a simulated driving task. The participants experienced different fatigue states and performance decrements after four hours of driving with no break and after two hours of driving before and after a 30 minute break. The first 30 minutes of the experiment in this research was used as a condition of a driver being fully alert and wide awake. Based on the information obtained during the experimental study of driver fatigue, it was observed that the majority of the subjects experienced gradual transitions from the state of being fully alert and wide awake to the state of being extremely tired and very difficult to concentrate or completely exhausted and unable to function effectively (performance decrements).

4.3.1 Correlation between Driver Psychophysiological Response and Driving Time with and without a break: eSense Metric for Attention

This section presents the relationship between the driver's psychophysiological state and time spent driving in all stages of the experiments (four hours of driving with no break and two hours of driving before a 30 minute break and two hours of driving after a 30 minute break). The evidence of the influence of time spent driving on the driver's level of fatigue or distraction or abnormality in this study was evaluated by examining the variation(s) in average psychophysiological responses (brain activity) of the subjects on each stage of the experiments (Figure 4-1A-D). For example, there is no significant difference between prolonged driving without a break and two hours of driving before a 30 minute break. On the other hand, prolonged driving without a break (between 150 minutes and 240 minutes of driving) was compared to the experimental phase of two hours of driving after a 30 minute break. The results of driving without a break demonstrated significant reductions in the psychophysiological responses of all the participants compared to driving after a break of 30 minutes (Figure 4-1). These results showed the significant impacts of 30 minute breaks on a driver's level of fatigue and performance decrements. These results also confirmed that the drivers exhibited signs of quicker recovery as a result of the short breaks (Figure 4-1A and B) when the psychophysiological response of driving before a 30 minute break is compared to driving after a 30 minute break. However, the effectiveness of breaks on psychophysiological responses of the drivers solely depends on their duration of driving and their fatigue state at the time the break was taken. It could, therefore, be concluded that the longer the duration of the scheduled break is, the better the recovery and the more likelihood of psychophysiological and performance functions of both male and female or young and old drivers. The findings could be interpreted as prolonged driving having a negative impact on the psychophysiological functioning and ability of the drivers to react to incidents/accidents, and time spent driving is an essential construct for understanding driver fatigue.

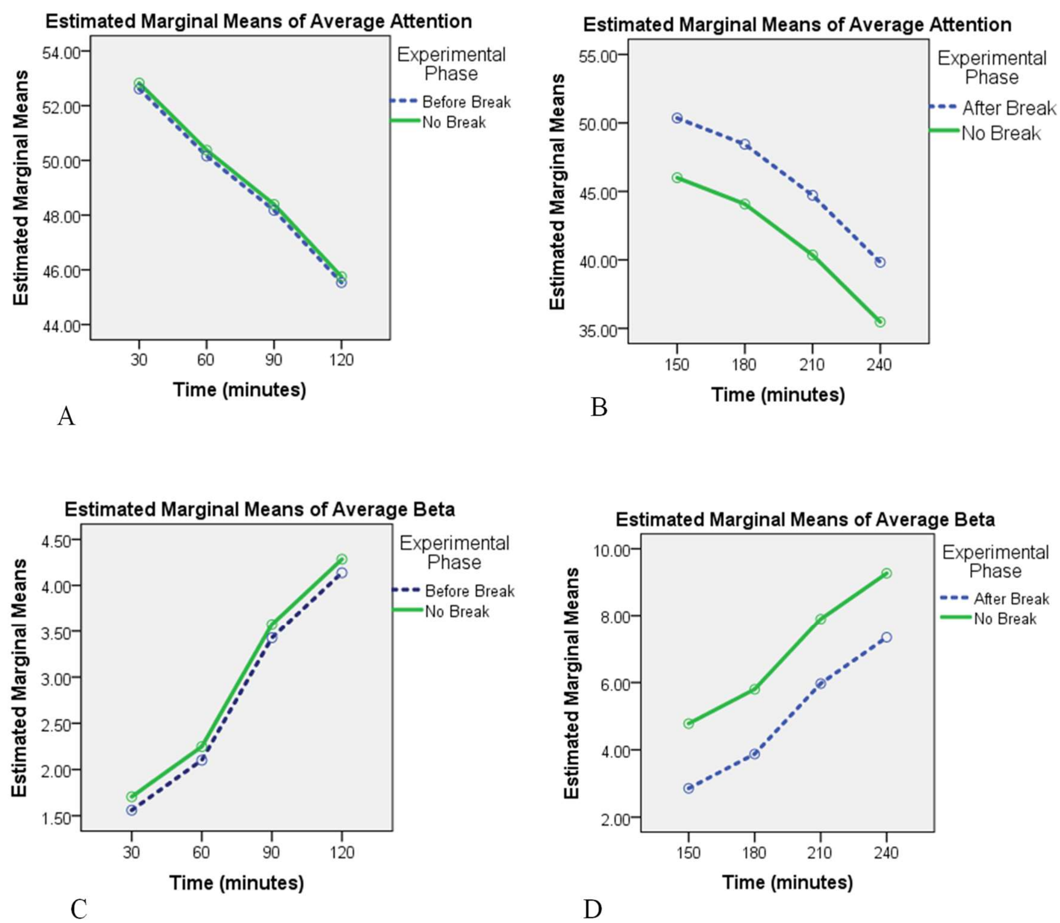


Figure 4-1: Changes in average driver psychophysiological response relative to the influence of driving time in different stages of the experiment

4.3.2 Correlation between Driver Psychophysiological Response and Driving with and without Breaks (Beta EEG frequency band)

The investigation of the influence of prolonged driving and breaks on a driver's psychophysiological responses demonstrated that there is variation in average beta brain activity of driving without a break and driving with a 30 minute break. An increase in average beta EEG brain activity appears to demonstrate deterioration in the level of alertness of the driver's as a function of time spent driving. These findings demonstrate that the sequence alterations of the beta EEG power spectrum indicate signs of changes in the psychophysiological responses of driver's relative to the influence of the driving time. For instance, the average beta brain activity in the first 30 minutes of the driving task without a break and before a break are 1.72 and 1.58, respectively (Figure 4-1C). On the other hand, the average responsiveness of the drivers in the first 60 minutes of driving after the break and 180 minutes of driving without a break are 3.75 and 5.82, respectively (Figure 4-1D). Therefore, the observed variability in average beta EEG brain activity as a function of driving time could be interpreted as a gradual deterioration in the driver's level of fatigue or alertness. The findings demonstrate that there is a significant difference between the psychophysiological responses (fatigue state) of driving after 30 minutes of break and driving without a break (Figure 4-1C and D). The driver's psychophysiological states deteriorate as the duration of driving increases. The average beta brain activity was at the highest level at 240 minutes of driving for both driving with and without a break. For example, the average beta brain activity relative to 210 and 240 minutes of driving without a break is 8.02, and 9.83, respectively while the corresponding proportion of driver's responsiveness after 30 minutes of break is 6.01 and 7.24, relative to the influence of driving for 210 and 240 minutes, respectively (Figure 4-1D). These findings demonstrated the significance of taking a break on the psychophysiological response (fatigue) of the long-distance driving task. The effectiveness of a rest break on the psychophysiological response of the drivers is good control measure and management of a driver's fatigue and alertness.

4.4 Modelling the Effects of Fatigue Associated with Length of Time Driving

An increase in urban population size requires more good delivery services that sometimes expose the HGV drivers to unscheduled operations or extended duty time from the management. In some areas, drivers experience prolonged driving without a break due to unforeseen circumstances (such as traffic congestion, changing schedules and other additional tasks, such as fuelling and loading/offloading of goods), which contribute to fatigue in both local and long-distance hauling. This section presents the modelling of driver-fatigue associated effects on performance decrements and the ability to react to factors of road incidents/accidents as a result of prolonged driving time. The models established the relationship between the influence of induced stimuli effect of driving time, along with age and gender on driver fatigue. Cumulative fatigue due to prolonged driving could be associated with decreases in driver's psychophysiological activation (decline in the level of fatigue or performance decrements) (Nilsson et al., 1997).

4.4.1 Evaluation of Driver's Psychophysiological Response to the Influence of Driving Time (before a 30 minute break and no break of the first two hours: eSense metric for attention)

The validation of the results was carried out by modelling the driver's psychophysiological response relative to the influence of the duration of driving. The corrected model row shows that the overall model was significant ($p < 0.01$) and the effect size shows that model explains 44.9% of the variance in the subject's responsiveness (fatigue or performance decrements). There is no significant difference between the experimental phases of driving before a 30 minute break and the first two hours of driving without a break. The durations of driving were also found to be statistically significant ($p < 0.01$). The effects size shows that time spent driving explains 43.5% of the variance of the dependent variable (brain activity) or driver fatigue (Table 4-2). It could be interpreted as the cumulative effects of prolonged driving having a significant impact on the extent of driver fatigue.

Table 4-2: Changes in driver fatigue as a function of the length of time spent driving before a break and no break (eSense metric for attention)

Source	Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	514.376	6	85.729	8.817	0.00	0.449
Intercept	170615.2	1	170615.2	17546.71	0.00	0.996
Phase	0.84	1	0.84	0.086	0.77	0.001
Time	486.283	3	162.094	16.67	0.00	0.435
Gender	4.783	1	4.783	0.492	0.48	0.008
Age	24.357	1	24.357	2.505	0.12	0.037
Error	632.027	65	9.723			

a. R Squared = .449 (Adjusted R Squared = .398)

4.4.2 Evaluation of a Driver's Psychophysiological Response to the Influence of Driving Time (After a 30 minute break and no break of the last two hours: eSense Metric for Attention)

The validation of results was carried out by modelling the eSense metric for attention (psychophysiological response) relative to time spent driving. The model "Test of Between-Subjects Effect" was applied by using ANOVA. There is a significant difference between the experimental phases of driving after a break of 30 minutes and driving for the last two hours with no break. The effect size shows that time spent driving attributed to 49.3% of the variance in driver fatigue (Table 4-3). The corrected model row shows that the overall model was significant ($p < 0.01$), and the effect size shows that the model explains 61.7% of the variance in a subject's responsiveness (fatigue or performance decrements). The duration of driving was also found to be statistically significant ($p < 0.01$). It could be interpreted as the cumulative effects of prolonged driving having a significant impact on the extent of driver fatigue.

Table 4-3: Changes in driver's psychophysiological response as a function of the length of time spent driving after a break and no break (eSense metric for attention)

Source	Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	1925.679	6	320.947	17.42	0.00	0.617
Intercept	134155	1	134155	7281.52	0.00	0.991
Phase	342.177	1	342.177	18.572	0.00	0.222
Time	1162.37	3	387.457	21.03	0.00	0.493
Gender	82.797	1	82.797	4.494	0.04	0.065
Age	302.473	1	302.473	16.417	0.00	0.202
Error	1197.56	65	18.424			

R Squared = .617 (Adjusted R Squared = .581)

4.4.3 Driver's Psychophysiological Responses as Function of the Influence of Driving Time (before a break and after the first two hours of no break: Beta Brain Activity)

The model "Test of Between-Subjects Effect" was applied using ANOVA to model the relationship between a driver's psychophysiological response on the experimental stage of driving for two hours before a 30 minute break and after the first two hours with no break. The results indicated that there is no significant difference between the psychophysiological responses of the subjects to the influence of the experiment's designed phases. The corrected model row shows that the overall model was significant ($p < 0.01$) levels, and the effect size indicates that the model explains 61.9% of the variance in fatigue or performance decrements, which can be attributed to the influence of the duration of driving (Table 4-4). It could be concluded that the cumulative effects of prolonged driving have significant impacts on the extent of driver fatigue. Also, the driver's related variables, such as age and gender, were introduced as part of the model. The results demonstrated that age is statically significant ($p < 0.01$). These results suggest that a driver's age has a significant impact on driver fatigue or performance decrements relative to the influence of the duration of driving.

Table 4-4: Changes in a driver's response to the influence of driving time before a 30 minute break and no break for the first two hours (beta EEG frequency band)

Source	Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	87.673	6	14.612	17.633	0.00	0.619
Intercept	583.627	1	583.627	704.299	0.00	0.916
Phase	0.384	1	0.384	0.463	0.49	0.007
Time	75.759	3	25.253	30.475	0.00	0.584
Gender	10.083	1	10.083	12.167	0.00	0.158
Age	2.293	1	2.293	2.767	0.10	0.041
Error	53.863	65	0.829			

R Squared = .619 (Adjusted R Squared = .584)

4.4.4 Driver's Psychophysiological Responses as a Function of the Influence of Driving Time after a Break and for the Last Two Hours with no Break (beta brain activity)

The validation of the results was carried out by modelling the relationship between the average beta EEG brain activity relative to the subject's time spent driving after a 30 minute break and driving without a break. The model "Test of Between-Subjects Effect" was applied using ANOVA. In this model, the duration of driving was found to be significant ($p < 0.01$). The results indicated that the variation between the average psychophysiological response of the participants to the influence of driving time after a 30 minute break and driving without a break after 120 minutes of driving is statistically significant ($p < 0.01$). The effects size indicates that the model explains 47.0% variance in participants' responsiveness to the influence of driving time. The corrected model row also shows that the overall model was significant at $p < 0.01$ levels and the effect size demonstrate that the model explains 61.7% of the variance in a subject's responsiveness (fatigue or performance decrements) to the influence of the duration of driving. This result could be interpreted as cumulative effects of prolonged driving having a significant impact on the extent of driver fatigue. Besides, the driver's related variables, such as age and gender, were introduced as part of the model. The results demonstrated that age is statically significant ($p < 0.01$) while the influence of gender is not. The results suggest that a driver's age also has a significant impact on driver fatigue or performance decrements relative to the duration of driving time (Table 4-5).

Table 4-5: Changes in a driver's response to the influence of driving time after a 30 minute break and no break of the last two hours.

Source	Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	403.350	6	67.225	17.485	0.00	0.617
Intercept	2512.33	1	2512.33	653.466	0.00	0.910
Phase	66.63	1	66.63	17.331	0.00	0.211
Time	221.292	3	73.764	19.186	0.00	0.470
Gender	99.439	1	99.439	25.864	0.00	0.285
Age	8.889	1	8.889	2.312	0.13	0.034
Error	249.9	65	3.845			

Squared = .617 (Adjusted R Squared = .582)

4.4.5 Age Influence on Driver Fatigue: eSense metric for attention

The impact of fatigue on different age groups is found to manifest at different rates to changes in a driver's ability to react to factors of incidents/accidents. The result of this study demonstrated that there is a significant relationship between the subject's psychophysiological response (eSense metric for attention) of different age groups and the duration of time spent driving (Figure 4-2A-B). The responsiveness of the drivers that are less than 30 years old after 120 minutes of driving indicated that the younger the driver, the greater their level of fatigue becomes over time. The results could be interpreted as prolonged driving having a significant impact on both young and old drivers' psychophysiological responses, but is more prominent on the participants that are less than 30 years old (Figure 4-2B).

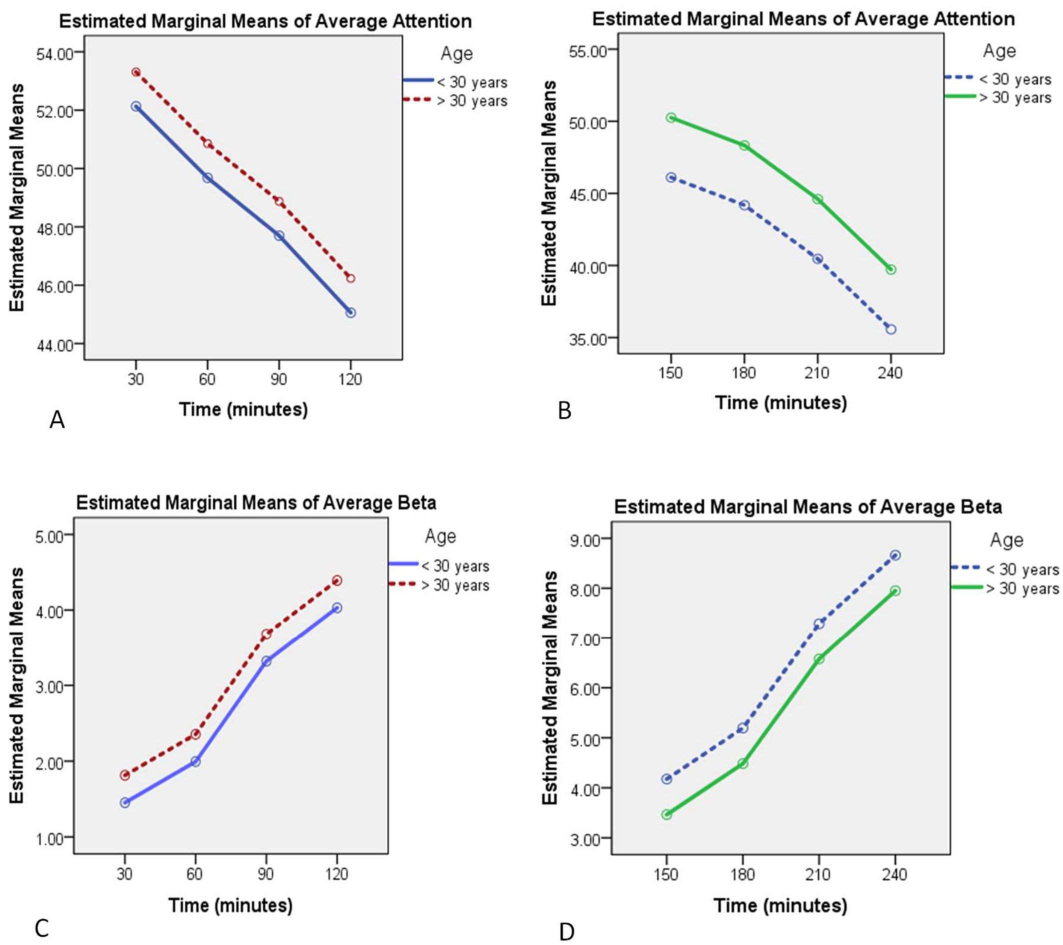


Figure 4-2: Changes in the average driver's psychophysiological response relative to the influence of driving time (age influence)

The results showed that drivers of different age groups exhibit and repeat different states of fatigue relative to the influence of driving time. Although the beta brain activity of both young and old drivers showed a significant increase relative to the influence of the duration of driving, the younger drivers exhibited higher levels of fatigue as a function of the duration of driving, as reflected by the psychophysiological response compared to older drivers (Figure 4-2C–D). For example, the average response of drivers who are less than 30 years old at 120 minutes, 210 minutes and 240 minutes of driving are 5.23, 7.43 and 8.66 beta brain activity, respectively, compared to those who are older than 30 years, with an average beta brain activity of 4.43, 6.5 and 7.83, at 120 minutes, 210 minutes, and 240 minutes, respectively (Figure 4–2D). However, the drivers who are older than 30 years appear to show more significant recovery from the rest breaks compared to those below 30 years. The results of the investigation demonstrated that the age of the driver should always form parts of the essential variable in research aims in order to establish the relationship between driver fatigue and driving time.

4.4.6 Gender Influence on Driver Fatigue: eSense metric for attention

This section presents the influence of a driver's gender on the analysis of the extensive simulated driving tasks conducted to establish the correlations between driver fatigue and duration of driving time. The effect of fatigue on drivers could vary by the gender of the participants. The evidence of variations in male and female driver performance decrements was validated by using the average psychophysiological response of the participants to the influence of driving time. The results demonstrated that both male and female brain activity change when there were transitions from the states of fully alert and wide-awake to fatigue relative to the influence of time spent on a driving task (Figure 4-3A-D). The results indicated that a more significant loss of psychophysiological activation and decrements in performance probably occur in female drivers compared to male drivers. The results showed that a lower average value eSense metric for attention was observed in females during the prolonged driving period compared to males (Figure 4-3B). However, the observed differences are not statistically significant ($p < 0.01$). Considering the beta brain activity, the observable increase in a driver's responsiveness to the influence of the duration of driving are statically significant ($p < 0.01$) see Figure 4-3D. Female drivers consistently rate themselves as being extremely tired compared to males. These results could be interpreted as female drivers exhibiting more of a level of fatigue and performance decrements that could impair their level of alertness, distractions and reaction time compared to male drivers.

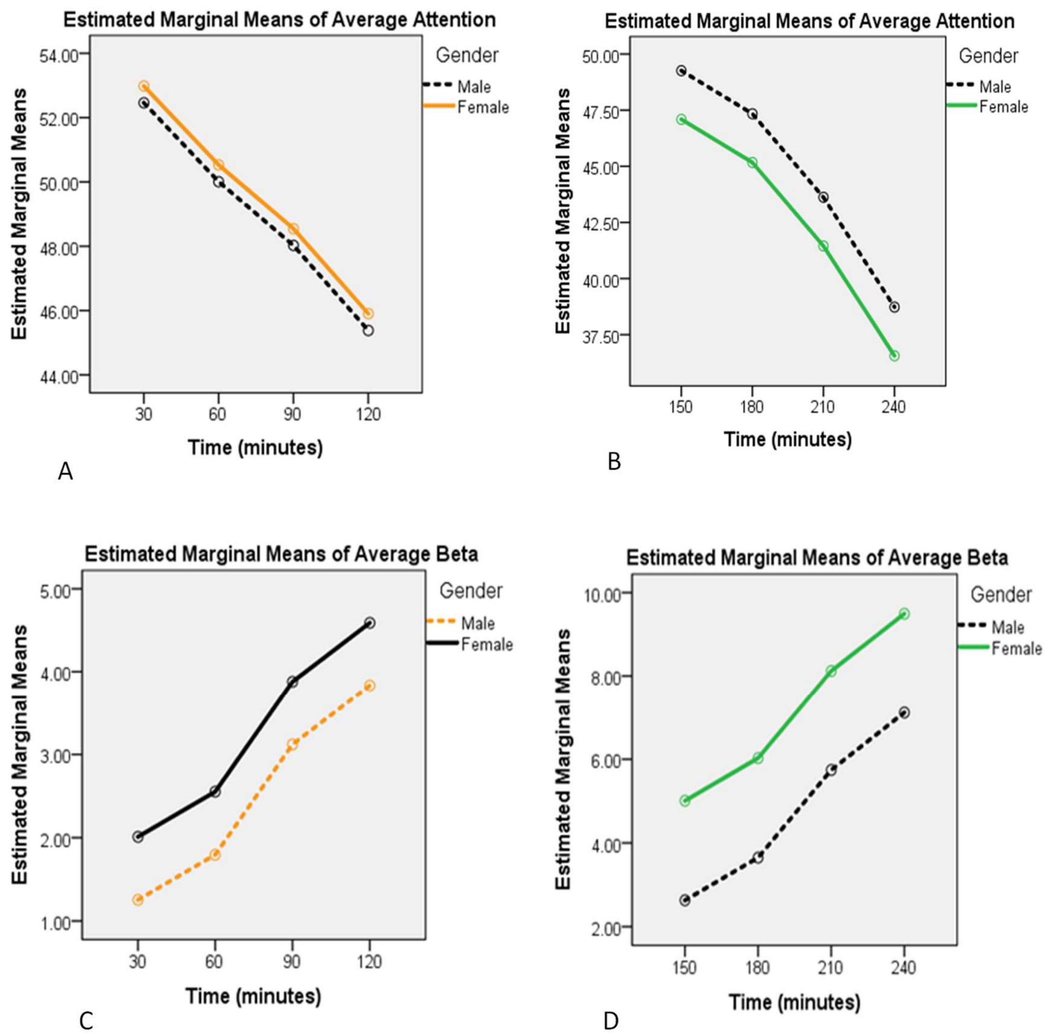


Figure 4-3: Changes in average psychophysiological response relative to the influence of the participants' gender

4.5 Relationship between the Average eSense Metric for Attention and a Drivers's Perception of Fatigue and Performance Decrements

This section presents the relationship between the average brain activity and subjective fatigue assessment ranking scale relative to the influence of driving time. The results of the analysis demonstrated that there is a significant relationship between the driver's psychophysiological response and subjective fatigue assessment (Figure 4-4A and B). Furthermore, the results demonstrated the correlations between the average psychophysiological response and transitions from a state of being fully alert and wide awake to being extremely tired and very difficult to concentrate or completely exhausted and unable to function effectively as a function of experimental stages seems to exist. Consequently, using the average eSense meter for the attention of the first 30 minutes on the HGV driving simulator as the baseline of psychophysiological response, and being fully alert and wide awake as the subjective assessment as the references point. The results of this study confirmed that a driver's level of attention decreases significantly in proportion to the ranking of the subjective fatigue assessment (Figure 4-4A and B). These findings could be interpreted as being when the psychophysiological response decreases, changes in subjective fatigue assessment scale also increase. The results could be concluded as the more the eSense meter of attention decreases, the more the driver's level of alertness, fatigue or performance deteriorates. For instance, the average psychophysiological responses of subjects that felt fully alert and wide awake, extremely tired and very difficult to concentrate and completely exhausted and unable to function and concentrate effectively are 51.96, 37.27 and 35.23, respectively (Figure 4-4B).

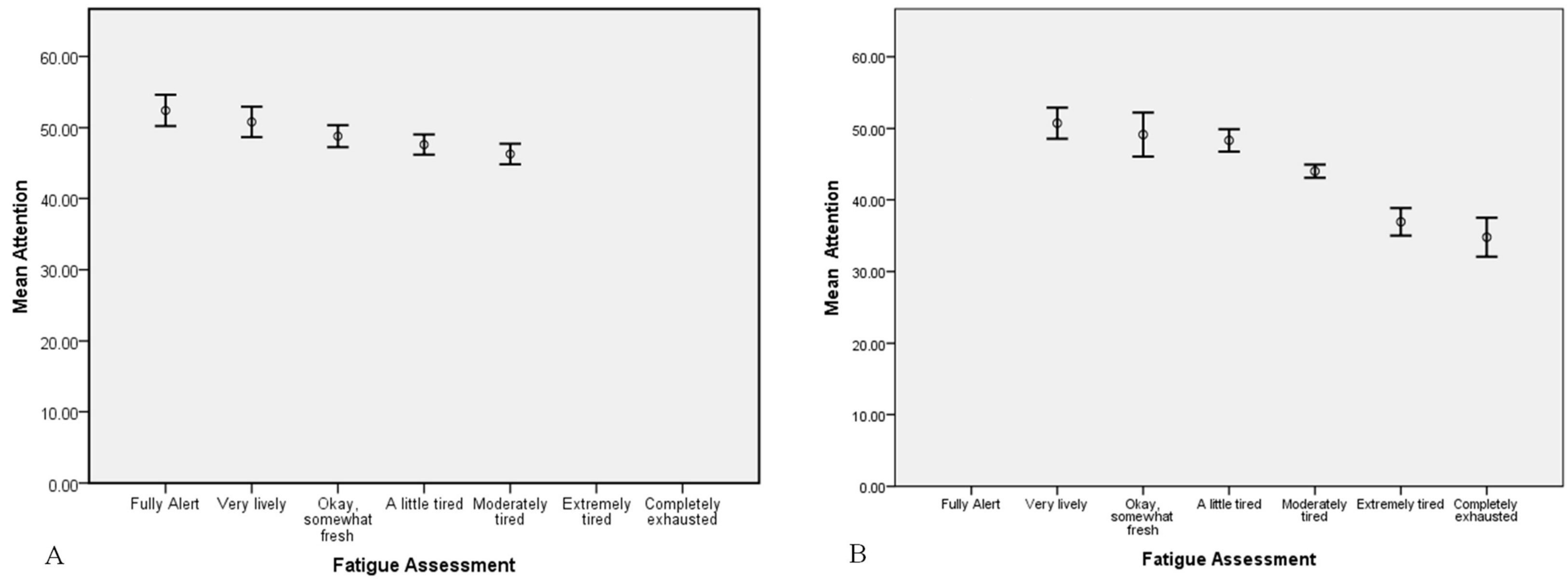


Figure 4-4: Relationship between the change of the average psychophysiological response and changes in driver's subjective fatigue assessments

4.5.1 Assessment of a Driver's Perception Relative to Changes in their Psychophysiological Response (eSense metric for attention)

Driver performance decrements relative to the influence of prolonged driving is generally known to be one of the significant human factors causing road incidents/accidents, injuries and damage of property (Nilsson et al., 1997). The validation of the relationship between the psychophysiological response and subjective fatigue assessment relative to time spent in driving was conducted by using the "Tests of Between-Subjects Effects" model. The results of the statistical analysis in Table 4-6 indicated that both the corrected model and the subjective fatigue assessment ranking scale concerning driver fatigue or performance decrement are statically significant ($p < 0.01$). The results of this finding demonstrated the possibility of using EEG as a tool to monitor driver fatigue (Lal & Craig, 2002). Also, the model extended further to test the influence of participant's age and gender on fatigue or performance decrements. The results revealed that the age of the participants is statistically significant ($p < 0.01$) and the effect size demonstrated that 9.9% of the variances in driver fatigue (eSense attention meter) could be attributed to the influence of age.

Table 4-6: Changes in psychophysiological response and driver's perception relative to the influence of the length of driving time (eSense metric for attention)

Source	Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	2120.304	8	265.038	16.649	0.00	0.679
Intercept	58629	1	58629	3682.81	0.00	0.983
Gender	46.246	1	46.246	2.905	0.09	0.044
Age	109.938	1	109.938	6.906	0.01	0.099
Subjective	1699.17	6	283.195	17.789	0.00	0.629
Error	1002.94	63	15.92			

R Squared = .679 (Adjusted R Squared = .638

4.5.2 Psychophysiological Response and Driver's Perception of Fatigue (eSense metric for attention): Parameter of Estimates

The concept that prolonged driving without a break may significantly affect driver fatigue is one of the factors that prompt the need for investigation in this study. Therefore, this study clarified the point that brain activity could produce an indication of changes in the psychophysiological response of drivers to influence the duration of driving. Table 4-7 presented the relationships between passengers' psychophysiological response (eSense metric for attention) and subjective fatigue assessment relative to the influence of the duration of driving. The statistical analysis “Parameters Estimate” showed that the correlation between the subjective fatigue assessment and psychophysiological responses are statistically significant ($p < 0.01$). The model intercept was significant ($p < 0.01$) and the effect size shows that the model explains 86.6% of the relationship between EEG brain activity and subjective fatigue assessment.

Table 4-7: Evaluation of the relationship between the psychophysiological response and drivers' perception (eSense meter for attention)

Parameter	B	Std. Error	t	Sig.	99% Confidence Interval Lower Bound	Upper Bound	Partial Eta Squared
Intercept	35.71	1.77	20.179	0.00	31.009	40.41	0.866
Gender	1.672	0.981	1.704	0.09	-0.934	4.279	0.044
Age	-2.633	1.002	-2.628	0.01	-5.294	0.028	0.099
Fully alert, wide awake	16.734	4.343	3.853	0.00	5.199	28.27	0.191
Very lively, but not at peak	14.211	2.211	6.427	0.00	8.338	20.085	0.396
Okay, somewhat fresh	14.231	2.142	6.643	0.00	8.541	19.922	0.412
A little tired, less than fresh	13.314	1.94	6.862	0.00	8.16	18.467	0.428
Moderately tired, let down	8.205	1.724	4.758	0.00	3.624	12.785	0.264
Extremely tired	2.048	1.948	1.052	0.29	-3.126	7.222	0.017

The parameter "Completely exhausted" is set redundant

4.5.3 Evaluation of the Relationship between the Psychophysiological and Subjective Responses of the Participants: Gender Influence

The graphical representation of the relationship between male and female driver's EEG brain-induced signals and their subjective assessment on the level of fatigue or alertness to the influence of the duration of driving is shown in Figure 4-5. These results demonstrated that there are no significant differences between male and female psychophysiological responses relative to the subjective assessment as a function of the duration of driving by using the eSense metric for attention. These could be explained as there is no significant difference in evaluating the relationship between male and female psychological responses and subjective assessments.

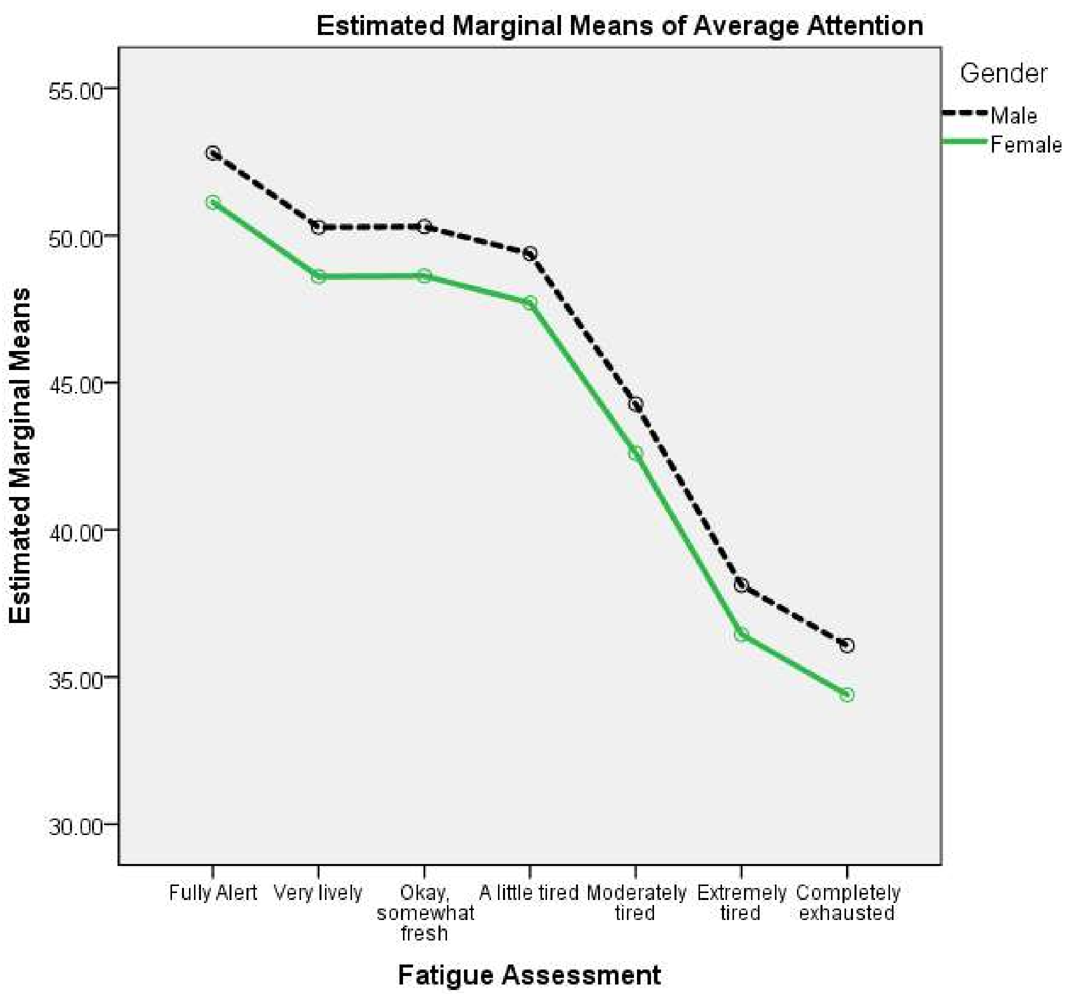


Figure 4-5: Driver's psychophysiological response (eSense metric for attention) and subjective assessment: gender influence

4.5.4 Evaluation of the Relationship between Psychophysiological and Subjective Responses: Age Influence

The results in Figure 4-6 shows the graphical illustration of the correlations between the average eSense metric for attention EEG brain activity and the subjective fatigue assessment of different age groups relative to the influence of the duration of driving. The results demonstrated that the psychophysiological activation of drivers who are less than 30 years old is lower compared to those who are older than 30 years. These results could be interpreted as young drivers exhibit a high level of fatigue and performance decrements compared to older ones relative to the influence of prolonged driving. Therefore, investigation of the transition from the state of being fully alert to the state of being extremely tired or completely exhausted (fatigue state) demonstrated a decrease in the eSense metric for attention brain activity.

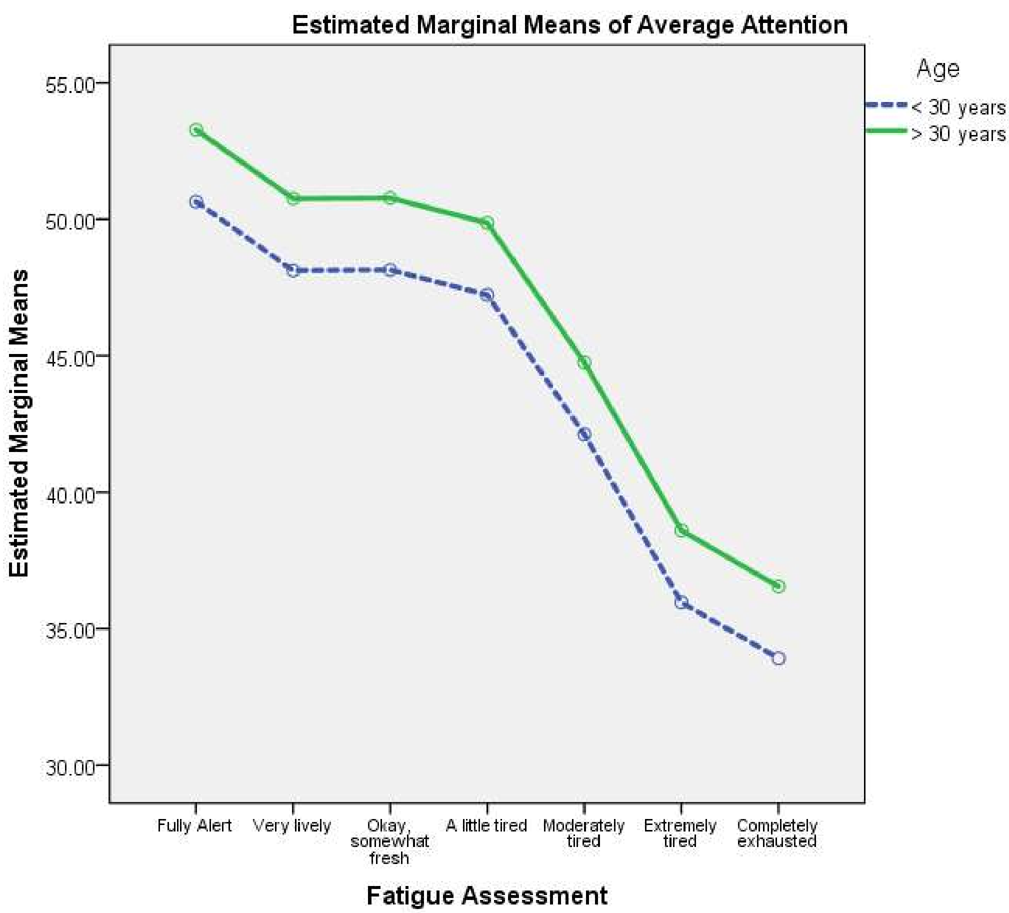


Figure 4-6: Driver's psychophysiological response (eSense metric for attention) and subjective assessment: age influence

4.6 Relationship between Average Beta Brain Activity and Driver's Perception of Fatigue and Performance Decrements

Driver's fatigue and distraction are related to cognitive functions and difficulties (Lal & Craig, 2001). This section presents the relationship between the average beta brain activity and subjective fatigue assessment. The results were used to validate the impacts of the duration of driving and rest breaks on driver fatigue (psychophysiological response). The results of this study revealed that the more the driver's psychophysiological signals (beta brain activity) increase relative to changes in rank of the seven-scale subjective fatigue assessment, the more the driver's level of alertness deteriorates. For instance, the average psychophysiological responses of subjects who felt fully alert and wide awake, extremely tired and very difficult to concentrate and completely exhausted and unable to function and concentrate effectively are 1.5, 7.79 and 10.44, respectively (Figure 4-7A and B). Therefore, it is evident that the more fatigue the drivers felt, the higher the average values of EEG beta brain activity were (psychophysiological responses).

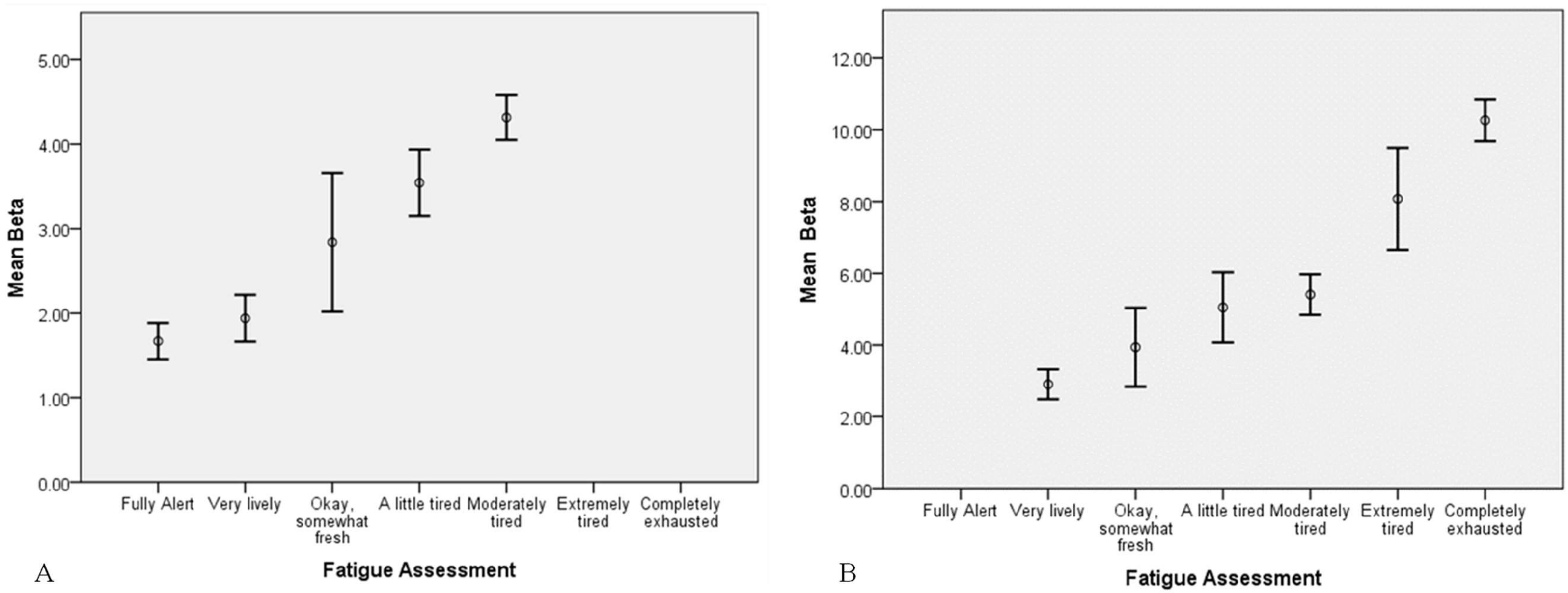


Figure 4-7: Relation of driver's psychophysiological response and perception

4.6.1 Assessment of Driver's Perception relative to Changes in their Psychophysiological Response (beta brain activity)

A driver's cognitive impairment and distraction is known to be one of the factors responsible for road-related incidents/accidents (Phillips, 2014). A significant increase in average beta brain activity relative to prolonged driving without a break and with a 30 minute break reflects the possibility of cumulative impacts of fatigue. It could be concluded that the beta brain activity increases significantly in proportion to the transition of drivers from the state of being full alert and wide awake to the state of being extremely tired and very difficult to concentrate or completely exhausted and unable to function effectively (Table 4-8). The results of the statistical analysis in Table 4-8 indicated that the corrected model and subjective fatigue assessment ranking scale are statistically significant ($p < 0.01$) and the effect size shows that the subjective fatigue assessment explains 49.4% of the variance in driver's psychophysiological response. Also, the model extended further to test the influence of participant's age and gender on fatigue and performance decrements. The results show that the influence of gender is statistically significant ($p < 0.01$).

Table 4-8: Evaluation of the perception of driver's relative changes in their psychophysiological responses (beta EEG frequency band).

Source	Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	381.202	8	47.65	11.035	0.00	0.584
Intercept	905.468	1	905.468	209.685	0.00	0.769
Gender	77.999	1	77.999	18.063	0.00	0.223
Age	0.174	1	0.174	0.04	0.84	0.001
Subjective	265.775	6	44.296	10.258	0.00	0.494
Error	272.048	63	4.318			

R Squared = .584 (Adjusted R Squared = .531)

4.6.2 Correlation between Psychophysiological Response and Driver's Perception of Fatigue (beta EEG frequency band): Parameter of Estimates

This section presents the "model parameter of estimate" on the investigation of correlations between driver's psychophysiological response and subjective fatigue assessment by using beta EEG brain activity. The results of the statistical analysis in Table 4-9 indicated that the model intercept is statically significant ($p < 0.01$) and the effect size established that 22.3% of the variances in driving fatigue and performance decrements (psychophysiological response) can be attributed to the duration of driving. The results in Table 4-9 demonstrated that all parameters of fatigue assessment scales are statistically significant ($p < 0.01$).

Table 4-9: Evaluation of psychophysiological response and driver's perception of the influence of the length of driving time (beta EEG frequency band)

Parameter	B	Std. Error	t	Sig.	99% Confidence Interval Lower Bound	99% Confidence Interval Upper Bound	Partial Eta Squared
Intercept	11.582	0.922	12.566	0.00	9.134	14.03	0.715
Gender	-2.172	0.511	-4.25	0.00	-3.529	-0.815	0.223
Age	-0.105	0.522	-0.201	0.84	-1.491	1.281	0.001
Fully alert, wide awake	-7.272	2.262	-3.215	0.00	-13.279	-1.264	0.141
Very lively, but not at peak	-7.107	1.152	-6.171	0.00	-10.166	-4.048	0.377
Okay, somewhat fresh	-6.65	1.116	-5.96	0.00	-9.614	-3.687	0.361
A little tired, less than fresh	-5.487	1.011	-5.43	0.00	-8.171	-2.803	0.319
Moderately tired, let down	-4.74	0.898	-5.278	0.00	-7.126	-2.355	0.307
Extremely tired	-2.659	1.015	-2.621	0.01	-5.354	0.036	0.098

The parameter "Completely exhausted" is set redundant.

4.6.3 Correlation between Psychophysiological Response and Driver's Perception (beta EEG frequency band): Age Influence

Figure 4-8 shows the graphical representation of the correlations between the average beta EEG brain activity and the subjective fatigue assessment of different age groups relative to the influence of time spent driving. The results in Figure 4-8 prove that there is no significant difference between the responsiveness of the young and old drivers to the influence of the duration of driving.

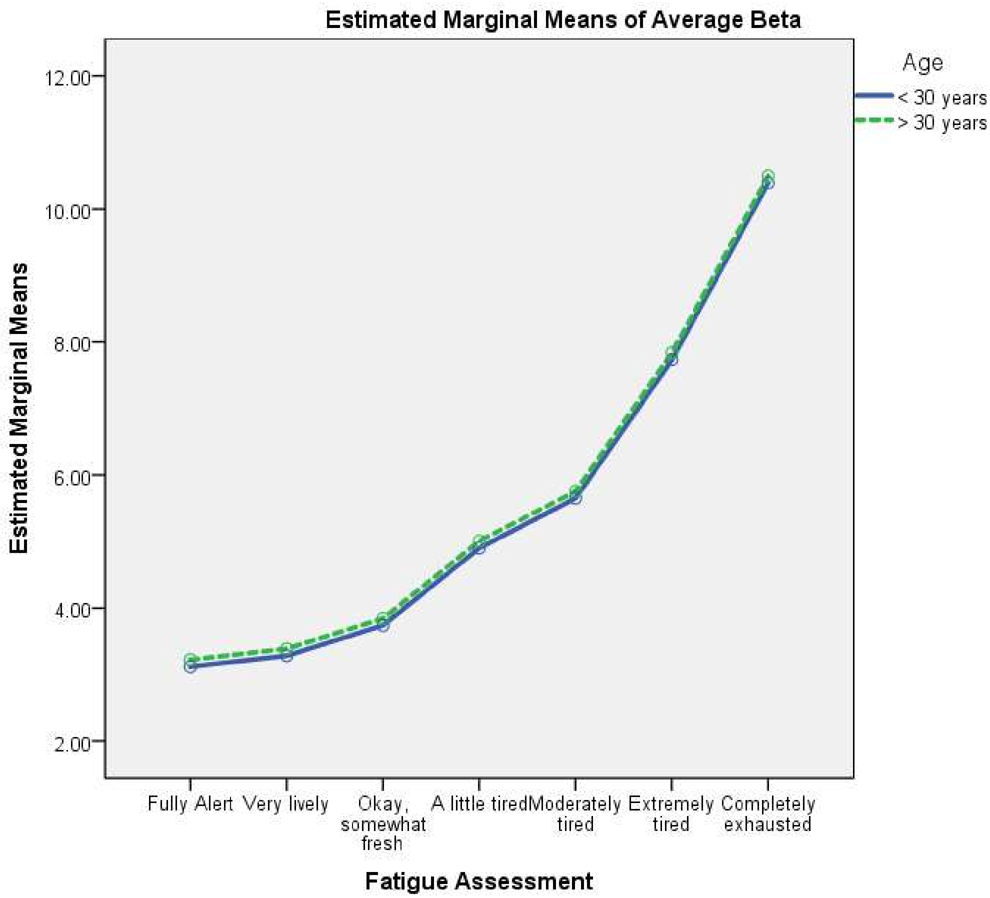


Figure 4-8: Driver's psychophysiological response (beta band) and subjective responses: gender influence

4.6.4 Correlation between Psychophysiological Response (beta EEG frequency band) and Driver's Perception: Gender Influence

The correlation between the average beta EEG brain-induced signals and the subjective assessment of drivers were investigated to evaluate the psychophysiological activation (level of fatigue and alertness) of male and female passengers relative to the influence of the duration of driving. A significant increase in average responses was found in female passengers compared to male passengers. The results showed that the psychophysiological activation is higher in female passengers compared to male passengers Figure 4-9. These results could be interpreted as female drivers experiencing more decline in fatigue and performance decrements relative to the influence of the duration of driving compared to male drivers. Therefore, it is evident that designing a study for investigating driver performance decrements or fatigue as a function of the influence of the duration of driving requires the influence of the driver's gender.

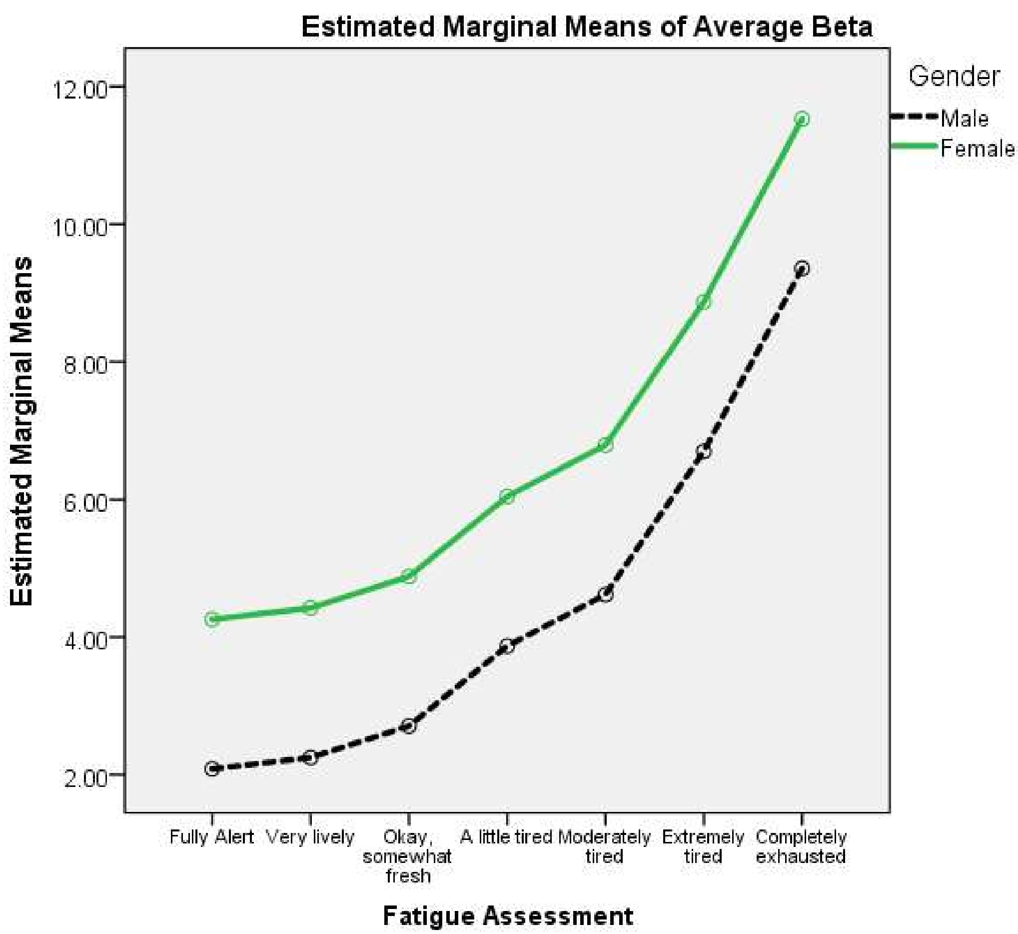


Figure 4-9: Driver's psychophysiological response (beta band brain activity) and subjective responses: age influence

4.7 Summary

The results of this chapter add to the growth of research, indicating the appropriateness of using the beta EEG frequency band and the eSense metric for attention brain activity in understanding driver fatigue as a function of time spent driving. Changes in a driver's psychophysiological states were reflected through the cerebral cortex and neural changes associated with the performance of driving an HGV simulator relative to the influence of driving time (as captured by EEG) were presented and modelled. The variables (duration of driving, experimental stage and subjective fatigue assessment) were analysed by using "Tests of Between-Subjects Effects" and "Parameter of Estimate". The subjective fatigue assessment was used to validate the psychophysiological response of the drivers to the influence of the duration of driving. The results of the statistical analysis showed that there is a positive correlation between the subjective comfort assessment and a driver's psychophysiological responses, and the correlation is statistically significant ($p < 0.01$). Also, the model extended further to test the influence of age and gender in order to ascertain their effects on the fatigue or performance decrements. The experimental results demonstrated significantly enhanced performance in fatigue detection and assessment as it is demonstrated by the study of (Lal & Craig, 2002). The results of the study also demonstrated the appropriateness of using EEG as a reliable approach to investigate the influence of driving time on driver fatigue.

The next chapter discusses the analysis of the application of beta brain activity on passenger comfort. It discusses the analysis of the effect of experimentally designed variables, such as road roughness, passenger posture, bus type and speed profile factors on urban bus passenger ride comfort.

CHAPTER 5 URBAN BUS PASSENGER RIDE COMFORT: APPLICATION OF BETA EEG BRAIN ACTIVITY

5.1 Introduction

Chapter 4 presented the application of EEG on driver fatigue, the effectiveness of driver rest breaks on fatigue and the cumulative effects of fatigue associated with the length of driving time by using an HGV simulator. This chapter presents the investigation of the effect of experimentally designed variables, such as road roughness, passenger posture bus type and speed profile factors on urban bus passenger ride comfort. The Event-Related Synchronisation (ERS) that shows the transient event-related changes in the amplitude of beta brain activity relative to the experimentally designed variables was also presented. Passenger ride comfort was investigated as the effect(s) of uncomfortability induced by the influence of the experimentally designed variables. The psychophysiological responses (comfort/discomfort) in this study were evaluated by examining the induced changes in the subject's cortical activities as captured by EEG signals.

Road roughness has been recognised for a long time as being a means of measuring and evaluating road performance and ride comfort. The influence of road roughness characteristics (pavement types) appears to be more prominent on passenger ride comfort compared to several other factors, such as passenger posture, ability, age, gender, bus type and many more. For instance, the study of Magnusson and Arnberg, (1976) demonstrated that the effects of road roughness are not limited to causing discomfort to drivers and passengers, but they also cause fatigue to be experienced during actual travelling or afterwards. Also, previous studies have suggested that prolonged exposure to psychophysiological stress could trigger various diseases associated with depression, heart attack, stroke and some other mental disturbance symptoms (Al-shargie et al., 2016). Furthermore, discomfort caused by the influence of road roughness, passenger posture, vehicular type and many other source(s) can sometimes lead to the activation of hypothalamus-pituitary-adrenocortical axis hormones (cortisol) in the adrenal cortex, which could cause poor health conditions.

5.2 General Overview of Human Response and Experimentally Designed Phases

This section presents a brief overview analysis of the influence of the experimentally designed variables (road roughness characteristics, passenger posture, bus type and driving behaviours) on a passenger's psychophysiological responses (level of comfort) by using the beta EEG brain spectral band. Generally, road-vehicle interaction produces a different form of sensation that does not have one specific human organ target, but affects all parts of the body of both drivers and passengers to some degree, which could have long-term health implications on passengers (Nahvi et al., 2009). Human psychophysiological responses associated with dynamic systems sometimes vary according to the frequency, direction and characteristics of the variable(s) that the sensations originated from and where they are transferred to. These cause-effects in public transport depend on the driving mode, road roughness characteristics and subject postures as well as vehicle types. Many researchers have used different approaches that are not limited to subjective assessment, such as physiological responses and behavioural change to evaluate emotion. The evaluation of the effects of experimentally designed variables on a passenger's response in the bus compartment for this study was carried out by using beta EEG brain activity (ERP). In this study, the ERP oscillations (beta brain activity) were evaluated by decomposing the beta EEG signals into magnitudes and phase information.

Generally, the human brain responds to changes that occur in both the internal and external environment. However, body neurons do not react without being triggered by a behaviour or an event. Therefore, our bodies respond directly to given events or conditions. For example, for a long time, the stress response has been traced to the central nucleus part of the brain known as the amygdala. This stress response causes a series of physiological changes, such as rapid breathing, change in blood flow to extremities, and increased heart rate and blood pressure. The nervous system allows the human body to respond to changes perceived in both internal and external environments. Variations in the responsiveness of the participants depend on the strength of force presented to the CNS. Sensation and cognitive events induce superimposed oscillations transmitted to brain tissue. These oscillations are characterised by various degrees of intensity that are proportional to the stimuli effect because the conditions in the human body need to be carefully controlled in order to function efficiently and survive. The stimuli effect causes changes in the activation of the electrical signal in response to the stimuli from the influences of experimentally designed variables. The experimentally designed phases (Table 5-1) for this study are based on the characteristics of variables, such as road roughness, passenger posture and bus type. These performance indicators (road roughness, passenger posture and bus type) are incorporated to form a system that serves as the basis for data collection. The feature of beta brain activity (participant's responses) was collated, processed and analysed in relation to the experimentally designed phase and variables.

Table 5- 1: Experimentally designed phase

Experimental phase	Stage	Parameter of estimate
Phase 1	N/A	Baseline (control)
Phase 2	Stage 1	Single-decker-seated asphalt pavement
	Stage 2	Single-decker-standing asphalt pavement
	Stage 3	Double-decker-seated asphalt pavement
	Stage 4	Double-decker-standing asphalt pavement
	Stage 5	Single-decker-seated sett pavement
	Stage 6	Single-decker-standing sett pavement
	Stage 7	Double-decker-seated sett pavement
	Stage 8	Double-decker-standing sett pavement

5.3 Processing Psychophysiological Time Teries Data

The data collection and analysis for the investigation of urban bus passenger comfort was performed within the framework of the road type, passenger posture and bus type, and controlled the effects of the operational variables (in-vehicle time, waiting time at the bus stop, or peak- or off-peak hours). Therefore, the nature of the impacts of the independent variables in psychophysiological activation on a passenger's sense of discomfort was investigated. The psychophysiological response of the subjects in each of the conditions were summarised by the average beta EEG and eSense metric of attention data. The algorithms for assessing the underlying EEG brain activity were used to reduced data not only among the subjects, but also across all the experimental conditions (independent variables). A total of 76,756 data points were obtained for each of the beta EEG and eSence metrics of attention brain activity. The corresponding proportion of the data points for the experimental phases of the baseline and onboard are 11,169 and 65,587, respectively. The value of the data points and the assignment of subjects to the conditions of the experiment for each of the subjects in relation to the study's experimental phases and conditions are detailed in Appendix I. The time series brain wave patterns were used to model how the brain reacts to certain stimuli under various experimental conditions.

The average values often reflect fluctuations ranging in the participant's psychophysiological responses over the duration of the experiments relative to the influence of the experimental conditions or events. In this study, the psychophysiological response of the subjects in each of the conditions of the experiment was summarised not only among the subjects, but also across all the experimental conditions (independent variables). Therefore, the data was reduced to a smaller set that explains variations between subject's effects (factors) and experimental conditions (Table 5-2).

The aggregated results (mean values) of the dependent variables (beta and eSence metrics of attention) were obtained by using the SPSS aggregate data function. The variable (participant) and the independent variables (road pavement type, posture and bus type) were used as the break variables to obtain the aggregated mean value of the dependent variables across cases (Hoormann et al., 1998). The computed ERP is the average of all the psychophysiological response epochs of each of the subjects as well as the conditions of passenger discomfort experiments. The experimental conditions (independent variables) and the obtained aggregated mean data (psychophysiological responses) were used for data analysis and modelling. The data points and assignment of subjects to the conditions of the experiment are detailed in Table 5-2.

Table 5-2: Passenger discomfort data points

	Seated	Standing	Baseline	Total
Baseline	-	-	20	20
Asphalt-Single-Seated	20	-	-	20
Asphalt-Single-Standing	-	20	-	20
Asphalt-Double-Seated	20	-	-	20
Asphalt-Double-Standing	-	20	-	20
Sett-Single-Seated	20	-	-	20
Sett-Single-Standing	-	20	-	20
Sett-Double-Seated	20	-	-	20
Sett-Double-Standing		20	-	20
Total	80	80	20	180

5.4 Average Response of Passengers to the Impact of the Experimentally Designed Phase

In this study, passenger comfort was evaluated by comparing changes in average psychophysiological responses of the passengers to the influence of the experimentally designed phases or variables and baseline (control experiment) see Table 5-3. This result demonstrated that EEG brain activity is spontaneous, but context-related; the EEG generated during the control experiment is quantitatively different from that generated during each experiment's stages. For instance, the average responsiveness of participants in control experiments is 1.45. In contrast, the corresponding average responsiveness of the subjects to the influence of sett pavement single-decker-seated and sett pavement double-decker-seated experimentally designed phases are 6.67 and 11.48, respectively. The results demonstrated that the influence of the experimentally designed variable's stimuli on bus passengers elicit a variety of cognitive and behavioural responses.

The results could be interpreted as the subjects exhibiting a different degree of strain (discomfort) relative to the influence of the characteristics of the experimentally designed variables compared to the control experiment. The evidence of variations in the psychophysiological responses of the passengers corroborated in the passenger response data, which showed higher average beta EEG brain activity relative to the influence of the experimentally designed variables (onboard bus), which is compared to the control experiments. This proves that beta brain activity is sensitive to the variations in evoked stimuli from the influences of variables that formed the experimental phases. The findings are in agreement with the study conducted by Basar et al., (1999) in the analysis of existing variation(s) in brain oscillation(s). Also, the results show that the experimental phases of asphalt pavement single-decker-seated buses seem to have little effect on passenger's discomfort when compared to other phases.

Table 5-3: Experimental phases and their corresponding mean and standard deviations

Beta Brain Activity		
Experimental Phase	**Mean**	**Std. Deviation**
Baseline	1.45	3.80
Asphalt-Single-Seated	3.93	2.08
Asphalt-Single-Standing	5.91	4.49
Asphalt-Double-Seated	6.09	3.14
Asphalt-Double-Standing	8.41	4.61
Sett-Single-Seated	6.67	3.45
Sett-Single-Standing	9.84	7.54
Sett-Double-Seated	11.48	6.90
Sett-Double-Standing	12.63	6.99

5.5. Influence of Experimentally Designed Phases on a Passenger's Psychophysiological Responses

The results of the statistical analysis show the influence of the experimentally designed variables on urban bus passenger discomfort by using the "Test of Between-Subjects Effect". The results indicated that the impacts of experimental phases were statistically significant ($p < 0.01$). The corrected model row shows that the overall model was significant ($p < 0.01$) and the effect size shows that the model explains 47.7% of the variance of beta EEG brain activity (passenger comfort), see Table 5-4. This study proves that there is an existing relationship between stimulus induced by the influence of the experimentally designed variables and passenger responsiveness (beta brain activity). The outcome of the model shows that experimental variables (independent variables) are statistically significant ($p < 0.01$). The effects size shows that road environment, posture and bus type explain 27.0%, 10.5% and 7.9% of the variance in a passenger's psychophysiological response, respectively. Passenger's related variables, such as age and gender, were introduced as part of the model. The results demonstrated that gender and age explain 6.0% and 2.9% of the variance in passenger comfort, respectively (Table 5-4).

Table 5-4: Changes in passenger's comfort as a function of experimental design variables (beta EEG brain activity).

Source	Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	4170.473[a]	6	695.079	26.343	0.00	0.477
Intercept	6189.772	1	6189.772	234.586	0.00	0.576
Road Environment	1689.440	1	1689.440	64.028	0.00	0.270
Posture	536.760	1	536.760	20.343	0.00	0.105
Bus Type	393.141	1	393.141	14.900	0.00	0.079
Gender	290.487	1	290.487	11.009	0.00	0.060
Age	136.820	1	136.820	5.185	0.02	0.029
Error	4564.772	173	26.386			

Squared = .477 (Adjusted R Squared = .459)

5.5.1 Passenger's Psychophysiological Response to the Influence of Experimentally Designed Variables

The sensations induced by the influence of experimentally designed variables are transferred to the brain and integrated to produce a subjective response relative to the stimuli effects. Therefore, the effects of a passenger's exposure to different road pavement types in this study could be described as a form of whole-body vibration that does not target a specific organ of the body. These usually lead to the activation of a large number of body receptors and the CNS, which could cause unbearable sensations (discomfort) to the passengers. Table 5-5 summarises the effect of experimental variables on bus passenger comfort. The results demonstrated that the correlation between the experimental variables (road environment, bus type and posture) and changes in beta EEG brain activity (psychophysiological response) seem to exist. This conclusion was supported by the results of the output of the model "Parameter estimate". The model intercept, road environment, age and gender are statically significant at $p < 0.01$ while bus type and posture are statistically significant at $p < 0.05$. The intercept model row also shows that the model explains 62.7% of the variance in passenger comfort (beta EEG frequency band RR). Furthermore, the model shows that 27.0% and 1.5% of the variance of the dependent variable (passenger comfort) can be explained by the influence of sett and asphalt pavements on a passenger, respectively.

Table 5-5: Relationship between experimentally designed variables and passenger comfort (beta brain activity): Parameter of Estimate

Parameter	B	Std. Error	t	Sig	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound	Partial Eta Squared
Intercept	19.153	1.124	17.040	0.00	16.935	21.372	0.627
Asphalt Pavement	-15.071	1.408	-10.707	0.00	-17.849	-12.293	0.399
Sett Pavement	-6.499	0.812	-8.002	0.00	-8.102	-4.896	0.270
Posture	-3.664	0.812	-4.510	0.00	-5.268	-2.061	0.105
Bus Type	-3.136	0.812	-3.860	0.00	-4.740	-1.532	0.079
Gender	-2.728	0.822	-3.318	0.00	-4.350	-1.105	0.060
Age	-1.801	0.791	-2.277	0.02	-3.363	-0.240	0.029

5.5.2 Passenger's Psychophysiological Response (beta frequency band) as a Function of Experimental Phases: Age Influence

The results demonstrated that the influence of experimentally designed phases on the psychophysiological responses of young and old passengers is statistically significant ($p < 0.01$). Significantly increased beta brain activity was noted during the experimental phase of double-decker-standing sett buses and double-decker-seated sett buses compared to single-decker-seated asphalt buses. The older subjects (greater than 30 years old) experienced a more significant shift from a state of being not uncomfortable to a state of being slightly or very uncomfortable compared to younger ones (less than 30 years old). Therefore, the psychophysiological responses of both young and old passengers were observed to increase as a function of change in induced stimuli strength from the influence of experimentally designed variables. The results in Figure 5-1 could be interpreted as old passengers being more tense or strained compared to those who are less than 30 years old.

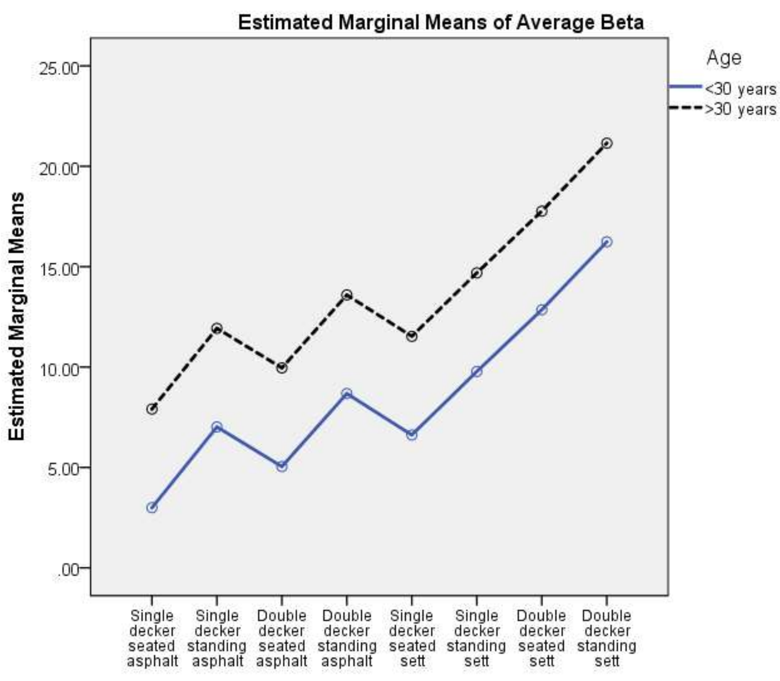


Figure 5-1: Passenger responsiveness to the induced stimulus of experimental phases: age influence

5.5.3 Effect of Experimental Phases on Passenger Comfort: Gender Influence

Figure 5-2 shows the psychophysiological responses of male and female passengers to the stimuli induced in experimentally designed conditions. The results in Figure 5-2 showed that there are variations in the average responsiveness of males and females to the stimuli effect of experimentally designed variables. The variations and effects of experimentally designed variables in the psychophysiological responses of bus passengers are more prominent in females compared to males. For instance, the minimum average responses of males and females to the influence of the experimental phases of single-decker-seated asphalt buses are 5.65 and 6.59, respectively. Furthermore, the maximum average psychophysiological responses of male and female passengers to the influence of double-decker-seated sett are 10.35 and 11.70, respectively. An increase in the psychophysiological response of female passengers compared to male passengers was observed in all phases of the experiments. This increase could be interpreted as female passengers being more tense compared to male passengers due to the influence of road-vehicle interactions. These results agreed with the study of Hoberock, 1976, which compared male and female average bus acceleration before losing balance, even though the author incorporated other variables, such as "the height of subject's shoes". The results of his study revealed that average accelerations (for both high- or low–heal shoes) obtained by male and female subjects before losing balance were 0.16g and 0.11g, respectively.

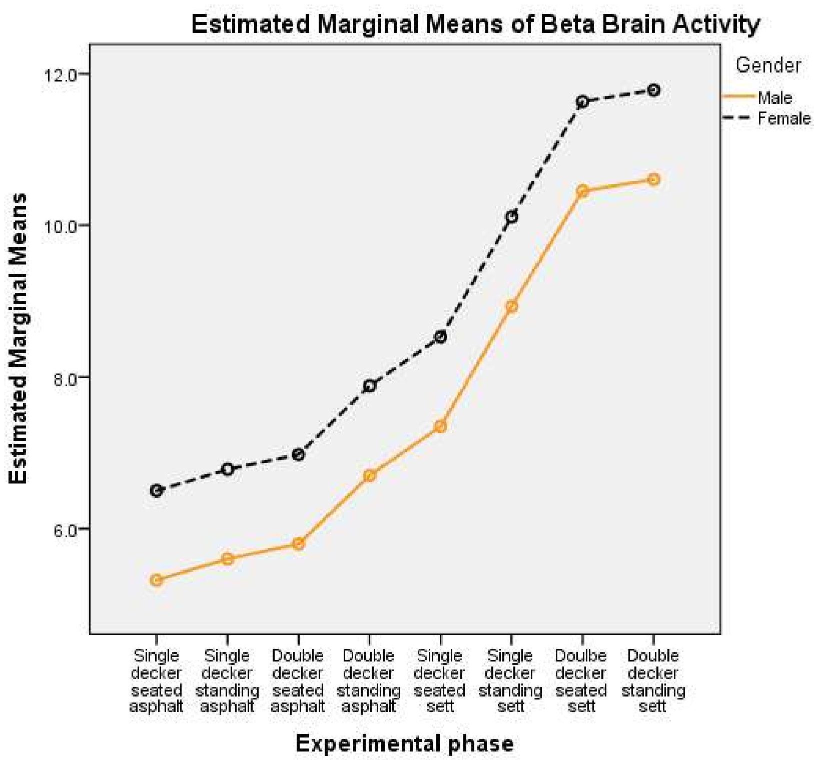


Figure 5-2: Responsiveness of male and female passengers to the influence of experimental phases

5.5.4 Effect of Road Roughness on Passenger Comfort: Influence of Bus Type

Studies have shown that passengers respond differently on large vehicles compared to small vehicles (Lima et al., 2015; Cooper at el., 1978). The correct designs of road pavement also depend on the type of vehicles using the route. Some roads could effectively tolerate the operating performance of some vehicular types, such as passenger cars, and that same road may penalise other vehicles, such as urban single- or double-decker buses. In the city of Edinburgh, some sections of Lothian bus routes were designed a long time ago to accommodate small vehicles. Using those roads or streets as part of Lothian Buses route has significant influences on sensations perceived by both the driver and the passengers. The results of the investigation of the influence of bus types on passenger ride comfort show that the sensory information sharply increases when the psychophysiological response of the participants are on single-decker buses compared to that of double-decker buses; most notably on sett pavement (Figure 5-3). These results were probably attributed to the association of the cerebral cortex and the degree of stimuli transmitted to the CNS, which prove that there is a significant difference ($p < 0.01$) between the responsiveness of passengers on single- and double-decker buses. For example, the average responsiveness of subjects on single- and double-decker buses to the influence of asphalt pavement are 4.67 and 5.42, respectively (Figure 5-3). These results could be interpreted as passengers being more strained on double-decker buses compared to that of single-decker buses under similar or the same experimental conditions. The results also show that passengers on double-decker buses are more strained on sett pavement compared to asphalt pavement. In addition, passengers reported that they are much more tense and unable to focus while on a moving double-decker bus, most importantly on sett pavement, compared to passengers on a single-decker bus on the same pavement. The results of this study showed that it is possible to investigate and evaluate the discomfort of passengers in relation to vehicular types by using EEG.

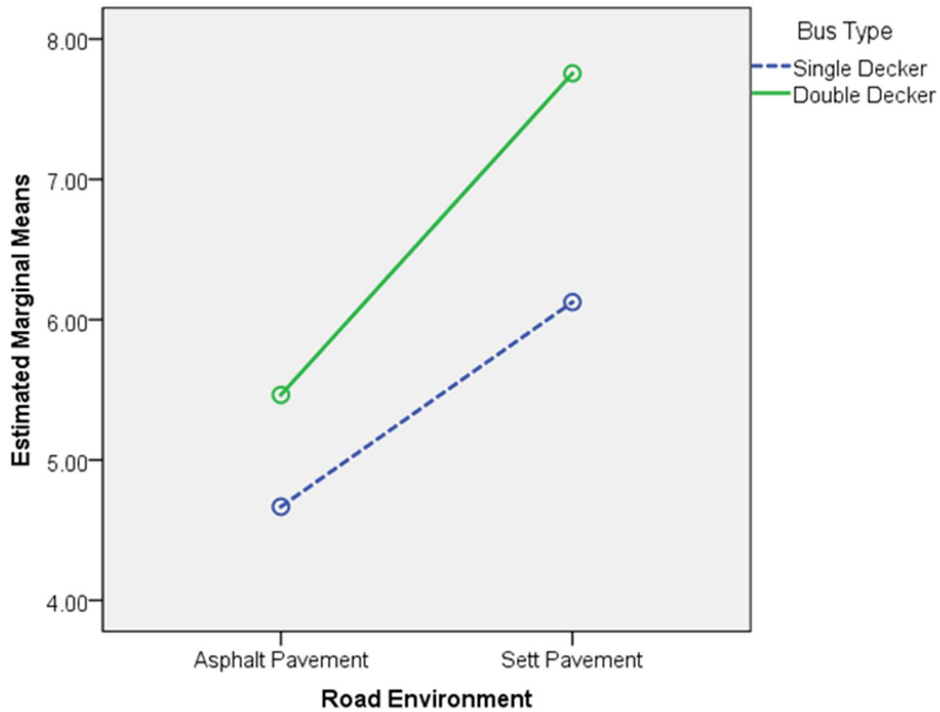


Figure 5-3: Effect of road roughness on sensibility: influence of bus type

5.5.5 Effect of Road Roughness Characteristics on Passenger Comfort: Posture Influence

Bus passengers are often found to adopt different postures (seated or standing) depending on the time of the day (peak- or off-peak hours) or their personal choice of posture. Knowledge of physiological and psychological responses of drivers or passengers to the mechanical characteristics, road characteristics and vehicle environmental factors during transit could assist in understanding the extent of the comfort, health and wellbeing of the people. Many factors contribute to urban bus passenger ride comfort; therefore, posture-related discomfort induced by experimental design that permits the possibility of examining changes in beta EEG power (responses) relative to the influence of posture was developed. This section presents the evaluations of the influence of posture (seated or standing) on psychophysiological responses (level of discomfort) of urban bus passengers. The results demonstrated that the psychophysiological curve of standing passengers increased sharply on both asphalt and sett pavements compared to seated passengers. Variations in the psychophysiological responses (RR) of standing passengers compared to seated ones are statistically significant ($p < 0.01$), see Figure 5-4. These results could be interpreted as bus passengers being more strained while standing compared to those who are seated, irrespective of the degree of the roughness of the road.

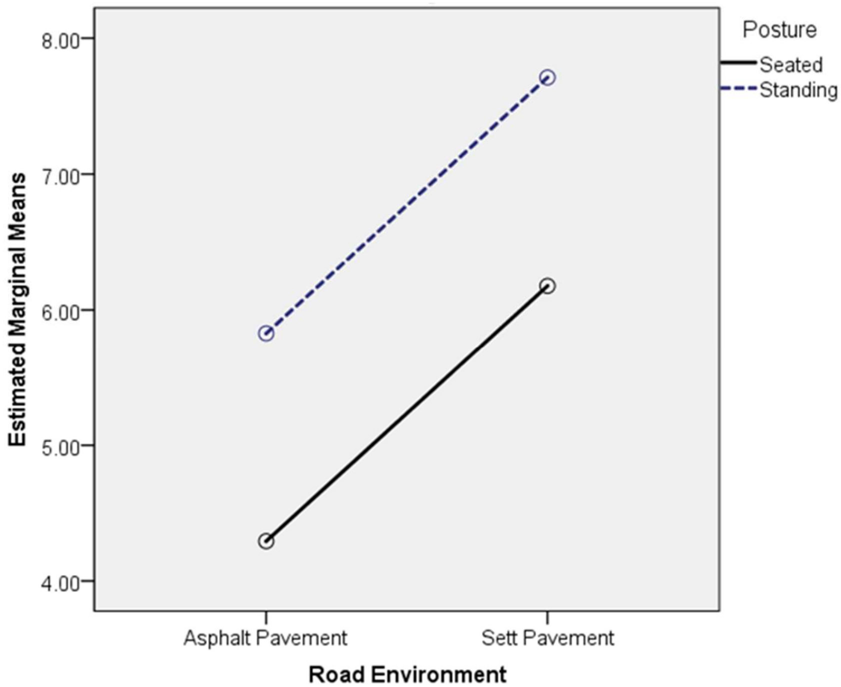


Figure 5-4: Effect of road roughness on psychophysiological responses: posture influence

5.5.6 Effect of Road Roughness Characteristics on Passenger Comfort: Age Influence

The passenger's age on psychophysiological responses of passengers to the influence of road roughness characteristics was validated in this study. The psychophysiological responses showed an increase in the activation of the activity of the CNS in old passengers compared to younger passengers (Figure 5-5). Also, older passengers consistently rated themselves as being more uncomfortable. Therefore, these results could be interpreted as older passengers exhibiting a higher level of discomfort that could impair their physical and mental fitness compared to younger passengers.

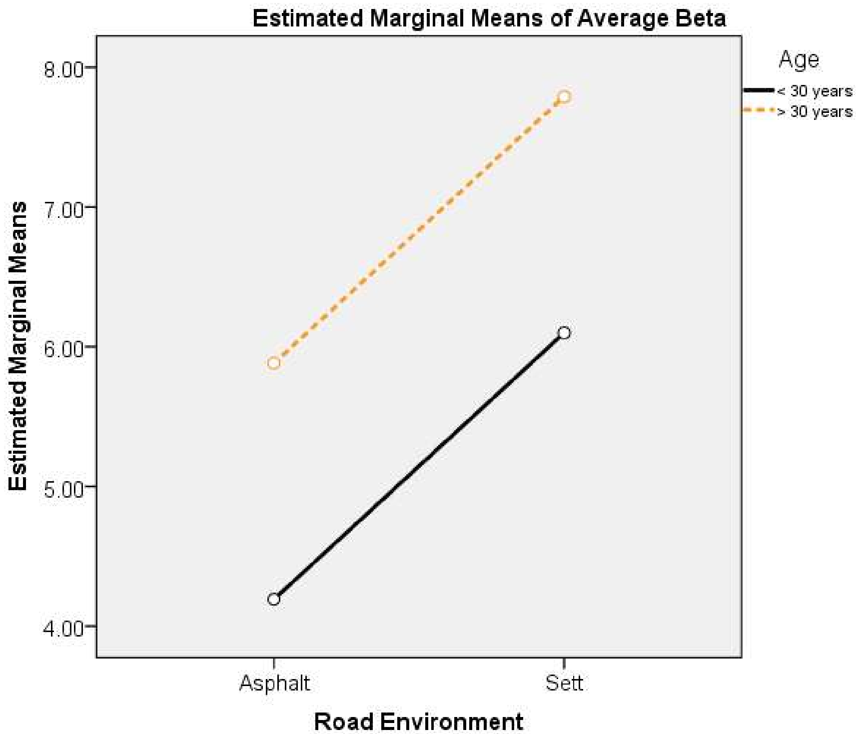


Figure 5-5: Passenger sensibility (beta EEG frequency band): age influence

5.5.7 Effect of Road Roughness Characteristics on Passenger Comfort: Gender Influence

It was hypothesised that the comfort of male and female bus passengers would vary significantly. The evidence of variations in psychophysiological responses of male and female passengers was validated by using the influence of road roughness characteristics. The results demonstrated that higher psychophysiological responses were observed in female passengers on both asphalt and sett pavements compared to male passengers. Also, female passengers consistently rated themselves as being more uncomfortable (Figure 5-6). The results seemed clear that the potential effect of experimentally designed variables has more influence on female passengers compared to male passengers. Therefore, this could be interpreted as female passengers exhibiting a higher level of discomfort that could impair their physical and mental fitness in the dynamic environment compared to male passengers.

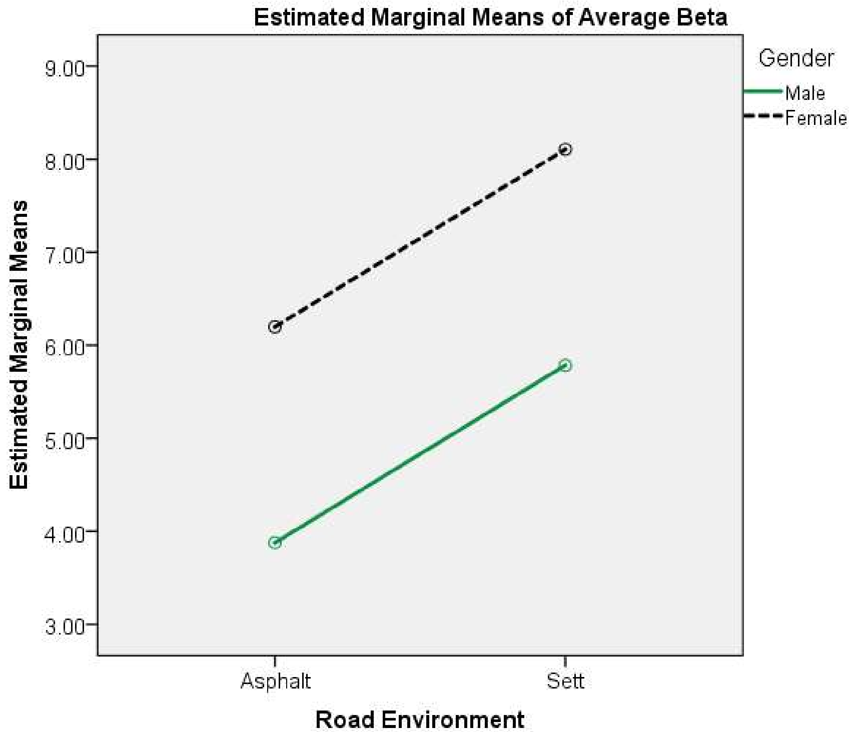


Figure 5-6: Passenger sensibility: gender influence

5.5.8 Passenger Psychophysiological Response (Comfort): Age and gender Influence

Figure 5-7 shows the responsiveness of male and female subjects to the influence of the experimentally designed variables relative to their age. The results of the estimated marginal mean showed that the subjects' gender and age have significant impacts on their psychophysiological responses. The results also demonstrated that event-related beta oscillations of young and old female passengers have a greater amplitude compared to male passengers. These variations are statistically significant ($p < 0.01$), and it could be interpreted as female passengers being more strained or tenser (experiencing more discomfort) compared to male passengers, irrespective of their age. For instance, the average psychophysiological response of female passengers older than 30 years is 8.68 while that of male passengers is 6.34 (Figure 5-7). This result demonstrates that the higher the influence of the experimentally designed variable is on passengers, the more activated the electrical potential of the brain becomes.

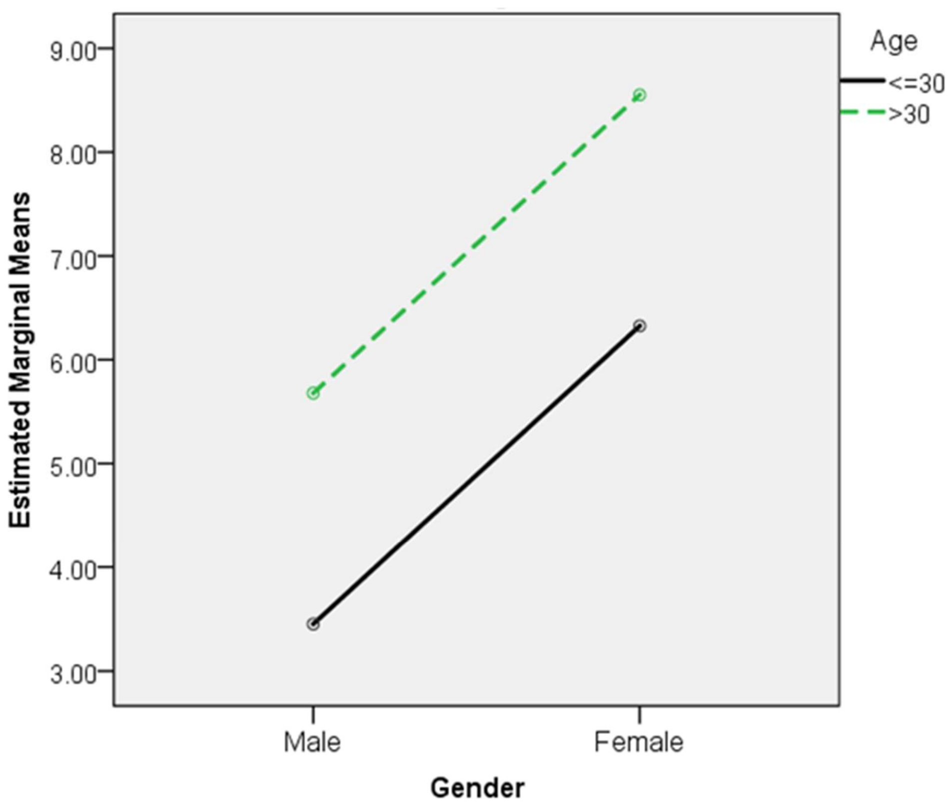


Figure 5-7: Passenger sensibility: relationship between age and gender influence

5.5.9 Passenger Sensibility: Influence of Bus Type and Posture

The results of the investigation of passenger ride comfort relative to the influence of bus types and posture show that the sensory information of double-decker bus passengers sharply increases compared to single-decker bus passengers as well as in standing compared to being seated. These results are probably attributed to the cerebral cortex and the degree of stimuli transmitted to the CNS. Figure 5-8 shows that there is a significant difference between the responsiveness of seated passengers and standing passengers in single-decker and double-decker buses. The average responsiveness of seated passengers in single- and double-decker buses is 5.29 and 7.32, respectively. This result could be interpreted as passengers (seated or standing) being more comfortable on single-decker buses compared to double-decker buses.

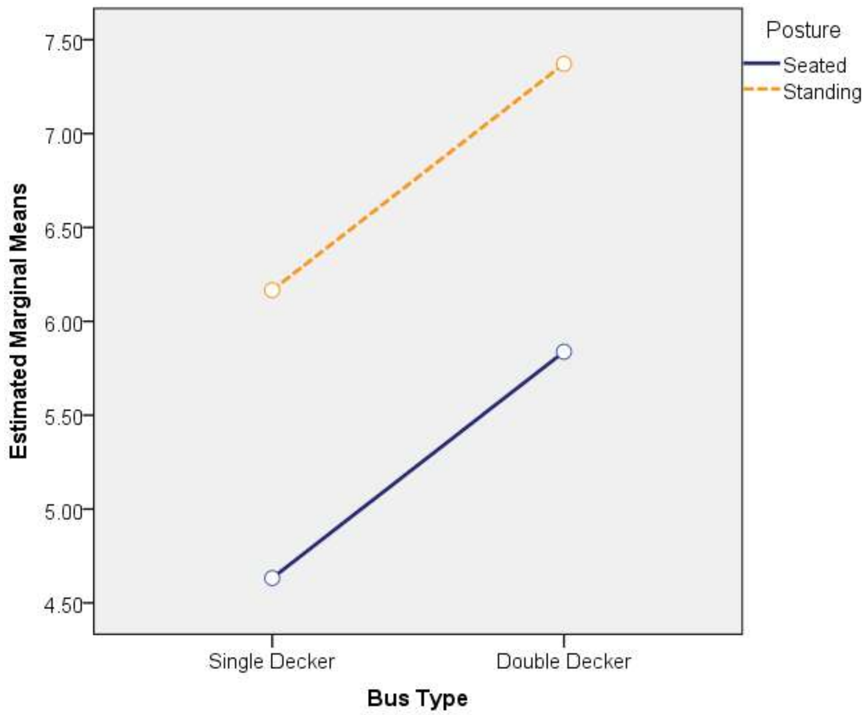


Figure 5-8: Passenger sensibility: bus type and posture influence

5.6 Relation between Psychophysiological Response and a Passenger's Perception of Discomfort

This section of the study estimated ride comfort by investigating the relationship between the feature of beta EEG brain activity and subjective comfort assessments. The subjective evaluation of the subject's opinions on average ride comfort on each phase of the experimentally designed variables was carried out by using the recommended assessment scale of the International Standard ISO 2631-1 for public transport. The results of this study revealed that the more the subject's psychophysiological signals increase, the more the level of the passenger's comfort deteriorates. For instance, the subjects with an average beta EEG brain activity of 8.8, 10.1 and 12.8 felt uncomfortable, very uncomfortable and extremely uncomfortable, respectively (Figure 5-9). Therefore, it is evident that the more uncomfortable a passenger felt, the higher their average psychophysiological responses were. Furthermore, the average beta EEG brain activity attained a peak value of 12.8 when the participants believed that they felt extremely uncomfortable. The results of this study finally prove that there is a strong positive relation between the beta EEG spectra activity and ISO 2631-1 subjective comfort assessment for public transport (Figure 5-9).

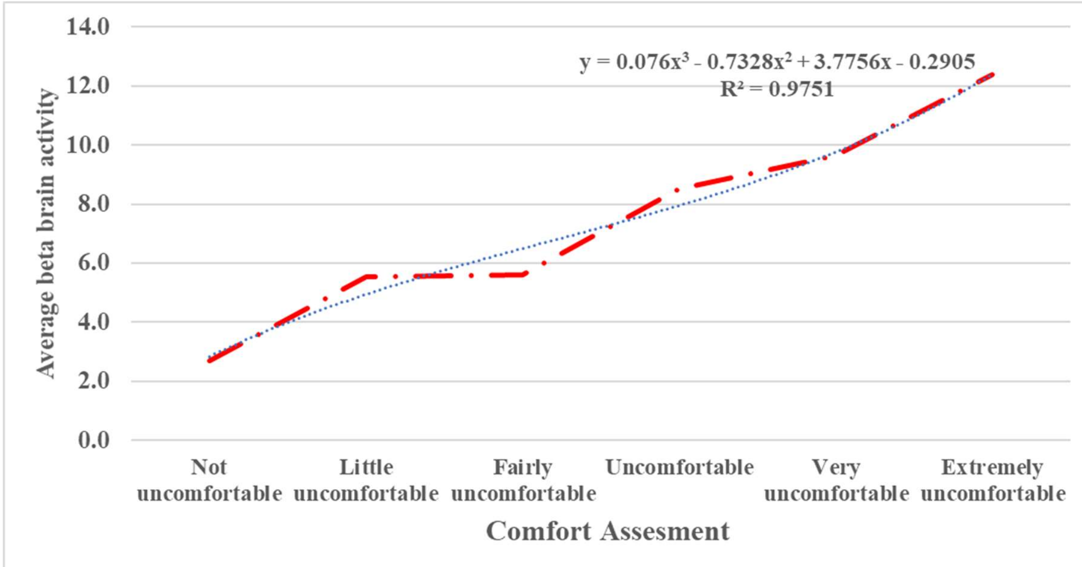


Figure 5-9: Cross-correlation of a passenger's psychophysiological response and subjective passenger assessment

5.6.1 Relationship between a Passenger's Psychophysiological Response and Subjective Passenger Assessment

The induced internal or external sensations of superimposed oscillations are transmitted to the cerebral cortex or brain tissues and the response is in proportion to the degrees of stimuli. The synchronisation of oscillations varies depending on the intensity of stimuli from the influence of experimentally designed phases or variables. Therefore, the response of the passenger to the influence of experimental design variables solely depends on the strength of the induced stimuli presented to the Central Nervous System (CNS). The parameter of estimates (subjective comfort assessments) was found to be significant ($p < 0.01$). The results showed that there is an existing relationship between stimulus intensity and a passenger's psychophysiological response. The corrected model row shows that the overall model was significant ($p < 0.01$) and the effect size shows that model explains 51.1% of the variance in beta brain activity (passenger comfort), see Table 5-6. In addition, variable age and gender were introduced to the model, and the results of the statistical analysis indicate that age and gender are also statistically significant ($p < 0.01$).

Table 5-6: Changes in passenger's response to the influence of experimental phases (beta EEG frequency band)

Source	Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	3640.470[a]	14	260.034	9.179	0. 00	0.511
Intercept	10575.6	1	10575.6	373.295	0. 00	0.752
Comfort Assessment	477.939	5	95.588	3.374	0.01	0.121
Experimental Phase	1111.91	7	158.845	5.607	0. 00	0.242
Age	588.204	1	588.204	20.762	0. 00	0.144
Gender	291.151	1	291.151	10.277	0.00	0.077
Error	3484.64	123	28.33			

R Squared = .511 (Adjusted R Squared = .455)

5.6.2 Influence of Experimental Designed Variables on Psychophysiological Response and Passenger's Perception

Table 5-7 presented the relationships between a passenger's psychophysiological response (beta EEG brain activity) and subjective comfort assessment (not uncomfortable, slightly uncomfortable, uncomfortable, very uncomfortable and extremely uncomfortable) in relation to experimentally designed variables. The multiple comparisons of average beta EEG under different ISO 2631-1 subjective comfort assessment parameters is shown in Table 5-7. The validation of the influence of the experimentally designed variable on a passenger's psychophysiological responses by using the passenger's perceptions demonstrated that experimentally designed variables seem to have significant impacts on a passenger's discomfort. The evaluation of the parameters that form the subjective comfort assessment relative to a passenger's psychophysiological responses are statistically significant ($p < 0.01$). The corrected model row shows that the overall model was significant ($p < 0.01$) and the effect size shows that the model explains 64.3% of the variance in beta brain activity. The results proved, as it's hypothesised, that the induced stimulus effects from the influence of posture, road roughness, characteristics and bus type could significantly affect the passenger's level of discomfort (psychophysiological response). The results also demonstrate that the passenger's comfort can be investigated and validated by examining the relationship between the objective measures (psychophysiological responses) and subjective comfort assessment in a dynamic environment. The results indicated that both age and gender are statistically significant and double-decker-standing, with the extremely uncomfortable parameter, are set to be redundant.

Table 5-7: Evaluation of psychophysiological response and passenger's perception of the influence of experimental phases (beta EEG band)

Parameter	B	Std. Error	t	Sig.	99% Confidence Interval Lower Bound	99% Confidence Interval Upper Bound	Partial Eta Squared
Intercept	25.707	1.727	14.885	0.00	21.188	30.226	0.643
Not uncomfortable	-6.727	2.836	-2.372	0.02	-14.148	0.695	0.044
A little uncomfortable	-6.263	2.029	-3.086	0.00	-11.573	-0.953	0.072
Fairly uncomfortable	-6.796	1.945	-3.495	0.00	-11.884	-1.708	0.090
Uncomfortable	-6.322	1.73	-3.655	0.00	-10.848	-1.796	0.098
Very uncomfortable	-4.559	1.529	-2.981	0.00	-8.56	-0.558	0.067
Single-decker seated asphalt	-9.781	2.217	-4.412	0.00	-15.581	-3.981	0.137
Single-decker standing asphalt	-6.015	2.057	-2.924	0.01	-11.397	-0.633	0.065
Double-decker seated asphalt	-7.834	1.944	-4.03	0.00	-12.92	-2.747	0.117
Double-decker standing asphalt	-7.173	1.838	-3.903	0.00	-11.982	-2.364	0.110
Single-decker seated sett	-6.505	2.136	-3.046	0.00	-12.093	-0.917	0.070
Single-decker standing sett	-4.479	1.858	-2.411	0.02	-9.339	0.381	0.045
Double-decker seated sett	-1.154	1.863	-0.619	0.54	-6.029	3.722	0.003
Age	-4.866	1.068	-4.557	0.00	-7.66	-2.072	0.144
Gender	-3.536	1.103	-3.206	0.00	-6.422	-0.65	0.077

5.6.3 Effect of Experimentally Designed variables on Psychophysiological and Subjective Responses: Age influence

Figure 5-10 shows the graphical representation of the correlations between the average psychophysiology responses (beta EEG brain activity) and the subjective comfort assessment of different age groups relative to the influence of the experimentally designed variables. A significant ($p < 0.01$) increase in average responses was found in passengers who were less than 30 years old compared to those who were older than 30 years. This increase could be interpreted as younger passengers being more strained or tenser (experiencing more discomfort) compared to older passengers. However, the psychophysiological activation and discomfort of bus passengers usually occur in both young and older passengers. Therefore, it was evident that when designing a study investigating passenger comfort as a function of the influence of road roughness, posture and bus type, along with the influence of passenger age on psychophysiological activation must be considered.

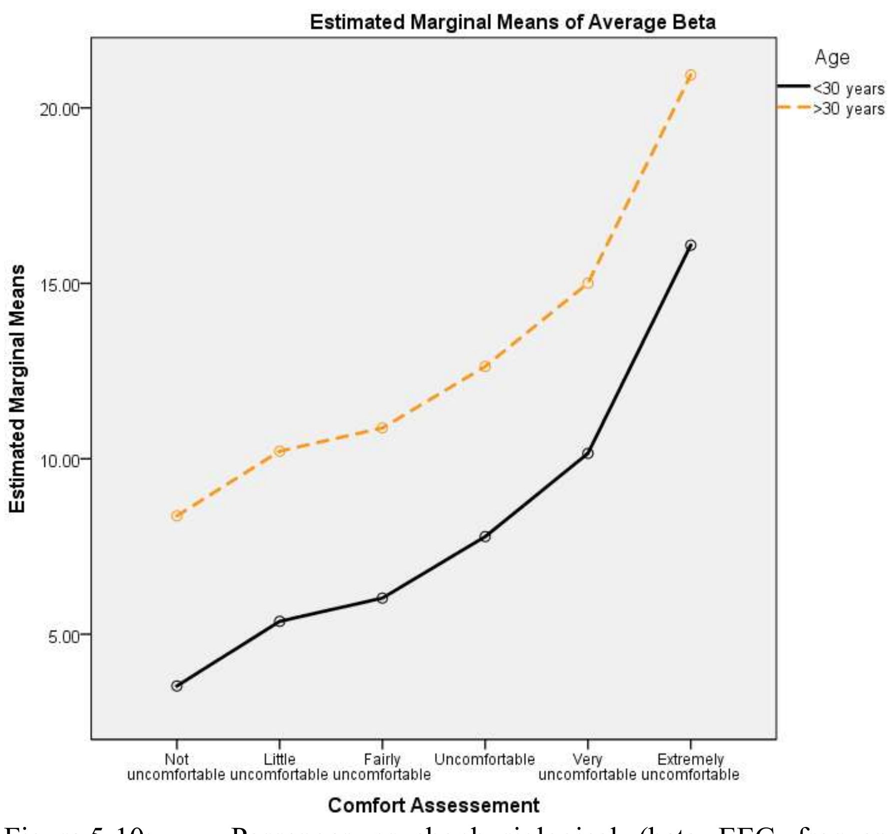


Figure 5-10: Passenger psychophysiological (beta EEG frequency band) and subjective responses: age influence

5.6.4 Effect of Experimentally Designed variables on Psychophysiological Response and Passenger Perceptions: Gender Influence

The correlation between the average beta EEG brain-induced signals and the subjective assessment of passenger comfort was investigated to evaluate the psychophysiological activation (level of comfort) of male and female passengers relative to the influence of the experimentally designed variables. The results in Figure 5-11 prove that male passengers exhibited lower psychophysiological response compared to female passengers. Also, the average responsive rate (EEG brain activity) of a passenger to the influence of the experimentally designed variables attained peak values for both males and females when the subjects believed they were extremely uncomfortable.

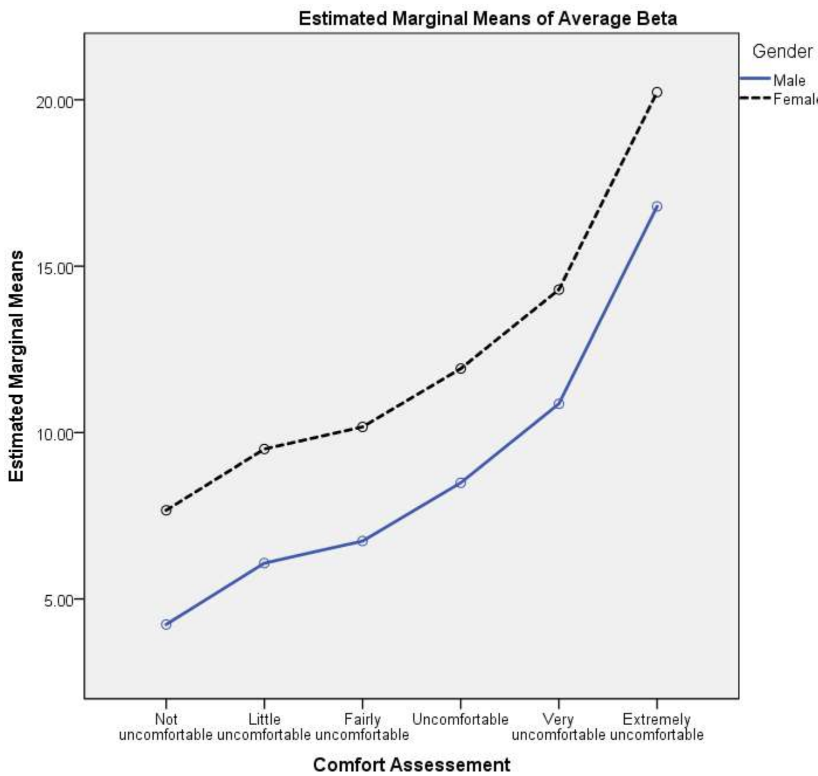


Figure 5-11: Passenger psychophysiological (beta band) and subjective responses: gender influence

5.7 The Effect of Speed on Passenger Sensibility

In urban bus transport systems, sharp starts and stops are inevitable as the bus is merging into high-speed traffic at close headway. The study of Castellanos & Fruett, (2014) investigated the dynamic factors that affect passenger comfort in public transport and define them as comfort disorders (jerk and uneven speed). The sensations evoke due to the experimentally designed factors that are transferred to the brain and integrated to yield subjective responses to the stimuli effects. This section presents the effect of urban bus driving speed on passenger comfort. The responsiveness of the passengers (beta brain activity) to the influence of induced stimuli from vehicular driving patterns shows that passengers are tenser when the average speed ranges from 11–20, 21–30 and 31–40 km/h compared to when the average speed is 0–10 and 51–60 km/h (Figure 5-12). In this study, the beta brain activity (the participant's psychophysiological response) showed significant variations relative to the influence of the vehicle speed compared to the control experiment. Therefore, it could be concluded that passenger ride comfort could be influenced by evoking forces produced by the change in vehicle acceleration, deceleration or speed.

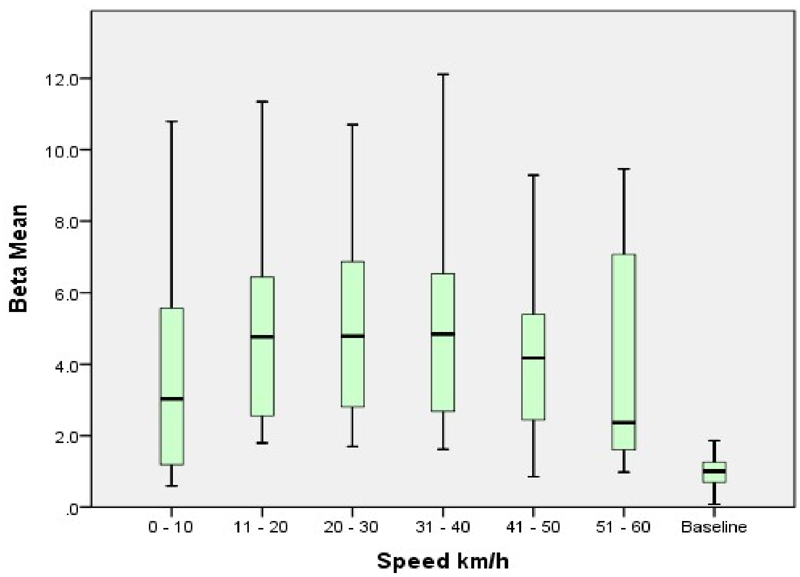


Figure 5-12: Effect of speed on passenger comfort

5.7.1 Effect of Speed on Passenger Comfort: Posture Influence

Bus passenger comfort is directly linked to factors of the bus driver's driving behaviours, such as rate of acceleration/deceleration, speed or jerk. The influence of bus speed on passenger comfort relative to a passenger's posture creates different magnitudes characteristic of beta brain activity (response). The results demonstrated that there is a significant difference between the responsiveness of seated and standing passengers to the influence of speed profile factors under the same/similar experimental conditions (Figure 5-13). Both seated and standing passengers showed variations in psychophysiological responses related to changes in vehicle speed. Therefore, it could be concluded that the psychophysiological responses showed either an increase or a decrease in the activations of CNS as the speed of the vehicle changes. Also, the results demonstrated that the responsiveness of the seated and standing passengers follows a similar pattern, even though standing passengers showed increased psychophysiological activation as a function of vehicle speed compared to seated ones. Generally, both seated and standing passengers are more strained when the average speed is 11–20 km/h, 21–30 km/h and above 50 km/h compared to 0–10 km/h and 41–50 km/h.

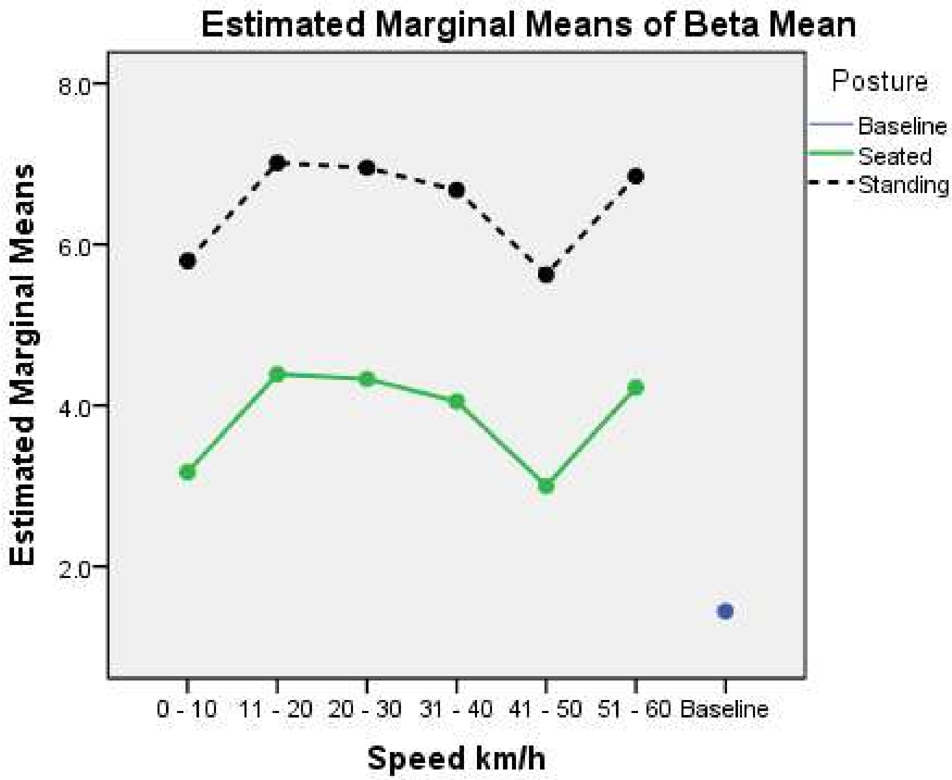


Figure 5-13: Impact of Speed on the passenger’s comfort: posture influence

5.8 Inter-Subject Variability

The psychophysiological response of passengers to the influence of road roughness characteristics, driving style, bus type or posture vary from one person to the other (Mcewen, 2000). Also, the effect of stimuli induced by the influence of experimentally designed variables in this study vary from one person to the other due to the influence of factors that are not limited to age, personality traits, social environment, genotype and gender. Therefore, as the psychological and physiological profiles of people vary, the subject’s psychophysiological responses to the influence of the road-vehicle effects vary. For instance, the average responses of subject 1 (12.7), subject 4 (11.4), subject 7 (12.8) and subject 12 (10.5) as well as subject 13 (12.7) and subject 18 (11.8) are slightly high compared to the responses of other subjects (Figure 5-14). This result could be interpreted as subjects exhibiting a higher level of discomfort compared to others because the more uncomfortable a passenger is feeling, the higher the psychophysiological activation (beta brain activity) is. Therefore, whenever the brain is perceiving induced stimuli effects like stress or discomfort, the responses usually lead to allostatic and adaptation, which vary from passenger to passenger (Mcewen, 2000).

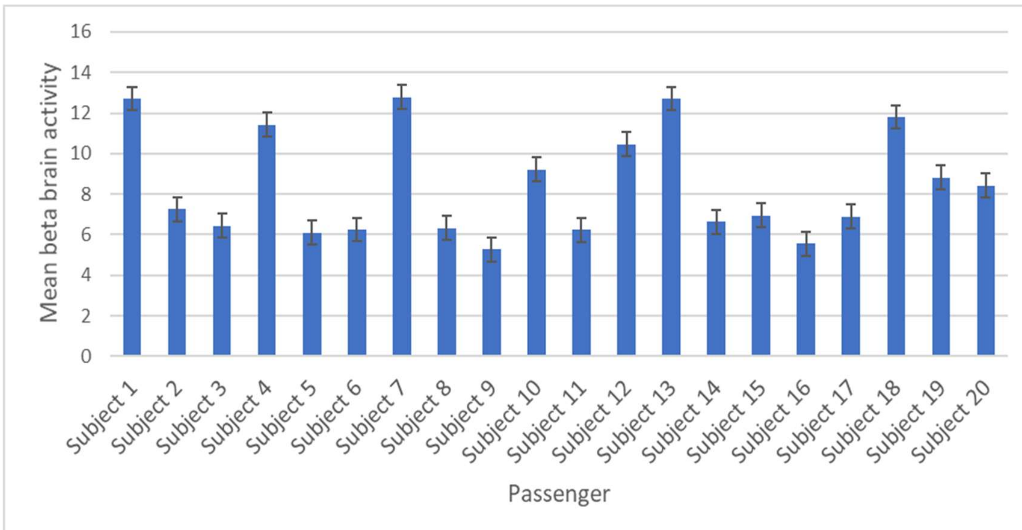


Figure 5-14: Variations in average psychophysiological responses (beta band) of a passenger to the influence of experimentally designed variables

5.8.1 Inter-subject Variability in Psychophysiological Responses of Passengers to the Influence of Experimentally Designed Variables

The patterns of variation in a subject's level of comfort in this section are associated with the ability of each subject to withstand the induced sensations from the influence of experimentally designed variables/phases. The observable variations in the average responses of subjects depends on the magnitude of induced sensations in the brain's cerebral cortex as captured via EEG. The results demonstrated that the overall model is significant ($P < 0.01$) and the effect size shows that the model explains 22.7% of the variance in beta brain activity (Table 5-8).

Table 5-8: Inter-subject variability of passenger psychophysiological response

Source	Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	1978.614	19	104.138	2.466	0.00	0.227
Intercept	14000.116	1	14000.116	331.529	0.00	0.674
Subject	1978.614	19	104.138	2.466	0.00	0.227
Error	6756.631	160	42.229			

R Squared = .227 (Adjusted R Squared = .135)

5.8.2 Evaluation of Inter-subject Variability as a Function of the Influence of Experimentally Designed Variables

The transient ERS of the beta EEG spectral band relative to the influences of the experimentally designed variables in this study varies from passenger to passenger. Table 5-9 presents the variability in psychophysiological responses (level of comfort) of the 20 sampled subjects in relation to the experimentally designed phases and variables. The results demonstrated that psychophysiological responses (level of discomfort) of the participants to the influence of the experimental conditions vary from passenger to passenger (Table 5-9).

Table 5-9: Statistical analysis of inter-subject variability

Parameter	B	Std. Error	t	Sig.	99% Confidence Interval		Partial Eta Squared
					Lower Bound	Upper Bound	
Intercept	7.924	2.166	3.658	0.00	3.646	12.202	0.077
Subject 1	5.938	3.063	1.938	0.05	-0.112	11.988	0.023
Subject 2	-2.951	3.063	-0.963	0.34	-9.001	3.099	0.006
Subject 3	0.611	3.063	0.200	0.84	-5.438	6.661	0.000
Subject 4	6.168	3.063	2.013	0.05	0.118	12.217	0.025
Subject 5	-1.186	3.063	-0.387	0.69	-7.236	4.864	0.001
Subject 6	0.882	3.063	0.288	0.77	-5.168	6.932	0.001
Subject 7	3.970	3.063	1.296	0.19	-2.080	10.020	0.010
Subject 8	-2.650	3.063	-0.865	0.39	-8.699	3.400	0.005
Subject 9	-2.914	3.063	-0.951	0.34	-8.964	3.136	0.006
Subject 10	2.529	3.063	0.826	0.41	-3.521	8.579	0.004
Subject 11	-2.667	3.063	-0.871	0.39	-8.717	3.383	0.005
Subject 12	4.169	3.063	1.361	0.18	-1.880	10.219	0.011
Subject 13	6.289	3.063	2.053	0.04	0.239	12.339	0.026
Subject 14	-3.438	3.063	-1.122	0.26	-9.488	2.611	0.008
Subject 15	-1.712	3.063	-0.559	0.58	-7.762	4.338	0.002
Subject 16	5.230	3.063	1.707	0.09	-0.820	11.279	0.018
Subject 17	-2.339	3.063	-0.763	0.45	-8.389	3.711	0.004
Subject 18	1.171	3.063	0.382	0.70	-4.879	7.221	0.001
Subject 19	0.805	3.063	0.263	0.79	-5.245	6.855	0.000

The parameter “Subject 20” is set to be redundant.

5.9 Summary

The emerging concept of the perceived satisfaction of the ground public transport system provides a means of augmenting the concept of “ride comfort” as a conceptual approach for explaining how the influences of road roughness, passenger posture, bus type, driving styles and other factors combine to affect the psychophysiological responses of passengers. The evidence available in the literature suggests that no or little attention was given to the investigation of bus passenger comfort by using objective data obtained directly from the passenger. There was also the need for reliable and accurate objective and subjective data to produce a more reliable and acceptable level of passenger comfort due to the influence of posture, road roughness and characteristics of bus type. The main contribution in this chapter is the investigation of bus passenger comfort by using reliable objective (EEG) and subjective datasets. This study produces new sets of analyses and models of impacts of posture, type of road roughness and type of bus on passenger’s psychophysiological responses (discomfort).

The ERP beta power spectral (magnitude) of this study depends on the induced variations in the passenger’s cerebral cortex and somatosensory nervous system activities as captured by EEG relative to the influence of experimentally designed phases and variables. The findings of the influence of road-vehicle interactions in this study are in agreement with the study conducted by Soliman (2006) in an investigation on the effect of road roughness on vehicle ride comfort. In an investigation of vehicle ride comfort, the author found that passenger ride comfort deteriorates as the road roughness coefficient increases. The next chapter discusses the influences of the study’s experimentally designed variable on bus passenger discomfort by using eSense for attention EEG brain activity. It also discusses the modelling of influences of road roughness characteristics, posture, bus type, gender and age of the bus passengers.

CHAPTER 6 URBAN BUS PASSENGER RIDE COMFORT: APPLICATION OF THE eSENCE METRIC FOR ATTENTION

6.1 Introduction

The previous chapter presented the analysis of the influence of the experimentally designed phases and variables on bus passenger ride comfort by using the beta EEG spectral frequency band. In this chapter, the influence of experimentally designed variables (posture, road types and bus type) that affect bus passenger comfort are analysed by using the eSense metric for attention. This chapter aims to establish the extent to which road roughness characteristics, driving styles, posture and bus types is causing significant changes in bus passenger discomfort by using objective data (EEG brain activity) and a subjective comfort assessment questionnaire. This chapter presents evidence of a passenger's psychophysiological activation (response) as a function of experimentally designed phases or variables, along with their gender and age.

6.2 General Overview of Analysis

In this chapter, the novelty includes the evaluation of passenger's ride comfort and the linking of psychophysiological responses. This chapter presents the analysis of the effects of road roughness types (asphalt and sett pavements) and bus types (single- and double-decker) on seated and standing passengers. Generally, road-vehicle interaction causes severe sensations to the driver and the passengers. These results could trigger the activation of body receptors connected to the CNS. Sett pavement was installed to reduce vehicle speed in order to improve the safety of pedestrians and people within the neighbourhood. Vehicle occupants usually experience different forms of discomfort when travelling on sections of sett pavement because of vibrations from road-vehicle interactions. This section presents changes in the level of distraction, agitation and abnormality of bus passengers contingent to road roughness characteristics, posture, bus type and other factors. In an attempt to understand passenger and driver discomfort, Soliman (2006) investigated the effects of road roughness on ride comfort. The author found that as the road roughness coefficient increases, the ride comfort deteriorates. Additionally, the study by Ismail et al. (2015) revealed that a rough surface induces higher force excitations to a cyclist, thereby increasing the level of discomfort compared to smooth pavement. Therefore, in order to understand urban bus passenger discomfort, this study investigated the change in a passenger's psychophysiological response (level of distraction and abnormality) as a function of the influence of road roughness characteristics, postures, bus types and gender and age influences.

6.3 Influence of Experimentally Designed Phases on Passenger Response

The average responsiveness (attention eSence meter) of the subject on a bus exhibits a decrease in average oscillations when compared to the control experiment (baseline). The values shown in Table 6-1 represent the mean, frequency and percentage of the responsiveness of the bus passengers in control and in dynamic (onboard bus) experiments. The study results showed that passenger(s) in a dynamic environment exhibit a repeated higher level of distraction, agitation or abnormality (discomfort) compared to baseline (control experiment). For instance, the corresponding percentage of the urban bus passenger's responses (brain activity) for 41–60 (neutral scale) of stable-seated-laboratory and onboard bus experiments are 55.54% and 38.51%, respectively (Table 6-1). These results showed a significant correspondence between the impacts of experimentally designed variables (control and dynamic experiments) on passengers and the degree of psychophysiological activation within the scale of 1–40 of the eSense metric for attention. Furthermore, the percentage of passenger responses in the stable-seated-laboratory experiment that is within 1–40 on the eSense metric for attention scale representing distraction, agitation or abnormality is 10% compared to the responses in the dynamic environment (41.44%). The results demonstrated that brain activity could show the degree of responsiveness of the subjects to the influence of experimentally designed variables. Therefore, significant activation of the cerebral cortex and somatic sensation as a result of the influence of experimentally designed variables is an indication of passenger stress.

Table 6-1: Attention eSense meter interpretation and subject's average response

Scale	**Control Experiment**			**Dynamic Environment Experiment**		
	Average	**Frequency**	**Percentage (%)**	**Average**	**Frequency**	**Percentage (%)**
81 - 100	89.92	797	7.14	88.88	2,779	4.24
61 - 80	68.39	3,053	27.33	68.14	10,375	15.82
41 - 60	50.53	6,203	55.54	49.54	25,256	38.51
21 - 40	32.51	959	8.59	31.80	22,167	33.80
1 – 20	14.50	157	1.41	13.65	5,010	7.64
Total		11,169	100.00		65,587	100.00

6.4 Average Passenger's Psychophysiological Responses to the Influence of Experimentally Designed Phases

The brain-induced signals investigated in this study were used to evaluate the psychophysiological state (level of mental fitness) of the bus passengers relative to the impacts of experimentally designed phases. The results demonstrated that bus passengers exhibit and repeat different emotions when travelling on sett pavement compared to asphalt pavement as well as when standing compared to sitting. The influence of these experimentally designed variables creates different amplitude components for information related to the awareness and alertness in the brainwaves. Table 6-2 shows that urban bus passengers exhibited different signature (responses) relative to changes in experimentally designed variables. For instance, the average responses (eSense metric for attention) of the passengers relative to the influence of the experimental phase of single-decker-seated asphalt and single-decker-seated sett experimental phases are 53.84 and 46.07, respectively (Table 6-2). The decrease in average psychophysiological responses could be interpreted as an indication of a reduction in cognitive ability and comfort. This result proves that variations in road pavement characteristics could influence bus passenger's mental states. Additionally, if the experimental phase of double-decker-seated sett is compared to double-decker-standing sett, the corresponding proportions of the average eSense metric for attention are 39.04 and 36.34, respectively. These results show that a relationship between bus passenger postures and changes in brain activity (attention eSence meter) seems to exist. It would otherwise cause an increase in bus passenger's levels of distractions, agitation and abnormality. Therefore, bus passengers and passengers of other public transport, such as rail, could experience undesired sensations that may require them to maintain full alertness due to their posture. Variations in the comfort of standing passengers compared to seated passengers have previously been found to occur in public transport (Beurier, 2012; Suzuki et al., 2000; Hoberock, 1976). Table 6-2 shows a constant and significant decrease in the average level of passenger attention relative to the variations in experimentally designed phases.

Table 6-2: Passenger's psychophysiological response to the influence of experimentally designed phases

Experimental phase	Mean Attention	Std. Deviation
Baseline	53.84	5.92
Single-decker-seated asphalt	57.34	7.93
Single-decker-standing asphalt	54.17	6.96
Double-decker-seated asphalt	50.84	5.69
Double-decker-standing asphalt	47.49	5.71
Single-decker-seated sett	46.07	5.01
Single-decker-standing sett	42.67	4.53
Double-decker-seated sett	39.04	4.34
Double-decker-standing sett	36.34	4.65

6.5 Analysis of the Impacts of Experimental Phases on Passenger Comfort

The models presented in this section established the relationship between the influence of induced stimuli of experimentallly designed variables (road roughness, passenger posture and bus type) and passenger's psychophysiological response (comfort). In order to evaluate the effect of experimentally designed variables on bus passenger discomfort, the experimental design variables were further divided into road roughness characteristics (asphalt and sett), posture (seated and standing and bus type (single- and double-decker). The above principle was adopted because it is presumed that bus passenger comfort could vary depending on road roughness, posture, driving style and bus type. Different methods of passenger comfort could, therefore, be established to describe each of the situations or conditions. In this study, the ANOVA method, the "Tests of Between-Subjects Effects" and "Parameters Estimate" was applied to test the impact of each of the experimentally designed variables on passenger comfort in order to obtain F-test and partial eta-squared effect sizes for each of the experimental variables.

6.5.1 Passenger's Psychophysiological Responses to the Influence of Experimentally Designed Variables

Validation of the results was carried out by modelling the psychophysiological response of passengers (eSense metric for attention brain activity) relative to the influence of experimentally designed variables. The model "Test of Between-Subjects Effect" was applied. The corrected model row shows that the overall model was significant ($p < 0.01$) and the effect size shows that the model explains 71.2% of the variance of a passenger's level of distraction, agitation or abnormality. The road environment, posture and bus type are statistically significant ($p < 0.01$) and the effect size shows that road environment, posture and bus types highly indicated the variance of the dependent variable (passenger's discomfort) at 56.7%, 9.6% and 30.2%, respectively. Passenger's related variables, such as age and gender, were introduced as part of the model (Table 6-3). The results demonstrated that both age and gender are statistically significant.

Table 6-3: Analysis of the influence of experimental phases on passenger's psychophysiological responses

Source	Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	9878.608	6	1646.435	71.343	0.00	0.712
Intercept	260497.335	1	260497.335	11287.885	0.00	0.985
RoadEnvironment	5225.849	1	5225.849	226.447	0.00	0.567
Posture	423.293	1	423.293	18.342	0.00	0.096
Bus Type	1727.939	1	1727.939	74.875	0.00	0.302
Gender	1608.444	1	1608.444	69.697	0.00	0.287
Age	31.956	1	31.956	1.385	0.24	0.008
Error	3992.426	173	23.078			

a. R Squared = .712 (Adjusted R Squared = .702)

6.5.2 Evaluation of Passenger's Psychophysiological Response to the Influence of Experimentally Designed Variables

Table 6-4 defined the model's parameters and presented the correlation ratio, standard deviation error with individual lower- and upper-bound at a 99% confidence interval and their corresponding p-values. Exposure to the influence of experiment variables in this study could be described as a form of activation of the whole body receptors and CNS (Byung-Chan et al., 2002). The emotions were evoked due to factors that formed the experimental phases, and were transferred to the brain and integrated to produce a subjective response to the stimuli effect of the influences of posture, bus type and road surface characteristics (experimental phases). Table 6-4 shows the correlation between the experimental phases and changes in attention (eSense meter). The statistical analysis supports the conclusion of the analysis of "Parameter estimate", which shows that the variations in the responsiveness of the passenger to the influence of asphalt and sett pavements are significant ($p < 0.01$). The effect size shows that the influence of asphalt and sett pavements explains 56.7% and 52.1% of the variance of passenger discomfort.

The intercept model row shows that the overall model was significant ($p < 0.01$), and the effect size indicates that the model explains 83.8%% of the variance in psychophysiological response of the passenger.

Table 6-4: ANOVA of the experimental phase on passenger responsiveness (Attention eSence)

Parameter	B	Std. Error	t	Sig.	95% Confidence Interval Lower Bound	Upper Bound	Partial Eta Squared
Intercept	31.466	1.051	29.935	0.00	29.391	33.541	0.838
Asphalt Pavement	18.049	1.316	13.710	0.00	15.450	20.647	0.521
Sett Pavement	11.430	0.760	15.048	0.00	9.931	12.929	0.567
Posture	3.254	0.760	4.283	0.00	1.754	4.754	0.096
Bus Type	6.575	0.760	8.653	0.00	5.075	8.074	0.302
Gender	6.419	0.769	8.348	0.00	4.901	7.936	0.287
Age	0.871	0.740	1.177	0.24	-0.590	2.331	0.008

6.6 Effect of Road Roughness on a Passenger's Psychophysiological Response: Gender Influence

Figure 6-1 showed that the sensory information of males and females sharply reduced on both asphalt and sett pavements. This result was probably conveyed to the association of the cortex and the degree of stimulus transmitted to the CNS. Figure 6-1 shows that there is a significant difference ($p< 0.01$) between the responsiveness of male and female subjects. For example, the average responsiveness of male and female passenger responses to the influence of asphalt pavement are 40.09 and 46.69, respectively. The existing variations in the responsiveness of male and female passengers relative to road pavement characteristics (asphalt or sett pavements) are statistically significant (Figure 6-1). The lower psychophysiological response of female passengers compared to male passengers revealed significant main effects of road roughness characteristics.

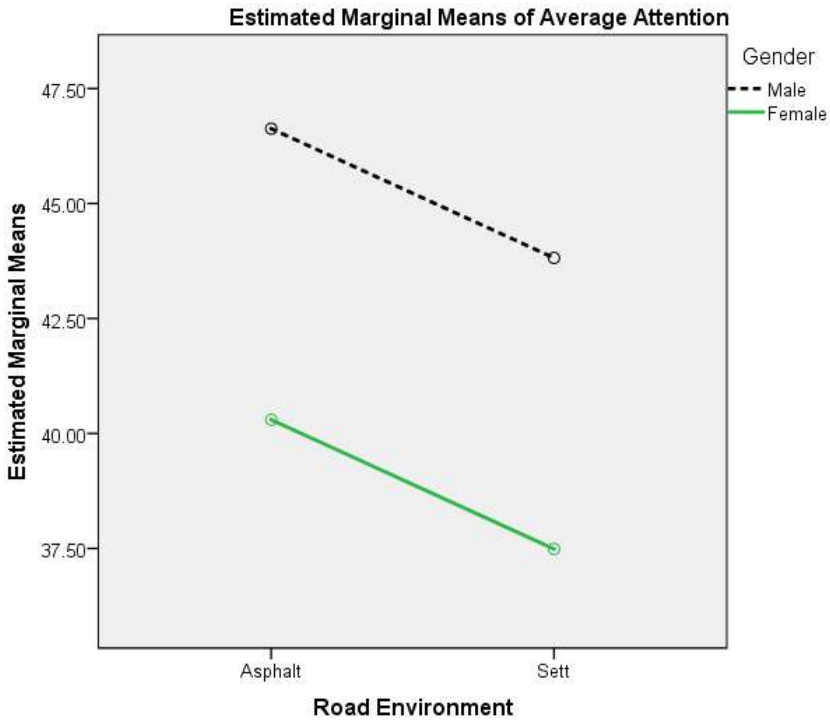


Figure 6-1: Influence of road roughness on comfort for gender characteristics (attention eSense meter)

6.6.1 Effect of Road Roughness on a Passenger's Psychophysiological Response: Age Influence

The impact of a passenger's age on psychophysiological responses of passengers to the influence of road roughness characteristics was validated in this study. The estimated marginal mean demonstrated that the psychophysiological response of young and old passengers vary significantly on both asphalt and sett pavements. In other words, the extent of activation of the activity of CNS on passengers older than 30 years is more significant compared to young ones (Figure 6-2). These results could be interpreted as older passengers exhibiting a higher level of discomfort that could impair their physical and mental fitness compared to young passengers.

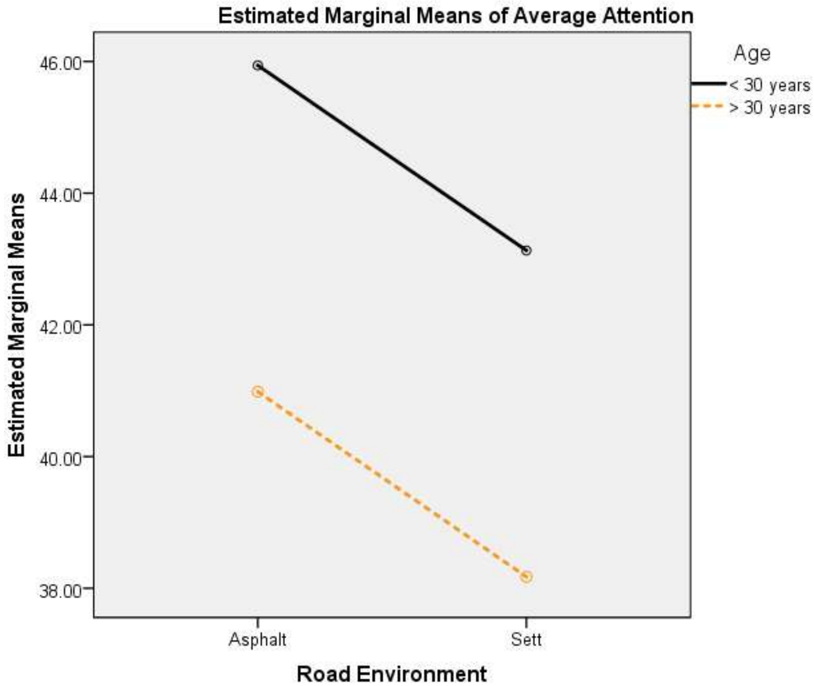


Figure 6-2: Passenger sensibility (eSense metric for attention): age influence

6.6.2 Effect of Road Roughness on a Passenger's Psychophysiological Response: Influence of Bus Type

When considering the influence of bus types on passenger's psychophysiological responses to the influence of road pavement characteristics, the results of this research demonstrated that it is statistically different ($p < 0.01$) between the responsiveness of passengers on single-decker buses compared to passengers on double-decker buses. An incongruent relationship was found between the psychophysiological response of passengers of single- and double-decker buses on both asphalt and sett pavements. The results indicated that vehicular types have a significant impact on a passenger's level of distraction, agitation and abnormality Figure 6-3).

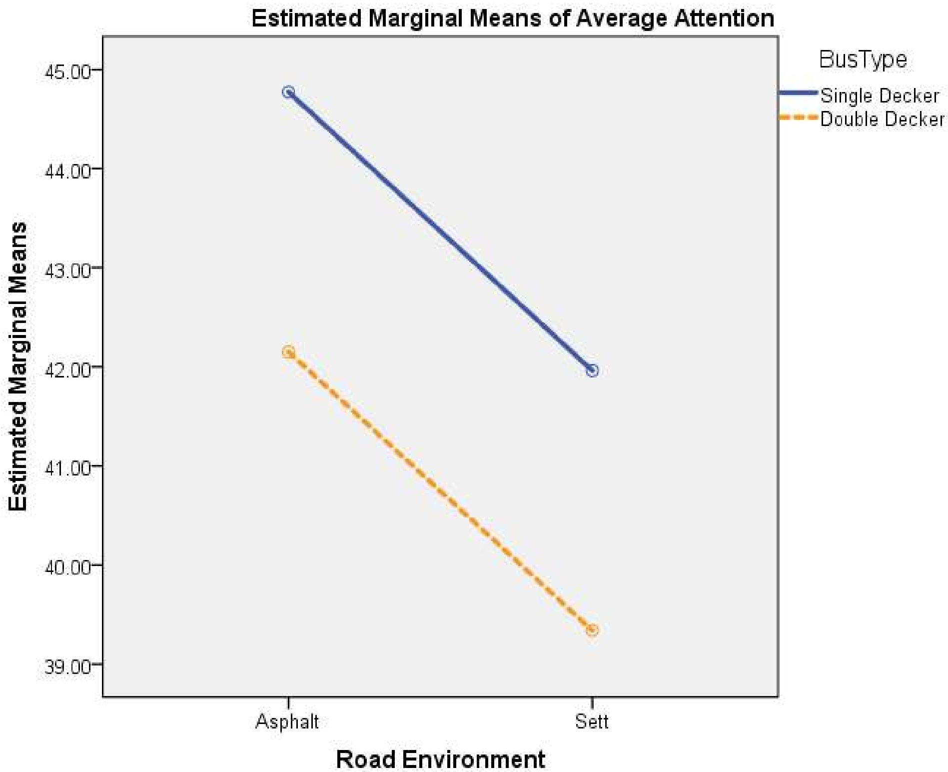


Figure 6-3: Influence of pavement types on passenger comfort (beta band) for vehicle characteristics

6.6.3 Effect of Road Roughness on a Passenger's Psychophysiological response: Gender Influence: Posture Influence

Considering the actual Lothian Buses operational situations, this section presents a sensitivity analysis of the variations between the extent of dissatisfaction, agitation or abnormality of seated and standing bus passengers under the influence of induced stimuli of asphalt and sett pavements. The results demonstrated that standing bus passengers were tenser compared to seated passengers. The average responsiveness of passengers on sett pavement, both seated and standing, reduced compared to asphalt pavement. For instance, the average responsiveness of seated and standing passengers on sett pavement is 48.1 and 45.5, respectively. The corresponding proportion of the average attention eSence meter of seated passengers on asphalt and sett pavements is 44.79 and 41.81, respectively (Figure 6-4). These results suggest that standing passengers experience more distractions and level of discomfort than seated ones. Therefore, standing passengers may require more attention and concentration to ensure stability and prevent falling in all forms of ground public transport. This study concluded that more significant losses of psychophysiological activation and alertness probably occur among standing passengers than among seated ones. However, it is speculated that standing passengers and those who are using buses regularly may be more sensitive to changes in physical and mental states, and they compensate for it in their responses.

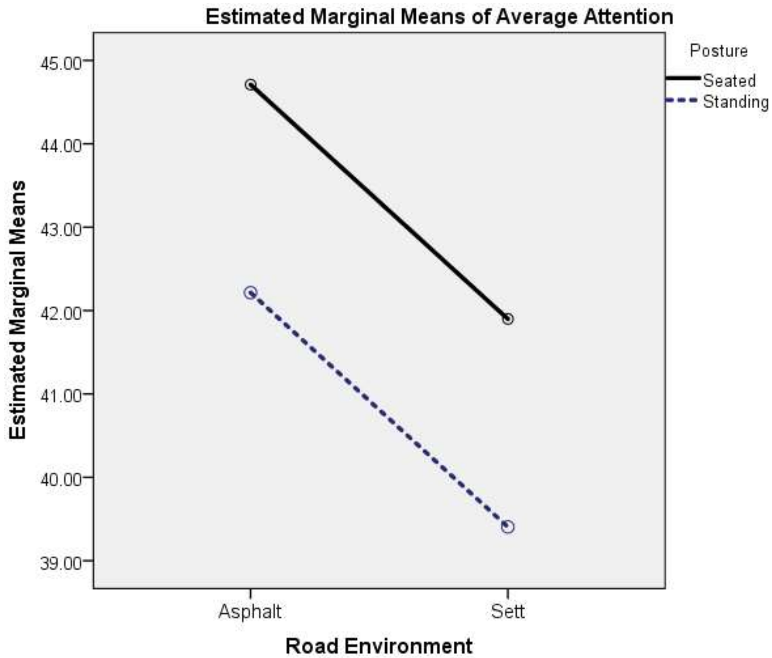


Figure 6-4: Effect of road roughness on passenger comfort (attention eSense meter): posture influence

6.7 Relation between Average Psychophysiological Response and Passenger Perception

The impacts of passenger's exposure to the influence of experimental design variables in this study could be described as activation of body receptors and the cerebral cortex. The emotions evoked during each phase of the experiments are transferred to the brain and integrated to produce a subjective response to the stimulus effects of the posture, bus type, road surface characteristics and other factors. Many researchers use approaches that are not limited to a physiological response, a behavioural change or a subjective assessment in order to investigate human responses (feelings) to internal or external stimuli. This section presents the statistical analysis of the brain-induced signals (attention eSence meter) as evaluations of bus passenger psychophysiological states (level of distraction, agitation or abnormality) or level of mental fitness relative to the ISO 2631-1 subjective comfort assessment. This study used the baseline of the objective data (average eSense metric for attention) of being not uncomfortable and a little uncomfortable on the subjective comfort assessment in order to establish the relationship between psychophysiological response and raking of the subjective comfort assessment. The observed decrease in psychophysiological signals (eSense metric for attention) in relation to an increase in ranking factors of the subjective comfort assessment could be interpreted as an increase in the passenger's level of distraction, agitation or abnormality (discomfort). For instance, the mean values of the brain activity of not uncomfortable, fairly uncomfortable and extremely uncomfortable relative to the influence of the experimentally designed variables are 67.0, 50.2 and 46.7, respectively. This result proves that the urban bus passenger state of distraction, agitation or abnormality could be objectively evaluated by observing the relationship between the average EEG brain activity and a passenger's perception (subjective comfort assessment). The results of this study prove that there is a positive relationship between the average eSense metric for attention (EEG brain activity) and the subjective comfort assessment (Figure 6-5).

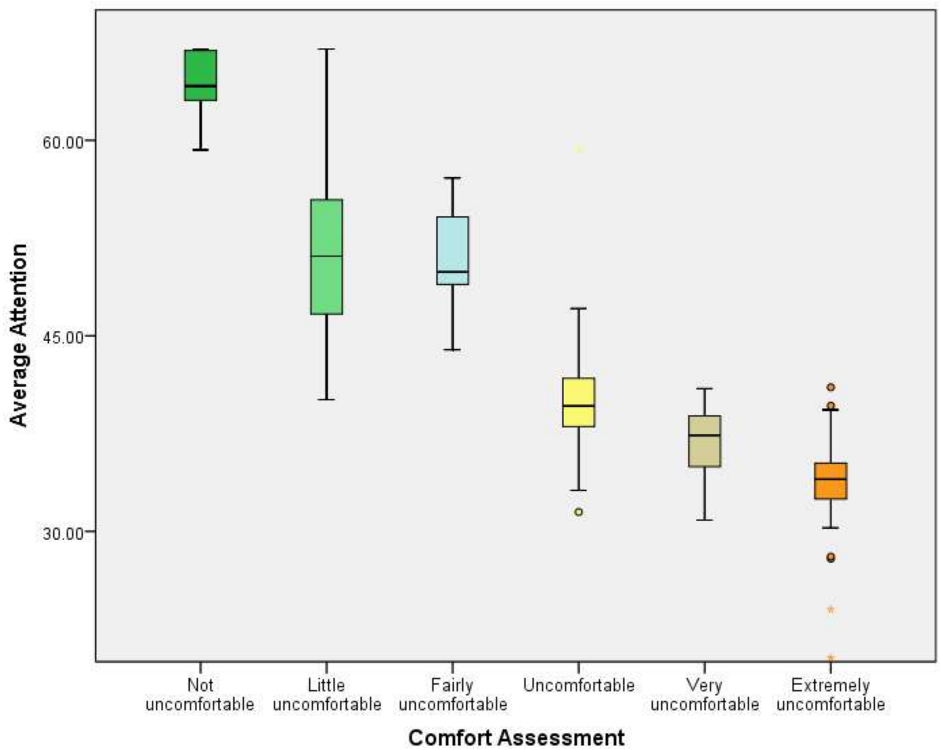


Figure 6-5: Passenger level of distraction, agitation or abnormality (attention eSense meter) and comfort assessment

6.7.1 Correlation between Psychophysiological Responses and Passenger's Perception of the Influence of Experimental Design Variables

The modelling of the effect of road roughness, passenger posture, bus type, and the demographical characteristics of the subjects are presented in this section. The statistical analysis of cross-correlation of the eSense metric for attention and the subjective comfort assessment information of the twenty participants were presented in Table 6-5, relative to the influence of experimentally designed variables, passenger responses (attention eSence brain activity) and subjective comfort assessment. The model test of the Between-Subjects Effect was applied to test the participant's level of distraction, agitation or abnormality by using ANOVA. The evaluation of comfort assessments relative to the experimental designed phases was found to be significant ($p < 0.01$). The corrected model row shows that the overall model was significant ($p < 0.01$) and the effect size shows that the model explains 78.9% of the variance of a participant's level of distraction, agitation or abnormality (Table 6-5).

Table 6-5: Changes in passenger's responses to the influence of experimental phases (eSense metric for attention)

Source	Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	10002.628	14	714.473	32.803	0.00	0.789
Intercept	187446.461	1	187446.461	8606.073	0.00	0.986
Comfort Assessment	5343.886	5	1068.777	49.070	0.00	0.666
Experimental phase	206.489	7	29.498	1.354	0.23	0.072
Age	23.609	1	23.609	1.084	0.30	0.009
Gender	13.449	1	13.449	0.617	0.43	0.005
Error	2679.029	123	21.781			

R Squared = .789 (Adjusted R Squared = .765)

6.7.2 Influence of Experimentally Designed Variables on Psychophysiological Responses and a Passenger's Perception

(Table 6-6 shows the analysis of the correlation between the average attention eSense meter and subjective comfort assessments by using the "Parameter of Estimate model". The results of the model indicate that the subjective comfort assessment is statistically significant ($p < 0.01$). These results keep with the reduction in psychophysiological responses (level of distraction, agitation or abnormality) of passengers relative to the subjective comfort assessment ranking. The model intercept row shows that the overall model is significant ($p < 0.01$), and the effect size shows that the model explains 80.3% of the variance in a passenger's psychophysiological response (passenger comfort) ((Table 6-6).

Table 6-6: Evaluation of psychophysiological response and a passenger's perception of the influence of experimental phases (eSense metric for attention)

Parameter	B	Std. Error	t	Sig.	99% Confidence Interval Lower Bound	Upper Bound	Partial Eta Squared
Intercept	33.960	1.514	22.425	0.00	30.962	36.957	0.803
Not uncomfortable	31.998	2.487	12.866	0.00	27.075	36.921	0.574
A little uncomfortable	18.096	1.779	10.169	0.00	14.574	21.618	0.457
Fairly uncomfortable	18.479	1.705	10.837	0.00	15.103	21.854	0.488
Uncomfortable	7.450	1.517	4.912	0.00	4.447	10.452	0.164
Very uncomfortable	3.599	1.341	2.684	0.01	0.944	6.253	0.055
Single-decker-seated asphalt	0.120	1.944	0.062	0.95	-3.727	3.968	0.000
Single-decker-standing asphalt	1.134	1.804	0.629	0.53	-2.436	4.705	0.003
Double-decker-seated asphalt	-2.510	1.705	-1.473	0.14	-5.884	0.864	0.017
Double-decker-standing asphalt	-0.878	1.612	-0.545	0.59	-4.068	2.312	0.002
Single-decker-seated sett	-2.960	1.873	-1.581	0.12	-6.667	0.747	0.020
Single-decker-standing sett	-1.675	1.629	-1.028	0.31	-4.899	1.549	0.009
Double-decker-seated sett	-0.533	1.634	-0.326	0.75	-3.767	2.702	0.001
Age	0.975	0.936	1.041	0.30	-0.879	2.828	0.009
Gender	-0.760	0.967	-0.786	0.43	-2.674	1.154	0.005

6.7.3 Effect of Experimentally Designed variables on Psychophysiological and Subjective Responses: Age Influence

The results in Figure 6-6 show the average psychophysiological responses (EEG brain activity) of different age groups. The evaluations are based on the average value of the eSense metric for attention and factors of subjective comfort assessment. An increase in the level of distraction or abnormality (discomfort) of the passengers was indicated by the low eSense meter of attention. Therefore, this study confirmed that there is a slight variation between the average level of distraction, agitation or abnormality of young and old passengers. However, the existing variation between the responsiveness of the age groups is not statistically significant. This could be explained as the age of a passenger has no significant influence on their level of attention.

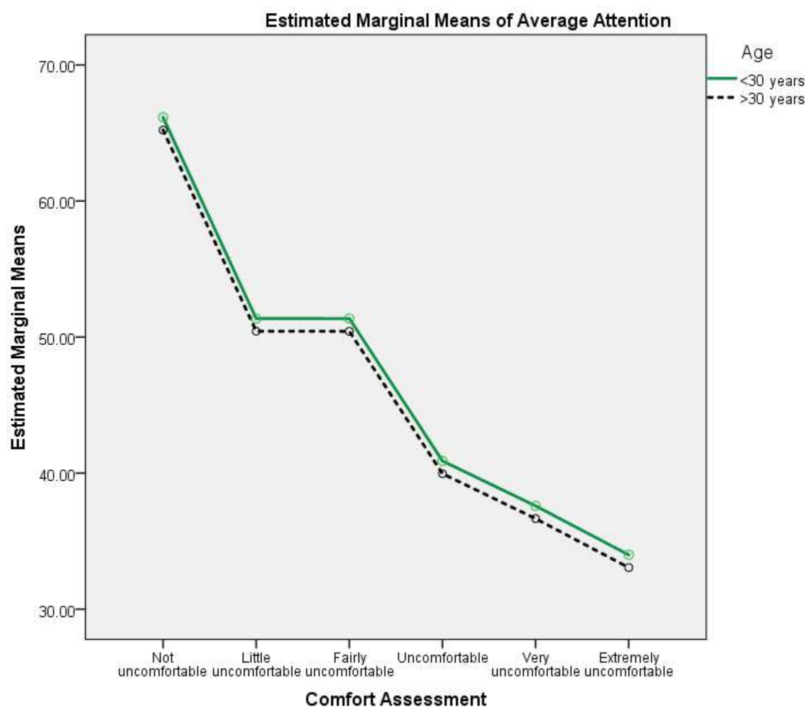


Figure 6-6: Passenger's psychophysiological response (attention eSense meter) and subjective responses: age influence

6.7.4 Relationship between Psychophysiological Response and Subjective Comfort Assessment: Gender influence

Figure 6-7 shows that statistically, there is no significant difference between male and female levels of distraction, agitation or abnormality in a dynamic environment by using the attention eSense scale. These results could be interpreted as both male and female passengers exhibiting the same/similar patterns of discomfort in a dynamic environment.

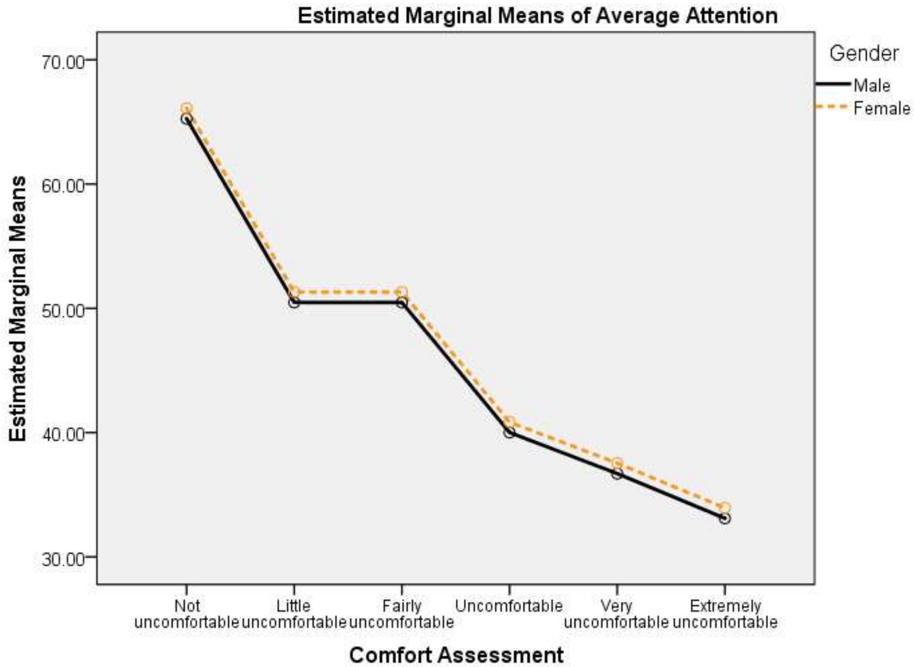


Figure 6-7: Passenger's psychophysiological response (attention eSense meter) and subjective responses: gender influence

6.8 Inter-subject Variability

The perceived ride comfort in public ground transport is known to vary from one vehicle to another as well as from person to person. For instance, the study of Richard et al. (1978) indicated that the responsiveness of individuals in the vehicle environment is not limited to only physical inputs, but also the individuals' characteristics. Generally, EEG in the human brain could demonstrate significant variations and fluctuation patterns within or between sampled subjects. Also, NeuroSky, 2010 indicated that EEG brain activity has a propensity of normal ranges of fluctuation and variation. Therefore, it could be difficult to obtain the same brain signals (level of distraction, agitation or abnormality) from all the participants even though they are exposed to the same/similar experimental conditions. This section presents the average, lower bound and upper bound responses of the 20 sampled passengers to the influence of experimentally designed variables (Figure 6-8). The results show the effects of the experimental phases on a passenger's level of distraction, agitation or abnormality as well as variations in average EEG brain activity of all the subjects.

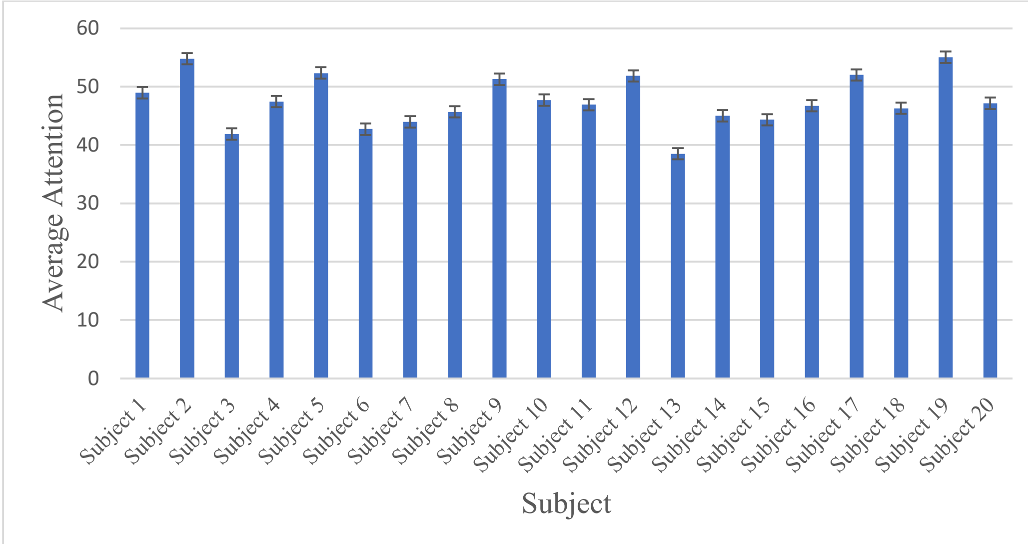


Figure 6.8: Inter-subject variability

6.8.1 Inter-subject variability (eSense metric for attention)

The effects of experimental phases on inter-subject variability of bus passenger's levels of distraction, agitation or abnormality are shown by using ANOVA. As shown in Table 6-7, the p-value of the subject (passenger) variability using the Test of Between-Subject Effect is much higher than 0.05, indicating no significant difference between the responsiveness of all the passenger's levels of distraction, agitation or abnormality in all phases of the experiment.

Table 6-7: Statistical analysis of inter-subject variability

Source	Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	3230.873	19	170.046	2.557	0.00	0.233
Intercept	406717.376	1	406717.376	6115.958	0.00	0.975
Subject	3230.873	19	170.046	2.557	0.00	0.233
Error	10640.161	160	66.501			

R Squared = .233 (Adjusted R Squared = .142)

6.8.2 Inter-subject Variability: Parameter of Estimates

Table 6-8 presents the analysis of the inter-subject variability of urban bus passenger's levels of distraction, agitation or abnormality by using the eSense metric for attention. There is no evidence from this study to support the factor(s) responsible for the existing variations in the average responsiveness (discomfort) of all the 20 participants.

Table 6-8: Analysis of Inter-Subject variability (Attention eSense meter)

Parameter	B	Std. Error	t	Sig.	99% Confidence Interval Lower Bound	99% Confidence Interval Upper Bound	Partial Eta Squared
Intercept	47.152	2.718	17.346	0.00	41.784	52.520	0.653
Subject 1	1.810	3.844	0.471	0.64	-5.782	9.402	0.001
Subject 2	7.642	3.844	1.988	0.05	0.050	15.233	0.024
Subject 3	-5.249	3.844	-1.366	0.17	-12.841	2.343	0.012
Subject 4	0.307	3.844	0.080	0.94	-7.285	7.899	0.000
Subject 5	5.203	3.844	1.353	0.18	-2.389	12.795	0.011
Subject 6	-4.424	3.844	-1.151	0.25	-12.016	3.168	0.008
Subject 7	-3.176	3.844	-0.826	0.41	-10.768	4.416	0.004
Subject 8	-1.461	3.844	-0.380	0.70	-9.053	6.131	0.001
Subject 9	4.126	3.844	1.073	0.29	-3.466	11.718	0.007
Subject 10	0.549	3.844	0.143	0.89	-7.043	8.141	0.000
Subject 11	-0.241	3.844	-0.063	0.95	-7.833	7.351	0.000
Subject 12	4.705	3.844	1.224	0.22	-2.887	12.297	0.009
Subject 13	-8.625	3.844	-2.244	0.03	-16.217	-1.033	0.031
Subject 14	-2.142	3.844	-0.557	0.58	-9.734	5.450	0.002
Subject 15	-2.869	3.844	-0.746	0.46	-10.461	4.722	0.003
Subject 16	-0.416	3.844	-0.108	0.91	-8.008	7.176	0.000
Subject 17	4.848	3.844	1.261	0.21	-2.744	12.440	0.010
Subject 18	-0.844	3.844	-0.219	0.81	-8.436	6.748	0.000
Subject 19	7.913	3.844	2.058	0.04	0.321	15.505	0.026

The parameter “Subject 20” is set to be redundant.

6.9 Summary

This chapter presented a laboratory and field study designed to investigate the influence of experimentally designed variables (road roughness, passenger posture and bust type) on a passenger's level of discomfort by using the attention eSense meter of EEG. The subjective evaluation of a subject's opinion on average ride comfort on each type of pavement was carried out by using the recommended assessment scale of the International Standard ISO 2631-1 for public transport. The approach used in this study is referred to as biophysical approaches of investigating brain responses to ERP in which the electrical signals' (attention eSense meter) magnitude depend on the sensory or cognitive state. The results show that the states of agitation or abnormality could be objectively determined by observing the relationship between the changes in responses of the bus passengers to the influence of road roughness characteristics, posture and bus type.

CHAPTER 7 GENERAL DISCUSSION

7.1 Study Background

The overall aim of the thesis is to investigate the appropriateness of using EEG in transport research. The primary objectives are to examine the extent of bus passenger comfort associated with the influence of road roughness characteristics, passenger posture and bus type, along with the level of driver fatigue relative to the impacts of driving duration. The results of the evaluation of bus passenger's psychophysiological responses could be used to improve the representation of the human body in a seated and in a standing position within the current comfort assessment standards for public transport systems (such as ISO 2631–1 (1997)). Previous studies have reported bus passenger comfort by using different approaches and factors (Mongelli et al., 2018; Šalinic et al., 2013; Beurier, 2012; Stradling & Carreno, 2007). However, none have considered the influence of road roughness characteristics, passenger posture and bus type by using the application of EEG. The approach taken in this thesis was to model these factors together and assess them separately through a series of field studies, and then provide an overall relationship between seated and standing passenger's responses to the influence of road roughness in single- and double-decker buses. Also, the results of the fatigue assessment could be used to improve a driver's attention and corresponding fatigue countermeasures as a function of the duration of driving. Several studies were previously carried out to investigate the nature of driving fatigue and its likely effects on traffic safety of other road users (Ma et al., 2019; Yin & Mu, 2016; Hanowski et al., 2003; Amundsen & Sagberg, 2003).

7.2 Overview of Urban Bus Passenger Comfort

Apart from the frequency of bus departures, the cost of the ticket, the number of transfers and punctuality, passenger comfort is an essential part of the element of the users. The investigation of bus passenger comfort appears to be challenging due to many factors, such as frequent stopping at bus stops and other road infrastructural facilities. Also, in order to understand the effectiveness of the bus public transport systems, researchers are trying to model and predict passenger demand and comfort, which increases the passenger's attractiveness and encourages more people to choose to use the bus (Kubek et al., 2019). The emotion that arises from the induced stimuli effects from road-vehicle interactions, driving behaviour and passenger posture could have significant impacts on psychophysiological states, health and the mental fitness of the driver and the passengers. Minimising such undesirable impacts requires an investigation of driver and passenger responsiveness to the influence of vibrations arising as a function of road-vehicle interactions. Sensations arisen from road-vehicle interactions could be classified as being unpleasant, uncomfortable, disturbing or annoying, and long-term exposure to it could result in chronic health-related issues.

The practical application of oscillatory neural activity through the CNS in this study began with the analysis of participant's responses to the experimental events. The nervous system allows the human body to respond to changes in an internal or external environment. Variations in the degree of responsiveness of the participants depend on the degree of force presented to the CNS. The sensation and cognitive events induce superimposed oscillations that are transmitted to brain tissue. These oscillations are characterised with various degrees of intensity that are proportional to the stimuli effect because the conditions in the human body must be carefully controlled in order to function efficiently and survive. For example, event-related oscillations of a passenger's sensory or cognitive ability as a function of the influence of stimuli effects of the variables that form the experimental designed phases and variables in this study were investigated and analysed. It is, therefore, essential to know that any observable change(s) in spontaneous EEG brain waves, which are referred to as oscillatory responses in this study, is temporally associated with a specific event, which is defined as experimentally designed phases or variables (Başar et al., 1999).

There are many situations when seated or standing passengers in the bus transport system are exposed to vibrations evoked by the influence of road roughness or driving styles, and they cause various stresses and/or discomfort. The higher the degree of perceived stress, the more likely the stress allostatic load will influence the brain and people's wellbeing and health. The approach used in this study is similar to what is described by Basar et al. (1999) as biophysical approaches of investigating brain responses in which the electrical signals' (beta brain activity or eSense metric for attention) magnitude depends on the sensory or cognitive state. Landström & Lundström (1985) revealed that the activation of the human brain varies depending on the degree of the stimuli evoked to the receptors of the body. In this study, a bus passenger's level of comfort was evaluated by using data collated via EEG.

7.2.1 Relationship between Road Roughness Characteristics and a Passenger's Psychophysiological Response

Different approaches have been used in space and time to assess mental and physical non-specific responses of the mind or body to any demand change relative to the influences of road roughness characteristics. Furthermore, uneven pavement causes road-vehicle dynamic interactions that sometimes reduce driver and passenger ride comfort (Loprencipe & Zoccali, 2017; Dedovic et al., 2013; Cantisani & Loprencipe, 2010). The weight criteria from ISO 2631–1, 1997 revealed that vibrations have significant impacts on bus passenger comfort. However, the effects of road roughness characteristics on passenger comfort depend on factors, such as the quality of the seat, adaptability, posture, age and gender. Road roughness is variations in road surface elevation that induce vibrations in traversing vehicles (Cantisani & Loprencipe, 2010), which has been recognised for a long time as a means of measuring and evaluating road performance and ride comfort (Soliman, 2006). The influence of the road roughness characteristics (pavement types) appears to be more prominent on bus passenger ride comfort compared to several other factors, such as passenger posture, ability, age, gender and bus type. A series of studies have been conducted to establish the relationship between road roughness and penalties imposed on road users. Therefore, in order to obtain a valid correlation between road irregularity and a bus passenger's ride comfort, standard riding comfort provided by the different road roughness characteristics as well as the extent of cause-effects of passenger discomfort as a function of road roughness characteristics need to be investigated. Therefore, passenger comfort was evaluated by comparing the average physiological and psychological responses of the passengers in baseline (control) experimental conditions with the responsiveness of the passengers being relative to the influence of experimentally designed variables.

The human capacity to withstand additional stressors, yet sustain attention has been discussed in previous studies (Hancock, 1989). The passenger level of comfort can be investigated and evaluated in terms of behavioural, perceptual and physical responses (Subhani et al., 2011). The results of the series of experimental investigations presented in chapters 5 and 6 indicated that the influence of road roughness on bus passenger comfort had yielded varying results. The results demonstrated that standing passenger's psychophysiological curve increased sharply on sett pavement compared to asphalt pavement in both seated and standing postures. An increase in beta EEG brain activity and a decrease in the Sense metric for attention are associated with the integration of the multi-modal somatosensory information or the cerebral cortex as a whole, which is essential for motor planning of bodily movement. It is evident from this study that the more the subject's psychophysiological sensations increase (beta EEG brain activity) or decrease (eSense metric for attention) relative to the influence of experimentally designed variables, the more the subject's comfort deteriorates. An increase in beta brain activity (increased discomfort) was found to be associated with the results of Chen et al. (2010) who reported that the component spectra monotonically increased with motion sickness levels in delta, theta, alpha and beta frequency bands.

Magnusson and Arnberg (1976) reported that the effects of road roughness are not limited to decreasing the comfort of drivers and passengers, but they also cause fatigue experienced during actual travelling or afterwards. Also, previous studies revealed that prolonged exposure to mental stress could lead to different diseases, such as depression, heart attack, stroke and other mental disturbance symptoms (Al-shargie et al., 2016). Furthermore, discomfort caused by the influence of road roughness or similar source(s) could sometimes lead to the activation of hypothalamus-pituitary-adrenocortical axis hormones (cortisol) in the adrenal cortex, which could cause poor health conditions. The average responsiveness (eSense metric for attention) of passengers on sett pavement in both seated and standing positions reduced compared to the responsiveness of passengers on asphalt pavement. For instance, the responsiveness of seated and standing passengers on sett pavement is 48.1 and 45.5, respectively.

7.2.2 Relationship between Passenger's Psychophysiological Responses, Passenger Posture and Bus Type

The psychophysiological response relative to the influence of passenger posture and bus type could make it possible to relate human physiological or psychological responses to the impact of the posture or the bus type. The objective of this study was not to develop a complex psychophysiological model to represent each passenger's posture impact relative to the influence of the driving style or the bus type. However, this study investigated and examined the application of a passenger's psychophysiological responses as an approach for identifying specific conditions where a passenger's comfort would likely be degraded. The comfort of seated or standing passengers due to the influence of vibrations or excitations in public transport has been presented in previous studies (Tirachini et al., 2016; George et al., 2013; Beurier, 2012; Thuong & Griffin, 2011; Robert, 2007). Standing passengers in public ground transport systems sometimes struggle to maintain balance, and experience a significant level of discomfort due to the influences of accelerations or decelerations, road-vehicle interactions and bus types. Table 5-4 demonstrates that the effect of passenger posture and bus type on bus passenger comfort is statistically significant ($p < 0.05$). The results of the model indicates that the influence of the posture and bus type explains 4.3% and 5.8% of the variance of passenger ride comfort, respectively. This may be interpreted as standing passenger's experiencing higher levels of discomfort and distractions compared to seated ones. It could be as a result of the degree of floating or fluttering of standing passengers in double-decker buses compared to single-decker buses.

The variations in the psychophysiological responses of standing passengers compared to seated passengers are statistically significant ($p < 0.01$). It could be concluded that standing passenger(s) require more attention to ensure stability and prevent falling compared to seated passenger(s) in all forms of ground public transport systems. Previous studies also showed that there are variations between the comfort of seated and standing passengers in public transport. For instance, the study of Suzuki et al. (2000) revealed that after a lateral acceleration of 1.0 m/s^2, the discomfort of standing passengers began to increase while the discomfort of seated passenger slowly evolved at 1.2 m/s^2. Also, the study of Shen et al. (2016) showed that the comfort perception of standing passengers decreased sharply compared to seated passengers. This study demonstrated that a correlation between passenger posture, bus type and psychophysiological response seems to exist, which might be because the activation of the brain occurs in relation to the induced stimulus effect of the influence of the experimentally designed variables to the body's receptors.

The variation in sizes of buses used by bus operators, such as Lothian Buses, depends on factors including the volume of passenger traffic on those routes. Both single- and double-decker buses have their strengths and weaknesses to the service users as well as bus operators. The results of this study indicated that bus types have a significant impact on passenger ride comfort. The impacts were observed when the responsiveness of the participants on single-decker buses is compared to those on double-decker buses, most importantly on sett pavement (Figure 5-3). These effects probably alluded to the association of the cerebral cortex and the degree of stimulus transmitted to the CNS. The findings prove that there is a statistically significant difference ($p < 0.01$) between the responses of passengers on single- and double-decker buses. For example, the average responsiveness of passengers on single- and double-decker buses to the influence of asphalt pavement is 4.67 and 5.42, respectively (Figure 5-3). It could be interpreted that passengers are more strained in double-decker buses compared to single-deckers under similar or the same experimental conditions.

The findings were in agreement with the study of Lima et al. 2015, which demonstrated that passengers of heavy vehicles are often subjected to a higher level of discomfort than passengers of light vehicles. The variations in the mass, height and geometry of single- and double-decker buses could form the factors responsible for the observable variations in ride comfort. Besides, changes in passenger comfort could arise due to the vehicle's suspension system and structural differences as mentioned in the study of Gillespie and Sayers, 1981. The results showed that passengers are more strained in double-decker buses compared to single-deckers on both asphalt and sett pavements. The variations in the average responsiveness of single- and double-decker buses on asphalt and sett pavements are 0.75 (16.06%) and 1.63 (26.63%), respectively.

Also, it is noted that vehicle designers ensure to keep the vehicle body's resonant frequency low in order to maximise the attenuation of the vehicle. Vehicle resonance that it is as low as 1 Hz. is achieved in some vehicles. The high frictional suspension that is common in commercial vehicles is 3 Hz. resonance, which could also vary depending on the size of the commercial vehicle. Previous research has shown that there is a linear relationship between the objective comfort assessment and speed, which is varied depending on vehicle type and road roughness characteristics (Cooper et al., 1978). In this study, the passengers reported that they were more strained in a moving double-decker bus, most importantly on sett pavement, compared to a single-decker on the same pavement type. The results of this study have shown that it is possible to examine and evaluate the degree of comfort of bus passengers based on vehicular types by using EEG.

The results of the subjective comfort assessment were used to validate the passenger's psychophysiological responses. The activation of the ERPs of the subjects occurs in various stimulus to the different receptors of the body relative to the influence of the experimentally designed variables. The subjective evaluation of the subjects' perceptions on average ride comfort in each phase of the experiments was carried out by using the recommended assessment scale of the International Standard ISO 2631-1 for the public transport of not uncomfortable, a little uncomfortable, fairly uncomfortable, uncomfortable, very uncomfortable or extremely uncomfortable (Loprencipe & Zoccali, 2017, ISO 2631–1, 1997b). However, using the baseline of the objective data (beta brain activity and eSense metric for attention) and not comfortable or a little uncomfortable of subjective evaluation as the reference point, the results confirmed that passenger comfort changes in relation to changes in the stage of the experimentally designed variables. The findings in this study reveal that the more the subject's psychophysiological signals increase (beta brain activity), the more the level of the subject's comfort deteriorates. For instance, passengers with an average beta EEG brain activity of 8.8, 10.1 and 12.8 felt uncomfortable, very uncomfortable and extremely uncomfortable, respectively (Figure 5-9). The average beta EEG brain activity attained the peak value of 12.8 when the participants believed that they felt extremely uncomfortable. Therefore, it is evident that the more uncomfortable the passenger felt, the higher the values of beta EEG brain activity were (psychophysiological responses). The results of the study revealed that the passenger's level of comfort could be objectively identified and determined by examining the relationship between beta EEG brain activity and the eSense metric for attention, and a subjective assessment as a function of the degree of stimuli from the influence of experimentally designed variables. Thus, it was evident that when designing a study investigating passenger comfort as a function of the influence of road roughness, posture and bus type as well as age and gender variations in psychophysiological activation must be considered. Also, the results prove that the passenger's level of comfort could be objectively identified and determined by observing the relationship between a passenger's psychophysiology and subjective response. The results demonstrated that there are cross-correlations between the objective evaluations and subjective responses of the passengers. For instance, the more uncomfortable the passenger felt, the higher the values of EEG beta brain activity were. Consequently, the cross-correlation of objective (beta EEG brain activity) data and subjective response demonstrates that the average beta EEG brain activity attained the peak value of 12.8 when the subject felt extremely uncomfortable.

In automated vehicles, especially urban bus transport systems, sharp starts and stops are inevitable as the vehicle merges into high-speed traffic at close headway. The changes in bus speed profile factors felt in all directions often influenced passenger comfort in the public transport system. The study of Castellanos & Fruett (2014) investigated the dynamic factors that affect passenger comfort in public transport and define them as comfort disorders (jerk and uneven speed). The perceived comfort is associated with the types and magnitudes of the stimuli transferred to the Reticular Activating System of the brain (Min et al., 2002). The influence of induced stimuli from vehicular driving patterns shows that passengers are tenser when the average speed ranges from 11–20, 21–30 and

31–40 km/h compared to when the average speed was 0–10 and 51–60 km/h (Figure 5-13). The study of Urabe & Nomura (1964) indicated that evaluating a vehicle's ride comfort requires data on a passenger's sensations and evaluating them quantitatively under various conditions.

7.3 Overview of Driver Fatigue

Driver fatigue is known as one of the leading factors of road traffic accidents, accounting for 14%–20% (Ma et al., 2019). It is a general and common disabling sign of many drivers that interfere with attention, reaction time and the ability to manage the occurrence of unforeseen road-related incidents or accidents. As captured via EEG, the investigation of the relationship between changes in beta brain activity and the eSence metric for attention (fatigue or alertness), along with time spent driving, were used for the assessment. In the transport system, cumulative fatigue due to driving time could have substantial impacts on a driver's vigilance and performance; therefore, a better understanding of the cause-effect of fatigue is required.

Generally, vigilance is known to be the central factor of safety for all transport operators, and there is also a significant relationship between vigilance and sleepiness or circadian factors. Additionally, the natural circadian cycle in psychophysiological response could have considerable impacts on a driver's level of alertness and fatigue. Consequently, the data collection for this study was performed within the framework of time spent in driving. For example, we ensured that all the participants had a good sleep the night before the experiments. Moreover, issues related to participant or individual life outside work, such as driving experience, health disorders and individual proneness were put into consideration when designing the experimental stages and the participant's quality. For instance, we ensured that all the participants were healthy adults with no display of any symptom of brain malfunction or mental illness. They had no record of psychological therapy nor a history of mental health-related issue(s). None of them was on any prescribed medication because all this could influence brain activity. Measurement of fatigue in this research underwent some refinement, and all the likely influence of equipment, environmental and operational factors were controlled.

7.3.1 Relationship between the Duration of Driving and a Driver's Psychophysiological Response

By analysing the measured brain activity of the participants to the influence of prolonged driving, the variations in psychophysiological responses of the participants could be compared over time. Duration of driving is one of the more frequently used factors for characterising the "to-the-body" physiological or psychological responses of the drivers (Miller & Mackie, 1978). Previous research shows that changes in wakefulness often lead to an increase in driving impairment as investigated by both road driving and simulated studies (Philip et al., 2005; Arnedt et al., 2005).

Changes in a passenger's psychophysiological responses as a function of driving time were assessed by using ANOVA. The findings demonstrated that there is a significant relationship between the total time spent driving and performance decrements (fatigue). For instance, there is a substantial increase in the levels of psychophysiological activation of drivers to the influence of driving time with a break (two hours after a break compared to two hours before). In the case of prolonged driving without a break, a significant and steadily higher level of psychophysiological responses was observed. This study proved the usefulness of the applications of EEG on driving fatigue and performance decrements. The most crucial finding in this study contradicted the results of the previous research of Philip et al. (2005) that demonstrated a lack of effect of the duration of driving on performance and sleepiness. However, the results of the analysis of Philip's group could be due to the length of the experiments (105 minutes). The average eSense meter of attention of driving without a break decreased sharply below the experimental phases of driving after a break when the simulated driving task was above 120 minutes. Figure 4-3 demonstrates that the longer the driving time, the lower the corresponding average of the eSense meter of attention of the participants is. This could be interpreted as prolonged driving time negatively impacting the psychophysiological functioning and ability of drivers to react to factors of incidents or accidents. Consequently, time spent driving is an essential construct for understanding driver fatigue.

Additionally, the results indicated that there is a significant difference between the fatigue state of male and female drivers. It is observed that the variations between the psychophysiological responses of male and female drivers and the influence of the duration of the driving task are statistically significant ($p < 0.01$). A good example is the average responsiveness (eSense metric for attention) of male and female drivers at 240 minutes of driving, which is 38.6 and 36.91, respectively. It could be interpreted that the female drivers exhibited a higher level of fatigue and performance decrements, which could impair their level of alertness and reaction time compared to male drivers. The age of the drivers also influences their psychophysiological responses to the influence of prolonged driving. The younger drivers (< 30 years old) perceived higher fatigue rates compared to the older ones (> 30 years) as a function of the duration of driving time.

This study was in support of the common notion that the duration of driving is an essential factor that needs to be controlled and managed in order to promote road safety (Parkes et al., 2009). The results also demonstrated a certain degree of congruency with previous research findings in which fatigue is classified as one of the distressing and disruptive symptoms in transit. It may be interpreted that prolonged driving could negatively impact psychophysiological functioning and the ability of the drivers to react to incidents or accidents.

CHAPTER 8 SUMMARY AND GENERAL CONCLUSIONS

The research presented in this thesis was designed to enhance the knowledge of the application of EEG in transport research studies in two key areas that have not been fully investigated. The areas included: i) the influence of driving time on driver fatigue or performance decrements, and ii) the effect of road roughness characteristics, passenger posture and bus type on bus passenger comfort.

8.1 Meeting Research Objectives

In recent years, there have been improvements in managing urban bus passengers comfort by bus operators and authorities in order to attract more passengers. This impact has been significant in managing traffic congestion and further reducing vehicle emissions. In an attempt to improve passenger comfort, different datasets (qualitative and quantitative) were used as an index of measuring and modelling the service quality of public transport systems with great emphasis on both passenger and driver overall satisfaction and perceptions. In data collection, there are still some limitations to the type and efficiency of data obtained. Further investigations are required to identify some of these shortfalls in type and method of data collection in order to improve passenger comfort evaluation and modelling. The following points outline the main conclusions of the thesis and summary of the key findings:

Examine the change in a driver's psychophysiological responses (from the state of focus or vigilance to fatigue or performance decrements) as a function of the duration of driving.

The use of driving as part of the factors to evaluate driving fatigue followed the recent trend and future forecast of managing road crashes. The influence of driving time on fatigue and fatigue-related accidents for drivers identified by Parkesat et al. (2009) and the European Parliament and the Council (EEC, 2006) were confirmed by the results and observations presented in chapter 4. Additionally, an interactive effect was found between the driver's average psychophysiological response and the time spent in driving. There were persistent increases in beta brain activity and decreases in the eSense metric for attention as fatigue progressed from the baseline through transitional states or stage performance decrements (fatigue). For example, the first 30 minutes of the experiment was meant to serve as the baseline of the experiments. The average psychophysiological responses demonstrated that the beta frequency band and the eSense metric of attention

EEG brain activity were still within the optimal level compared to the driving time of 180 minutes and above.

The results of driving fatigue as a function of prolonged driving corroborated the standard acceptable view that human performance decrements on specific tasks reach their lowest level when the duration of working (working hours) is beyond the acceptable limit or the individuals bearing capacity. This period of high-performance degradation or poor performance could represent the state of being extremely tired and very difficult to concentrate or unable to function effectively in task performance. These effects could offer significant benefits in determining the extent of the links between prolonged driving or working hours and driver fatigue. It may also have significant implications on the extent to which limiting hours of driving or work could help prevent fatigue-related incidents/accidents. Therefore, appropriate break time should be provided in all lengthy driving task(s) to compensate for any potential loss of performance or psychophysiological ability.

Investigate the effect of road roughness on the passenger's psychophysiological responses in public bus transport systems.

The emerging concept of perceived satisfaction in the ground public transport system provides a means of augmenting the concept of "ride comfort" as a conceptual approach for explaining the influences of road roughness. The magnitudes of sensations or vibrations found on some sections of Lothian Buses routes (sett pavements) were similar to those reported in the previous studies. Statistical analyses (ANOVA) shows an explicit agreement between road roughness characteristics and a passenger's psychophysiological response (EEG brain activity). Discomfort is associated with the psychological and physiological responses to a situation that requires homeostatic imbalance that occurs due to the discrepancy between what is experienced and what ought to be experienced (Subhani et al., 2011). Reduced comfort due to rough road exposure positively correlates with psychophysiological response as captured via EEG. The results prove that there is a significant difference ($p < 0.01$) between the psychophysiological responses (discomfort) of passengers on asphalt and sett pavements. For example, the average responsiveness of passengers in single-decker buses to the influence of asphalt and sett pavements is 4.67 and 6.2, respectively. The corresponding responsiveness of passengers in a double-decker bus to the impact of asphalt and sett pavement is 5.42 and 7.9. The results supported the assumption that road pavement type might reduce bus passenger comfort, the effects being less produced on asphalt pavement than on sett pavement. Also, by using the eSense meter scale, the results demonstrated that the variations between the responsiveness of young (< 30 years) and old (> 30 years) passengers are statistically significant ($p < 0.01$). The eSense meter scale shows that values ranging from 0–40 represent distraction, agitation and abnormality (Table 3-5). Sett pavement was installed to reduce vehicle speed and improve the safety of pedestrians and people within the neighbourhood. Vehicle occupants usually experience different forms of unpleasantness when travelling on sections of sett pavement because of vibrations from road-vehicle interactions. The results showed that passengers were more strained and uncomfortable on sett pavement than on asphalt pavement (Figure 6-4). Cantisani & Loprencipe (2010) reported a reasonable agreement between road roughness characteristics inducing user discomfort. The upsetting effects of road pavements on passenger comfort demonstrated that passengers are more strained on sett pavement compared to asphalt pavement. This result was in agreement with Soliman's (2006) study that investigated the effects of road roughness on ride comfort and found that as the road roughness coefficient increases, the ride comfort deteriorates. Ismail et al. (2015) reported a reasonable agreement between passenger comfort decrements and road roughness characteristics. The above study revealed that rough surfaces induce higher force excitations to the cyclist, thereby increasing participant's discomfort on sett pavement compared to smooth pavement.

The results showed that there are variations in the participant's average responses to the influence of posture, road roughness (asphalt and sett pavements) and bus types (single- and double-decker) even though they were all exposed to the same or similar experimentally designed conditions. The findings demonstrated that there is inter-subject variability in the psychophysiological responses of the passengers. The patterns of variations are associated with each subject's ability to withstand the induced sensations from the influence of experimentally designed variables. The inter-subject variability depends on each passenger's body system's ability to regulate or manage the strength of the simulation presented to the CNS. Also, whenever the brain perceives induced stimulus effects like stress or discomfort, the responses usually lead to allostatic adaptation, which vary from passenger to passenger (Mcewen, 2000). Mansfield's (2005) research demonstrated that the impacts of induced sensations differ from one person to another, and no evenly adequate approach predicted the variations from the anthropometric measurement.

Quantify changes in a passenger's psychophysiological responses in public bus transport systems relative to the influence of posture in single- and double-decker buses.

Comfort perceived by the passenger in the ground public transport system varies among factors, including vehicle type and size, the passenger's posture or body orientation, and the ability of the individual to withstand the factors of stress. Generally, automatic transmission systems used in public transport vehicles produce inevitable sudden and sharp accelerations/decelerations relative to the influence of the driving style. Sometimes, this effect makes standing passengers struggle to maintain balance or experience a significant amount of discomfort (George et al., 2013). These factors interact to cause a short- or long-term change in a passenger's physiological and psychological state. Bus passengers usually experience a different level of discomfort on transit that sometimes results in musculoskeletal disorders (MSDs) (Armstrong et al., 1993). These disorders are usually referred to as repetitive trauma disorders, cumulative trauma disorders or repetitive strain injuries that could affect muscles, bones and joints. The influence of posture and bus type on a passenger's psychophysiological response are presented in chapters 5 and 6.

The conditions in which passenger comfort deteriorated were found to correspond to the condition that demonstrated the most significant influence on the body's physiological and psychological response. The passenger's posture, particularly standing posture, resulted in the most significant deterioration of passenger comfort. In this study, the effects of road-vehicle interactions on the comfort of standing passengers in single-decker buses were not significant compared with the extent of double-decker buses. Also, the comfort of the seated passengers in single-decker buses was the least affected. Measurements of the human body's psychophysiological responses to the influence of the effect of road-vehicle interactions in different postures could, therefore, be used as the basis for predicting the likelihood of passenger comfort in single- and double-decker buses.

Furthermore, studies have shown that passengers respond differently to large vehicles than to small-sized vehicles (Lima et al., 2015; Cooper et al., 1978 part 1). The correct designs of road pavement also depend on the type of vehicle using the route. Some roads could effectively tolerate vehicles, such as passenger cars, and that same road may penalise other vehicles, such as HGVs or double-decker buses. In Edinburgh, some sections of Lothian bus routes were designed a long time ago to accommodate small vehicles. However, using those roads as part of the Lothian bus route significantly influences driver and passenger perceived sensations (comfort). An increased average beta EEG brain activity and a decreased average eSense metric for attention (sensory stimulations) as a function of the influence of road-vehicle interaction predicts a reduction in passenger comfort. The variations in average psychophysiological responses of passengers in the control experiment, and onboard seated and standing postures in single- or double-decker buses support the assumption that posture and bus type could influence bus passenger's comfort. The results prove that the emotions evoked during each phase of the experiments were transferred to the brain and integrated to produce a subjective response (discomfort) relative to the induced stimulus effects from the influences of a passenger's posture and bus type. This study's results could have implications for the proper planning and allocation of buses to specific routes by the bus operators in order to minimise passenger standing, especially during the peak hours.

Investigation of change(s) in EEG brain activity relative to subjective comfort assessments was corroborated in this study. The subjective evaluation of passenger ride comfort was carried out by using the recommended assessment scale of the ISO 2631-1 for public transport. An interaction effect was found between the passenger's psychophysiological response and subjective evaluations. For instance, the more the psychophysiological (beta) signals increase or the eSense metric for attention decreases relative to changes in the comfort assessment scale, the further the passenger comfort deteriorates. The results in chapters 5 and 6 demonstrated that passenger comfort could be predicted and validated by the cross-correlation of EEG brain activity and comfort assessment for public transport. There are strong positive cross-correlations between changes in EEG brain activity and subjective comfort assessment.

Driving fatigue showed progressive degradation with increasing driving time. In two hours of driving before a 30 minute break, there were no significant adverse effects associated with duration of driving without a break, and two hours of driving after a 30 minute break showed variable effects of prolonged driving. The average beta power appeared to increase significantly while the average eSense meter of attention decreased significantly from 180 minutes of driving during four hours of continues driving tasks. The participants were often subjected to a considerable influence of variations in psychophysiological activation associated with prolonged driving. The findings show a significant relationship between the psychophysiological responses of the drivers and subjective fatigue assessment as a function of time spent driving. The results showed the correlations between the psychophysiological response (beta frequency band and the eSense metric for attention), and it transitions from a state of being fully alert and wide awake to extremely tired and very difficult to concentrate or completely exhausted and unable to function effectively as a function of the duration of driving (Figure 4-7). The qualitative data's application alongside quantitative data helped in interpreting and providing a better understanding of the implications of the quantitative data.

8.2 Conclusions

The EEG signal has temporal resolution, and what generated during quiet rest is quantitatively different from what generated during defined cognitive processing. In this study, the EEG methodology was used to examine the relationship between brain electrical activity and experimentally designed variables. Changes in the postsynaptic neurons are immediately reflected in the EEG (Bell & Cuevas, 2012), making the EEG methodology outstanding for investigating changes in the psychophysiological response of passengers and drivers in this study. Furthermore, EEG is more suitable for studying urban bus passenger comfort and driving fatigue because it allows the investigation of developmental changes without interfering with regular spontaneous brain activity. In this study, the EEG was recorded in all urban bus passenger discomfort stages and driving fatigue was compared with the EEG recorded during the baseline experiment.

Evidence of cumulative fatigue in all the participants is strongly affected by the duration of time spent on the driving task and may also be associated with age, gender and influence of the break. The evidence for this conclusion includes the average psychophysiological responses and subjective fatigue assessment rating involving driver performance decrements or inattentiveness that was high for all participants in the last 45 minutes of all stages of the driving tasks, but more pronounced in the diving task with no break.

The variability in the driver's psychophysiological responses to the influence of the duration of driving occurred in a systematic way when the full-length driving task of four hours with no break was compared with driving for four hours with a break of 30 minutes after two hours of driving. The variations in the average psychophysiological responses of the participants in the baseline (the first 30 minutes) was compared to when the participants had spent more than 60 minutes on the driving task, which suggested progressive changes in driver fatigue or performance decrements toward the end of the driving tasks. A dramatic change is seen in the driver's psychophysiological response in the last 60 minutes of the driving task compared to the first 30 minutes (baseline) of the driving task. These findings indicate that a pronounced psychophysiological response exists in the performance of driving tasks. This psychophysiological response is aligned such that the driving performance was worse during the last 60 minutes of driving for four hours without a break, but better during the first 30 minutes. However, significant decreases in the eSense metric of attention and increases in beta EEG brain activity occurred during the last 60 minutes of the driving task of hours without a break, and in the last 30 minutes of the driving task with a break. This certainly reflects a relaxation of cortical arousal following the heightened arousal required to drive effectively at the start of the experiments (baseline).

This study's findings show that a baseline state of high arousal could be a prerequisite for generating functional neurological symptoms. There is no clear evidence of fatigue effects or performance decrements in the eSense metric of attention and beta EEG brain activity measured during the first 30 minutes of the experiments. These results demonstrated that the driver's performance significantly deteriorated during the last 60 minutes of the driving task of four hours of driving without a break. Thus, it appears that the participants were unable to maintain the sensitive level of cortical arousal of the first two hours of the driving task, and that they were equally unable to adequately compensate for this loss of arousal in order to maintain a high level of concentration. The eSense metric of attention and beta EEG brain activity patterns in the last two hours of driving with no break, and in the last 30 minutes of the second stage of four hours of driving with a break of 30 minutes show elevations in cortical arousal. The effect appears to be progressive, and it is seen particularly to have had significant impacts on the participant's ability to concentrate during the last 45–60 minutes of the experiments. These observed effects could be interpreted as the requirement to drive well necessitating progressively higher cortical arousal after about three hours of driving, especially in the driving task of four hours with no break. Since these effects were not seen during the first 30 minutes (baseline), this could be regarded as evidence of a cumulative fatigue effect or a driving performance decrement.

In sum, the eSense metric of attention and beta EEG brain activity patterns demonstrated signs of cortical arousal during the last hour of the driving task, and is associated mainly with performance decrements or fatigue, regardless of the experiment task (driving without or with a break). The correlation between the average brain activity (increases or decreases in responsiveness) and subjective fatigue assessments demonstrates significant deterioration in a subject's fatigue and performance decrements. The observed decreases or increases in the psychophysiological responses in this study were statistically significant. Furthermore, a slight increase in average eSense metric of attention and decreased average beta EEG brain activity following the rest break indicates the post-break recovery of the participants. The subjective fatigue assessments also demonstrated that the driver showed evidence of recovery at the beginning of the second stage of the experiment of driving with a break (after 30 minutes of break).

Variations in duration spent driving are very influential in the extent of the cumulative effect seen when hours of driving tasks are concluded without a break. In this study, whenever driving time influences a mediate stimulated psychophysiological state, few or no cumulative fatigue or performance decrement effects were observed. At the end of the driving task of four hours with no break when the psychophysiological effects depressed the arousal level, strong cumulative fatigue effects were experienced by all the participants. The results also demonstrated a significant change in the driving performance and decreases in fine steering were appearing in the last 60 minutes of the driving tasks without a break, as compared to 30 minutes of the driving task with a 30 minute break. There is a significant increase in average beta EEG brain activity, a lower average value of the eSence metric of attention and higher ratings of subjective fatigue assessment in the last 60 minutes of performing the driving task for four hours without a break compared to four hours of driving with a 30 minute break after two hours of driving.

Elements such as gender and age of the participants showed more variation among factors of driving fatigue. This study examined the effect of gender and age of the participants on driver fatigue. Female and young participants reported the highest levels of subjective fatigue or performance decrements in all of the three stages of the experiments, but they were more noticeable in the last 60 minutes of driving without a break. The results of the study demonstrate that there is a significant difference in psychophysiological responses within genders and different age groups. It was found in this study that female drivers express more fatigue than males under the same experimental conditions. These results fall in line with the most previous studies, suggesting that female drivers are more inclined to fatigue than male drivers. It could be concluded from the results of this study that female drivers are more liable to deviate from an optimal condition of being fully alert and able to concentrate to a state of being fatigued and unable to concentrate. Such effects would even be more prominent in female drivers due to the relatively lower ability of many females to continually engage in challenging tasks for a long time. Therefore, the decision-makers should no longer neglect the requirements that the female drivers have for driving performance decrements or fatigue. The gender variations in the level of the participant's driving fatigue in this study indicate that females have, on average, a more significant need for individual management and adaptive actions of fatigue compared to males. Therefore, it could be suggested from the results of this study that females should mainly be used as the principal subjects when investigating and evaluating driver fatigue requirements.

Furthermore, there is variation in the psychophysiological responses of drivers of different age groups. The results demonstrated that younger drivers exhibit a higher level of performance decrement as the influence of time spent in conducting the driving tasks, most especially driving tasks of four hours with no break versus older drivers. The practical implication is that researchers should no longer neglect the significant needs that younger drivers have for driving fatigue. Also, the differences in age groups indicate that younger drivers have, on average, a potential need for driving-fatigue adaptive actions rather than older drivers. Therefore, it can be concluded from the results of these studies that young drivers should be used as the principal subjects in decision making as well as in any study to enhance improvements that could help uncover the nature of driving fatigue or performance decrement conditions that certain age groups are more vulnerable of.

Passenger discomfort's multidimensional nature makes it possible to study the interplay between the various dimensions of comfort when using EEG. The results of the within-subject effects analysis test showed that different factors of discomfort could be distinguished by using EEG. Road roughness characteristics, passenger posture and bus type all affect passenger discomfort in different ways and magnitudes.

The findings of this research indicated that the brain's electrical activity could be recorded in an operational environment, including on asphalt and sett pavements. The findings demonstrated that the impacts of road roughness on passenger comfort are prominent on sett pavement compared to asphalt pavement. Such effects could result in poor musculoskeletal conditions in the neck, back and shoulders or could even result in stress-related heart diseases (Sezgin and Arslan, 2012). The psychophysiological effects significantly depressed (eSence metric of attention) and activated (beta EEG brain activity) the level of arousal, strong cumulative discomfort, or stress effects that were experienced by all the participants. Passenger discomfort effects are evident on sett pavement, both while standing or seated in single- or double-decker buses as compared to asphalt pavement. The main finding from the data was that travel on sett pavement (seated or standing) showed higher passenger discomfort, resulting in dissatisfaction, compared to riding on asphalt pavement in seated or standing postures. The evidence for this conclusion includes significant changes in the psychophysiological response and variations in subjective comfort assessment of all the participants relative to the influence of pavement types. These responses demonstrate that discomfort was perceived on sett pavement in all postures in both single- and double-decker buses compared to asphalt pavement. The results indicate the multidimensional nature of the passenger's discomfort and re-affirms that the passenger's psychophysiological responses can either benefit or detriment the long-term psychophysiological condition of individuals. Besides, the subjective assessment results showed that passengers are more strained or tensed on sett pavement. The results of this study indicated that passenger comfort deteriorates as the road roughness coefficient increases. This effect is probably because significant changes were obtained in the passenger's psychological and physiological responses from the optimal states (asphalt-pavement-seated) to the state of discomfort or stress on sett pavement.

Posture is one of the most significant factors in the evaluation of the cumulative effects of passenger discomfort. Passengers who are standing in urban buses suffer more significant subjective discomfort and psychophysiological stress than passengers who are seated on the same bus at the same time. The evidence for this conclusion includes significantly greater feelings of discomfort experienced by passengers during the experiments (trips) that involved travelling on asphalt or sett pavements in single- or double-decker buses. These findings indicate that a pronounced psychophysiological response exists relative to the influence of the passenger's postures. This psychophysiological response is aligned such that passenger's comfort is significantly affected while standing and is better while seated on either single- or double-decker buses. Also, there are variations in the passenger's responsiveness to the influence of posture, which is characterised by a sharp decrement (eSence metric of attention) and increment in beta EEG brain activity.

This study examines the effect of gender and age on bus passenger's discomfort. The results of the study demonstrate that there is a significant difference in psychophysiological responses within the genders and different age groups. It was found in this study that female passengers express more discomfort/dissatisfaction than males under the same experimental conditions. It could be concluded from the results of this study that female passengers are more sensitive than males to deviation from optimal comfort conditions. Therefore, the ergonomics, planners and decision-makers should no longer neglect the requirements that the female passengers have for discomfort. The gender variations in the psychophysiological responses (comfort or discomfort) in this study indicate that females have, on average, a more significant need for individual management and adaptive actions of discomfort compared to males. Therefore, it could be suggested from the results of this study that females should mainly be used as the principal subjects when investigating and evaluating urban bus passenger discomfort because if females are satisfied and comfortable, then it is positively sure that males will also be satisfied and comfortable.

Furthermore, there is variation in the psychophysiological responses of passengers of different age groups. The results demonstrated that younger passengers are more strained than older ones due to the influence of road roughness, posture and bus type. These results depict the need to consider the variations and interactions between different types of age effects. The age group differences indicate that younger passengers have, on average, a potential need for discomfort management and adaptive actions than older passengers. The practical implication is that researchers should no longer neglect the needs that younger passengers have for discomfort. Therefore, it can be concluded from the results of these studies that a decision should be made to enhance improvements that could help uncover the nature of travel-stress related discomfort in which certain age groups are vulnerable.

8.3 Research Contributions

The EEG data application in this study is designed to link the brain activity dynamics to changes in experimental design variables or tasks by correlating increased or decreased measured brain activity. The primary dependent measure in most studies is determining whether the average brain activity measured through event-related-potential or field component amplitude increases or decreases relative to the experimental design variables or tasks compared to the baseline. The study added values to the implicit assumption that localised psychological and physiological processes are specific to brain regions, and can be measured by an increase or a decrease in average psychophysiological responses in different experimental conditions.

Also, this study presented a unique contribution to the body of research on the respondent's psychophysiological responses, impacts of road roughness characteristics, posture and bus type on a passenger's discomfort, and the influence of duration of driving and rest break time on driving fatigue. It also presented how passenger discomfort and driver fatigue appear to shift across genders and age groups. These findings may be leveraged in future research by examining how female and young participants are affected by the experimentally designed variables, and thus, help understand how participants respond and what they mean.

Over time, conventional evaluations of passenger ride comfort have been conducted by different researchers using subjective approaches, which are characterised by the problem of indistinctness of evaluation criteria (Muto et al., 2013). An objective and subjective approach of comfort assessment that cannot evaluate human feelings were directly used (Zhao et al., 2016; Zhang et al., 2014; (Tan et al., 2008)(Tan et al., 2008)(Tan, Delbressine, Chen, & Rauterberg, 2008)(Tan, Delbressine, Chen, & Rauterberg, 2008)Kottenhoff & Jerker Sundström, 2012; Eboli & Mazzulla, 2011; Lin et al., 2010; Cascajo & Monzón, 2007; Hoberock, 1977; Hoberock, 1976). Consequently, this research established the need for evaluation methods of using biological signals that can directly reflect the human state and sensations (physiology or psychology). The methodology presented in this research and the obtained results could contribute to the development of system solutions to significantly optimise passenger comfort in the public transport system. The observed changes in average psychophysiological response (brain activity) could be used to develop an algorithm to identify the different levels of passenger comfort and driver fatigue. The results from this study demonstrate that the EEG analysis indicated significant signal alterations in both passenger comfort and driver fatigue. These research findings demonstrate the possibility of using EEG as a reliable or potential approach to monitoring bus passenger comfort and driver fatigue in real life.

A few contributions were made in this research. However, this research's significant contributions have been the application of EEG to investigate the influence of road roughness characteristics, passenger posture, and bus type on bus passenger comfort in real-world driving conditions. Additionally, findings in this research proved the effectiveness of using EEG to investigate passenger comfort and monitor driving fatigue.

It is also provided with a new perspective and standpoint to adapt a novel machine learning procedure and system for investigating the nature of physiological and psychological signals relative to the influence of passenger comfort and driving fatigue experimentally designed variables. Another contribution of this research has been the development of a novel approach that incorporates EEG brain activity and subjective assessments. These results corroborate and enhance the classification performance of EEG-based bus passenger comfort assessments and driving fatigue detections.

8.4 Limitation

There are obvious limitations to this study, mostly related to the generalisability of some of the results. This study's main limitations are the number of artefacts in the EEG data regarding the poor-to-noise ratio. The number of artefacts identified in this study is widely varied by conditions of the experiments and the participants (Kim et al., 2019; Bell & Cuevas, 2012; Mognon et al., 2011). The artefacts' influence causes small different variations in data points that are available to analyse the participant's psychophysiological responses in the same experimental stage (baseline and task-related). In the research design for this study, the participants were assigned to different experimental tasks. It is essential to verify that the amount of data between each experimental task or group is similar per participant. Therefore, EEG data cleaning and processing required a significant amount of time, thereby influencing the study sample size (Kim et al., 2019; Mognon et al., 2011). Only the EEG data associated with the cognitive process of interest (experimentally designed variables) are included in the data analysis. Therefore, future studies should work more on designing experimental tasks and taking adequate care to ensure a high-quality EEG signal that is free of non-EEG electrical signals or "noise during electrode application.

Many dimensions characterise EEG data; therefore, there are many possible statistical comparisons across frequency, time and the power/phase of the EEG data. From the feasibility study conducted in this research, the interactions among EEG data dimensions, using time-domain averages, make spurious Type I errors possible, especially when using exploratory analyses (Cohen, 2011). In this study, the balance opens to unpredicted and unexpected, but robust patterns of data analysis results. Therefore, this study's experimental data analysis was conducted by using only the time-domain average approach to analyse and present psychophysiological data.

Also, due to taking on a cross-sectional design and time available for the study, more longitudinal studies would be required to provide more insight into the relationship between a passenger's posture, road roughness characteristics and bus types as well as a passenger's psychophysiological response. Also, the full spectrum of road roughness characteristics over every section of the sample route should be investigated to determine the degree of roughness that is crucial for a passenger's ride comfort. Furthermore, an urban passenger study was conducted on only two bus corridors, and 20 subjects were sampled in only one city. Future studies should include many routes and many participants in different cities to generalise results and to have more robust evidence of relationships between the dependent and independent variables. In other words, a significant number of sample routes and participants will be required to increase the research's statistical power, thereby improving the validity of the findings and making them acceptable to larger populations.
Although the urban bus passenger experimentally designed variables in this study may be similar across studies, it is impossible to generalise findings across gender and age groups. Also, the missing vulnerable people, such as pregnant women, passengers in a wheelchair and old-age groups can be targeted for further study. Therefore, further research can be inclusive in approach and extended to cover a larger sample size or studies, different age groups, and research contexts based on the method developed in this study by using EEG. Thus, more studies are required to conclude the observable variations across such variables, most importantly, the age group that is only considered < 30 years and > 30 years.

The study on driver fatigue was conducted by using a simulator, and future research should be conducted in real life by using a larger sample size. The laboratory experiments investigated only the influence of the duration of driving and rest breaks on fatigue. Other factors such as circadian cycle, time of the day, time at work and cumulative sleep deficit and recovery should be incorporated or form part of the independent variables to increase the statistical power of the analysis and improve the results' validity.

Despite the compelling results being achieved in this research, future research should investigate and use state-of-the-art algorithms to enhance EEG performance on passenger discomfort and driver fatigue. Future research should explore other vital factors, such as BMI, frequency of using the bus and body fitness that drives and affects urban bus comfort or discomfort, along with how these factors are valued across development and urban transport ergonomists. This study's limitations and considerations reinforce the approach that analysing the temporal dynamics of neural activity brings this research closer to the real complexity of the relationship between the participant's psychophysiological response and experimentally designed variables. Even though the above limitations could prevent using this research to draw a generalised conclusion, the outcomes demonstrated the capability of applying EEG in the understanding of human behaviours, performance and decisions in transport applications.

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APPENDIX I

Table 1: Driving fatigue data onts er subject

Experimental Phase	Time (minute)	Subject 1	2	3	4	5	6	7	8	9	Total
2 hours of driving before 30 minutes break	30	1655	1660	1655	1658	1651	1646	1654	1662	1650	14891
	60	1658	1658	1659	1651	1668	1653	1651	1655	1656	14909
	90	1667	1650	1672	1661	1654	1671	1648	1671	1653	14947
	120	1648	1663	1669	1648	1659	1650	1664	1651	1664	14916
2 hours of driving after 30 minutes break	30	1646	1653	1669	1654	1649	1665	1652	1653	1658	14899
	60	1669	1660	1651	1659	1663	1655	1649	1650	1652	14908
	90	1660	1664	1657	1662	1662	1662	1665	1667	1663	14962
	120	1649	1673	1653	1640	1655	1652	1658	1664	1668	14912
4 hours driving with no break	30	1675	1655	1664	1655	1649	1648	1662	1645	1646	14899
	60	1655	1666	1643	1657	1658	1663	1654	1661	1650	14907
	90	1653	1658	1670	1647	1663	1669	1649	1655	1652	14916
	120	1647	1651	1667	1655	1667	1660	1655	1658	1664	14924
	150	1673	1654	1654	1661	1657	1656	1652	1669	1654	14930
	180	1654	1663	1642	1667	1658	1664	1658	1651	1658	14915
	210	1662	1653	1667	1648	1647	1657	1662	1664	1669	14929
	240	1659	1664	1670	1667	1661	1653	1669	1651	1659	14953
Total		26530	26545	26562	26490	26521	26524	26502	26527	26516	**238717**

Table 2a: Passenger discomfort data point per subject (subject 1 – 10)

Experimental Phase	Subject									
	1	2	3	4	5	6	7	8	9	10
Bassline	557	560	553	577	575	552	562	548	567	553
Asphalt-single-seated	761	789	767	782	759	774	772	780	770	778
Asphalt-single-standing	456	495	447	479	483	483	473	488	466	471
Asphalt-Double-seated	773	777	768	751	771	778	781	766	772	791
Asphalt-Double-standing	465	468	489	466	485	446	483	462	453	471
Sett-single-seated	208	199	196	202	192	188	184	204	199	196
Sett-single-standing	205	192	204	189	194	201	202	196	201	198
Sett-double-seated	201	214	199	209	210	203	198	191	202	203
Sett-doble-standing	207	201	192	207	198	197	205	193	205	195
Total	3833	3895	3815	3862	3867	3822	3860	3828	3835	3856

Table 2b: Passenger discomfort data point per subject (subject 11 – 20)

Experimental Phase	Subject									
	11	12	13	14	15	16	17	18	19	20
Bassline	561	552	555	563	559	551	568	561	546	549
Asphalt-single-seated	775	779	791	751	772	772	790	774	785	779
Asphalt-single-standing	465	467	453	471	450	475	459	469	447	472
Asphalt-Double-seated	783	760	781	780	782	764	773	769	780	764
Asphalt-Double-standing	466	462	466	465	464	456	464	470	475	463
Sett-single-seated	190	195	200	197	196	191	199	197	211	195
Sett-single-standing	188	203	212	192	201	203	208	202	206	200
Sett-double-seated	195	202	196	202	211	192	195	208	205	198
Sett-doble-standing	186	191	187	182	198	213	202	218	184	204
Total	3809	3791	3841	3803	3833	3817	3858	3868	3839	3824